

A deep learning-based pin precision weeding machine with densely placed needle nozzles[☆]

Hyungjun Jin ^{a,1}, Dewa Made Sri Arsa ^{a,b,c,1}, Talha Ilyas ^{a,f,g}, Jong-hoon Lee ^a, Okjae Won ^d, Seok-Hwan Park ^e, Kumar Sandesh ^{a,b}, Sang Cheol Kim ^a, Hyongsuk Kim ^{a,b} ^{*,*}

^a Core Research Institute of Intelligent Robots, Jeonbuk National University, Republic of Korea

^b Division of Electronics and Information Engineering, Jeonbuk National University, Republic of Korea

^c Department of Information Technology, Universitas Udayana, Indonesia

^d Production Technology Research Division, Rural Development Administration, National Institute of Crop Science, Republic of Korea

^e Division of Electronic Engineering, Jeonbuk National University, Republic of Korea

^f Faculty of Engineering, Monash University, Melbourne, Australia

^g AIM for Health Lab, Faculty of IT, Monash University, Melbourne, Australia

ARTICLE INFO

Keywords:

Deep learning
Needle nozzle
Precision weed control
Precision agriculture
Weeding machine

ABSTRACT

With advancements in artificial intelligence and robotic technology, the demand for innovative weed control methods has increased. This paper proposes a novel weeding machine concept that integrates artificial intelligence with micro-needle nozzles, enabling precise and selective herbicide application based on weed size and type. The system employs deep learning-based semantic segmentation to accurately identify weeds at the pixel level. Following identification, densely arranged needle nozzles deliver fine streams of herbicide directly to targeted weeds. The herbicide dosage is regulated by time-controlled shooting, facilitated by solenoid valves. The developed pin-precision weeding machine features a 1.20-meter-wide nozzle plate bar equipped with 128 injection needles, enabling simultaneous herbicide application to multiple weeds. In an open bean field, the detection accuracy of the proposed Spray-Net achieved a mean Intersection over Union (mIoU) of 88.6% for bean instances and 90.9% for weed instances. Furthermore, the system demonstrated a detection speed of 28 frames per second (fps) and a hitting accuracy of 86.1%. Notably, the proposed weeding machine boasts a weeding capacity of up to 4266 weeds per second with 128 nozzles in operation. The proposed pin-precision weeding machine represents a pioneering approach in environmentally friendly, intelligent weed management.

1. Introduction

In response to recent challenges, such as the declining availability of human labor and the detrimental effects of excessive pesticide usage, advanced technologies are increasingly being integrated into agriculture. This shift has led to the rise of artificial intelligence (AI), robotics, and automation-based smart farming, marking a new paradigm in the field (Li et al., 2022; Rai et al., 2023). The significant development of robot vision technology can be attributed to the advent of convolutional neural networks (CNNs) (LeCun et al., 2010; Aarathi and Harini, 2018). This technology analyzes images in various ways, combines them, and extracts only features for learning while going through several convolutional layers (Ma et al., 2020). In addition, if the output deviates from

the desired value, the parameters of each layer are adjusted according to the learning rule, refining the model's accuracy.

One of the most active applications of the CNNs is image classification (Howard, 2014; Guo et al., 2017). The use of CNNs have brought bright shine in the research areas of deep learning (Aloysius and Geetha, 2017). To make CNNs more robust to image transformations, such as translation, scaling, and rotation, Shen et al. (2016) introduces a method that randomly alters activation maps during training. This approach helps each kernel produce more transformation-invariant results by processing input feature maps across various transformation levels. Guo et al. (2017) further presents a simple image classification framework.

[☆] This article is part of a Special issue entitled: 'Intelligent Machinery and robot' published in Computers and Electronics in Agriculture.

* Corresponding author.

E-mail addresses: lskyl01@jbnu.ac.kr (H. Jin), 202155383@jbnu.ac.kr, dewamsa@unud.ac.id (D.M.S. Arsa), talha@jbnu.ac.kr (T. Ilyas), jonghoon@jbnu.ac.kr (J.-h. Lee), ojwon@korea.kr (O. Won), seokhwan@jbnu.ac.kr (S.-H. Park), sandeshkumar@jbnu.ac.kr (K. Sandesh), sckim7777@gmail.com (S.C. Kim), hskim@jbnu.ac.kr (H. Kim).

¹ First authors equally contributed.

Recent advancements in CNN-based applications in agriculture have gained significant attention. For instance, [Milioto et al. \(2018\)](#) proposed a real-time semantic segmentation approach for crop and weed recognition in precision agriculture robots, utilizing CNNs that leverage existing vegetation indexes to classify data in real time. [Jiang et al. \(2020\)](#) introduced a CNN feature-based graph convolutional network (GCN) for weed and crop recognition, constructing a GCN graph using CNN-extracted weed features and their Euclidean distances. Similarly, [Zou et al. \(2022\)](#) developed a modified U-Net for segmenting wheat and weeds, incorporating spatial and channel attention mechanisms ([Ma et al., 2022, 2024](#)) alongside a novel activation gate. [Ruigrok et al. \(2023\)](#) investigated the generalization error of plant-detection models for precision weed control, reducing errors through incremental training and achieving a plant-detection model with an average generalization error of 0.06 mAP. Additionally, [Ilyas et al. \(2023\)](#) addressed the challenge of variable field conditions, which often hinder CNN performance in agricultural applications. By employing an unsupervised domain adaptation approach, [Ilyas et al. \(2023\)](#) effectively reduced the domain gap, thereby enhancing model robustness across diverse environmental conditions. Finally, [Cui et al. \(2025\)](#) proposed a hybrid model combining CNNs with a Transformer-based architecture, achieving a high F1-score of 98.56% for weed recognition.

As artificial intelligence (AI) technology advances, agricultural robots utilizing AI have been developed. There is increasing demand for new weed control robots that can selectively target specific weeds, execute weed control swiftly and precisely, and improve efficiency both economically and practically compared to traditional methods. Although herbicide application is an effective way to reduce weeds, redundant herbicide application is inefficient and costly, and it can increase weed resistance to herbicides ([Midtiby et al., 2011](#); [Young and Giles, 2013](#)). The growing need to minimize herbicide use due to health and environmental concerns has spurred the development of more eco-friendly and economical systems, such as those applying ultra-low doses of herbicides directly to the target weeds ([Midtiby et al., 2011](#)).

Various targeted robotic spraying systems and adjustable spraying machines have been developed for micro-dose herbicide applications. Some researchers have designed robot systems that use herbicide application end-effectors to apply herbicides exclusively to weeds, avoiding inappropriate chemical use ([Jeon and Tian, 2009](#); [Zhao et al., 2016](#)). [Luck et al. \(2010\)](#) demonstrated that map-based automatic boom section control technology in agricultural spraying can significantly reduce off-target chemical application errors. Similarly, [Faiçal et al. \(2017\)](#) introduced a computer-based system that uses autonomous route adaptation for Unmanned Aerial Vehicles (UAVs), optimizing pesticide spraying under varying weather conditions and ensuring more precise, environmentally friendly pesticide deposition. [Xiao et al. \(2017\)](#) integrated color and depth information using Microsoft's Kinect system to propose equations for calculating the average distance between the Kinect system and fruit trees, as well as leaf wall area (LWA) density, enhancing the precision of pesticide spraying and improving efficiency while reducing waste and environmental pollution in intelligent orchard production. Furthermore, [Hong et al. \(2018\)](#) developed a software tool to estimate spray efficiency and drift from orchard air-assisted sprayers. [Li et al. \(2023\)](#) also developed a high-precision patch-spraying robot system for site-specific weed management, enabling precise droplet delivery and efficient weed control.

A different weeding technology, laser weeding robots equipped with laser pointers, has also emerged ([Zhenyang et al., 2013](#); [Xiong et al., 2017](#); [Arsa et al., 2023](#)). These robots autonomously navigate cultivation areas, scanning and eliminating weeds with lasers. However, they consume significant energy for laser operation and often struggle to hit weeds precisely, as the laser scans from a distance of around 300 mm from the crops. Additionally, managing large numbers of mature weeds, which require multiple laser strikes, is challenging in practice. The high

production costs of laser weed control equipment further impose an economic burden on farmers.

Other systems employ fluid delivery to individual seedlings, guided by a six-jointed arm with image-capturing and inverse kinematics to direct the spray nozzle at each target ([Underwood et al., 2015](#)). [Berenstein and Edan \(2017b,a\)](#) designed an adjustable spraying machine mounted on a robotic sprayer for precise pesticide application. This machine features an adjustable spraying machine with a spray nozzle, a servo motor, and a camera, and it was developed for site-specific agricultural applications.

In the realm of agricultural robotics, various studies have focused on controlling and navigating robots for precision agriculture. [Zhang et al. \(2022\)](#) used a Many-objective Evolutionary Algorithm to solve the route-planning problem for agricultural mobile robots, achieving efficient route planning and reducing navigation distances during agricultural tasks. [Firkat et al. \(2023\)](#) introduced FGSeg, a ground segmentation algorithm based on LiDAR technology, which effectively distinguishes between horizontal and sloped terrains for agricultural robots. Additionally, [Hizatate and Noguchi \(2023\)](#) proposed an optimal work-scheduling algorithm for autonomous spraying electric robots in orchards, using multi-layered genetic algorithms to optimize work schedules.

The closest study to the proposed work is by [Özliüoymak \(2022\)](#), who introduced a needle nozzle weeding tool. This system utilizes a single needle nozzle, which moves horizontally to cover the conveyor belt area using a tripod-type robotic arm. When laser-based weeding robots were gaining attention as eco-friendly weeding methods, this study stood out for its innovative use of cost-effective herbicide application instead of expensive lasers. In their weeding experiment, artificial flowers were transported on a conveyor belt, and herbicides were sprayed onto weeds. However, a significant limitation was the need for the robot arm to move to the weed's location each time one appeared, leading to a movement time of over 1000 ms. Additionally, the system lacked functionality to distinguish between weeds and crops, limiting its practical application.

In contrast, the proposed study addresses these issues by densely arranging needle nozzles in fixed positions, eliminating the need for nozzle movement and reducing the time required to target each weed. The use of 128 parallel nozzles allows for the simultaneous shooting of small amounts of herbicide, enabling a high-speed weeding capacity of up to 4266 weeds per second (128 nozzles, 30 ms/shooting). Moreover, the system's ability to distinguish between weeds and crops at the pixel level makes it highly practical for real-world applications.

The aim of this study is to achieve precise weeding by using deep learning to identify weeds and deliver an appropriate amount of herbicide based on their size and type, using needle nozzles. The novel spraying machine was tested on a conveyor belt to assess its feasibility for weeding applications. The contributions of this work are as follows:

1. Weed identification with semantic segmentation and pin precision weed control using needle nozzles.
2. Very high accuracy rate of hitting the weeds due to the fixed and densely positioned nozzles.
3. High speed of weeding with a maximum of 4266 weeds/second (128 nozzle case)
4. Accurate hitting of weeds using needle nozzles with a linear and non-dispersive shoot-out.
5. Controllable herbicide quantity depending on the type and size of weeds through high-speed control of solenoid valves.
6. Effective recycling of leaked herbicide in the solenoid valves utilizing the difference between the adhesion force of the metal plate and surface tension of water.

The remainder of this paper is structured as follows: Section 2 provides a detailed description of the proposed weeding system and its components. Section 3 presents the experimental results. Finally, Section 4 concludes the paper with a summary of the findings.

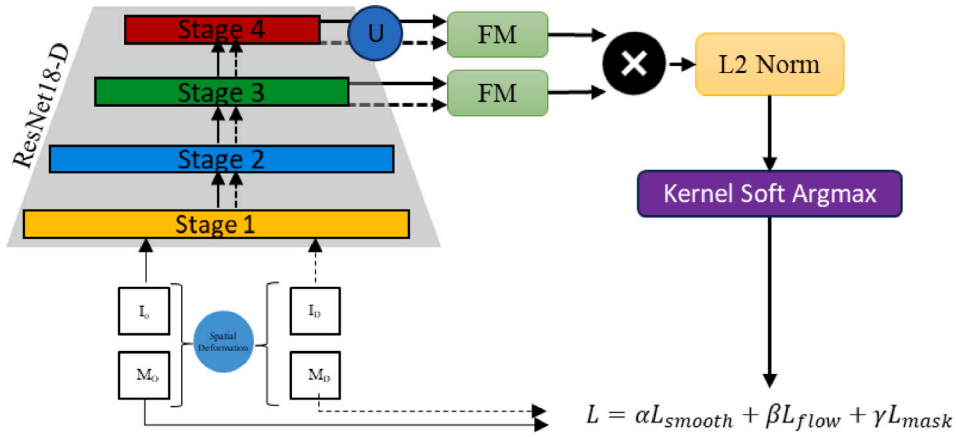


Fig. 1. Network architecture, the solid arrows show the flow of the original input image, and the dashed arrow shows the flow of the deformed input image. Both images are passed through the network one by one to extract features and then further processing is done. During inference, only the input image is used.

2. Materials and methods

2.1. Spray-Net: A real-time crop (bean) and weed recognition neural network

In our study, we address the challenge of real-time crop and weed recognition in bean fields by utilizing semantic segmentation technology, which enables pixel-level classification of beans and weeds. Numerous previous works have explored semantic segmentation technologies (Noh et al., 2015; Long et al., 2015; Chen et al., 2017; Liu et al., 2018; Chen et al., 2018), which employ operations like unpooling, deconvolution, and rectification to generate dense, pixel-wise class probability maps. The algorithm frames semantic segmentation as an instance-wise segmentation problem, where the network takes a sub-image (potentially containing an object, referred to as an instance) as input and produces pixel-wise class predictions as output. To perform semantic segmentation on an entire image, the network is applied to each candidate proposal extracted from the image, and the outputs of all proposals are aggregated back into the original image space.

As the backbone network, ResNet (He et al., 2016) is employed for semantic segmentation in the bean and weed classification task. ResNet (Residual Neural Network) is a deep learning model in which the weight layers learn residual functions with respect to the layer inputs. ResNet uses skip connections that perform identity mappings, which are then merged with the layer outputs via addition. This design allows deep learning models with dozens or even hundreds of layers to be trained efficiently, improving accuracy as the model depth increases.

Specifically, we propose the Spray-Net architecture (see Fig. 1), which integrates ResNet18-D (He et al., 2016) as its backbone to reduce the computational footprint and enhance inference speed. This methodology is optimized to distinguish between two primary foreground classes: crop (bean) and weed, labeled as ‘1’ and ‘2’ respectively, along with a background class labeled as ‘0’.

Our dataset consists of images sourced from bean fields, with each pixel annotated into one of three categories: ‘0’ for the background, which includes soil and other non-relevant elements, ‘1’ for bean plants (crops), and ‘2’ for weeds. These annotations serve as the ground truth during the training phase, enabling the network to learn the subtle differences between crops and weeds.

The ResNet18-D backbone is employed to extract a rich hierarchy of features from the input images. As the input image passes through the network’s layers, the model captures hierarchical features at different levels. The initial layers capture basic features such as edges and textures, while deeper layers capture more complex and abstract patterns. The output of each convolutional layer is a feature map that represents the spatial distribution of specific features in the input image.

Upon extracting features from both the original image and its spatially deformed counterpart, they are channeled through the Feature Matching (FM) layer. Traditional methods might falter to capture the spatial deformations necessary for fine-grained localization. To overcome this, we incorporate additional adaptation layers that extract task-specific features, ensuring high discrimination in terms of both appearance and spatial context. This process produces a feature map with dimensions $h \times w \times c$ for each image, where $h \times w$ represents the grid of c -dimensional local features. After feature extraction, L2 normalization is applied to the c -dimensional features, resulting in a semantically rich and highly discriminative feature set. The detailed architecture of the FM layer is illustrated in Fig. 2.

Subsequent to feature extraction and matching, the features are passed to the Kernel Soft Argmax layer. This layer is pivotal in establishing dense correspondences, or semantic flow, between images. Traditional argmax operations, being non-differentiable, are not suitable for end-to-end deep learning training. The Soft Argmax (Lee et al., 2019), a differentiable approximation of argmax, addresses this issue. Its “Kernel” variant further refines the approximation, ensuring resilience against multi-modal distributions and offering sub-pixel level flow fields. The kernel, which can be Gaussian or another suitable function, assigns weights based on the distance from the peak, enhancing robustness against multi-modal distributions. For more detailed information, readers can refer to Lee et al. (2019).

2.1.1. Loss function

The success of the proposed architecture in differentiating between crop and weed in real-time hinges on a composite loss function. This loss function is meticulously designed to ensure that the network’s predictions align closely with the ground truth, maintain spatial consistency, and produce smooth transitions between class predictions. In this study, we combined three loss functions, such as mask consistency loss $\mathcal{L}_{mask}$, flow consistency loss $\mathcal{L}_{flow}$, and smoothness term $\mathcal{L}_{smooth}$.

The mask consistency loss, $\mathcal{L}_{mask}$, ensures that the predicted segmentation masks are consistent with the ground truth annotations by measuring the pixel-wise difference between the two. Formally, it is defined as:

$$\mathcal{L}_{mask} = \frac{1}{N} \sum_{i=1}^N |P_i - GT_i| \quad (1)$$

where P_i represents the predicted value for the i th pixel, GT_i denotes the ground truth value, and N is the total number of pixels in the mask. The flow consistency loss, $\mathcal{L}_{flow}$, ensures that spatial relationships between pixels in the predicted output align with those in the ground truth. This is particularly important for capturing local changes and preserving the structural integrity of objects. The function F captures

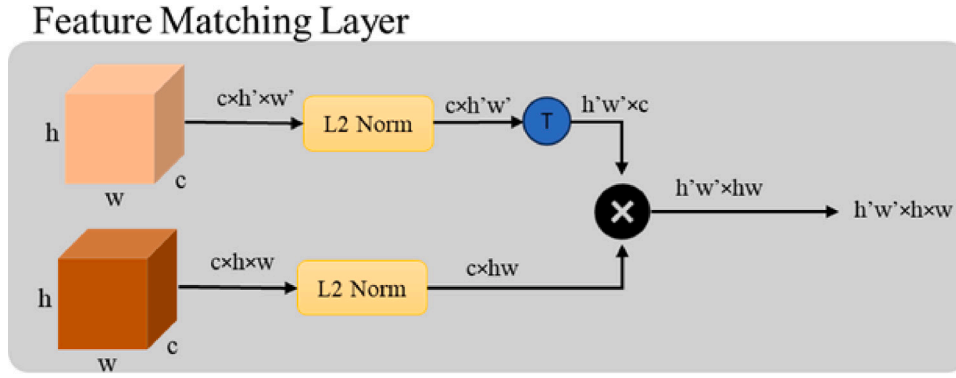


Fig. 2. Overview of feature matching block (FM).

both local changes in feature values and the overall similarity of each pixel with its neighbors. The spatial gradient at a pixel (x, y) , computed for both horizontal (G_x) and vertical (G_y) directions, is defined as:

$$G_x(x, y) = I(x + 1, y) - I(x - 1, y) \quad (2)$$

$$G_y(x, y) = I(x, y + 1) - I(x, y - 1) \quad (3)$$

Additionally, the local similarity S is calculated over a window w centered at pixel (x, y) . The local similarity S captures the similarity of a pixel's feature values with those of its neighbors. The local similarity is computed as:

$$S(x, y) = \frac{1}{|w|} \sum_{(i,j) \in w} I(x + i, y + j) \quad (4)$$

Combining the spatial gradient and local similarity, F is expressed as:

$$F(x, y) = \lambda_G \sqrt{(G_x^2(x, y) + G_y^2(x, y))} + \lambda_s S(x, y) \quad (5)$$

where λ_G and λ_s are weights for the spatial gradient and local similarity, respectively. The flow consistency loss can be written as:

$$L_{flow} = \frac{1}{N} \sum_{i=1}^N |F(P_i) - F(GT_i)| \quad (6)$$

Furthermore, the smoothness term, $\mathcal{L}_{smooth}$, enforces smooth transitions between class predictions. It is especially crucial in regions where crops and weeds are in close proximity, ensuring that the boundary between these classes in the predicted mask is smooth and not jagged. The smoothness term can be implemented as a regularization term that penalizes abrupt changes in the predicted mask. It can be represented as:

$$L_{smooth} = \frac{1}{N} \sum_{i=1}^N |\nabla P_i| \quad (7)$$

Here, ∇P_i is the gradient of the predicted value of the i th pixel, indicating the change in prediction values between neighboring pixels. The overall loss function, $\mathcal{L}$, is a weighted combination of these three components:

$$\mathcal{L} = \alpha \mathcal{L}_{smooth} + \beta \mathcal{L}_{flow} + \gamma \mathcal{L}_{mask} \quad (8)$$

Here, α , β , and γ are hyperparameters that control the relative contribution of each component to the overall loss. In our study, we determined that setting $\alpha = 0.4$, $\beta = 1.0$, and $\gamma = 0.6$ achieved the optimal performance, as supported by the ablation results discussed in Section 3.3. In conclusion, our composite loss function plays a pivotal role in training the network effectively. By balancing mask consistency, flow consistency, and smoothness, it ensures that the network produces accurate and visually coherent predictions for real-time crop and weed recognition.

2.1.2. Training and inference

During the training phase, apart from the input image, a target image is generated using synthetic geometric deformations. The network is trained to establish dense correspondences between the input and the deformed target image by utilizing the annotated masks. A key advantage of our approach is that, during inference, no target masks are required. The trained model can directly predict the class of each pixel in real-time from field images, making the process highly efficient and streamlined. The output is a semantic map that distinctly identifies crops, weeds, and background, enabling immediate and precise weed control actions. This semantic map can then be utilized by the spraying algorithm to target and eliminate weeds effectively.

2.2. Pin precision parallel weeding with densely positioned needle nozzles

Traditional agricultural nozzles, predominantly broadcast-type sprayers, are designed for general use, applying treatments indiscriminately to both pests/insects or weeds. However, nozzles for the weeding should be different from that for pests/insects since misusing herbicide to crop results in serious damage to crops or missing weeds will lead to the failure of weed control.

The configuration of the proposed weeding machine is as shown in Fig. 3. The machine features an array of 128 needle nozzles, adapted from medical injection technology, which are capable of delivering herbicide with high precision. These needle nozzles provide a straight, fine stream, making them ideal for selective weeding. Unlike traditional spray-based systems that indiscriminately cover broad areas—including regions devoid of weeds—our needle-based approach allows for targeted herbicide application. This reduces the risk of harming non-target organisms, preserving soil health, and minimizing the accidental spraying of crops. Fig. 4 highlights the contrast between conventional spray nozzles and the proposed needle system: while spray nozzles apply herbicide to wide areas, often unnecessarily affecting crops and the surrounding ecosystem, the needle nozzles provide a focused, controlled method for targeting only the weeds. Additionally, the machine is equipped with multiple solenoid valves (denoted as S.V #) and hoses to regulate the opening and closing of each nozzle. These are managed via a control unit that interfaces with the system through a USB GPIO module, allowing precise control of herbicide release. Each of the 128 solenoid valves (Solenoid Valve #0 to Solenoid Valve #127) can be individually activated to ensure optimal weed control while minimizing collateral damage to crops.

The weeding process is guided by a deep learning system embedded in the control computer. This system analyzes camera images in real-time using deep learning inference to select the appropriate solenoid valves and determine the precise amount of herbicide to be discharged onto the target weeds. In this intelligent operation, the acquired images are analyzed in real-time, detecting the crop/weed type, and their locations. Once crops or weeds are detected, the system selects the

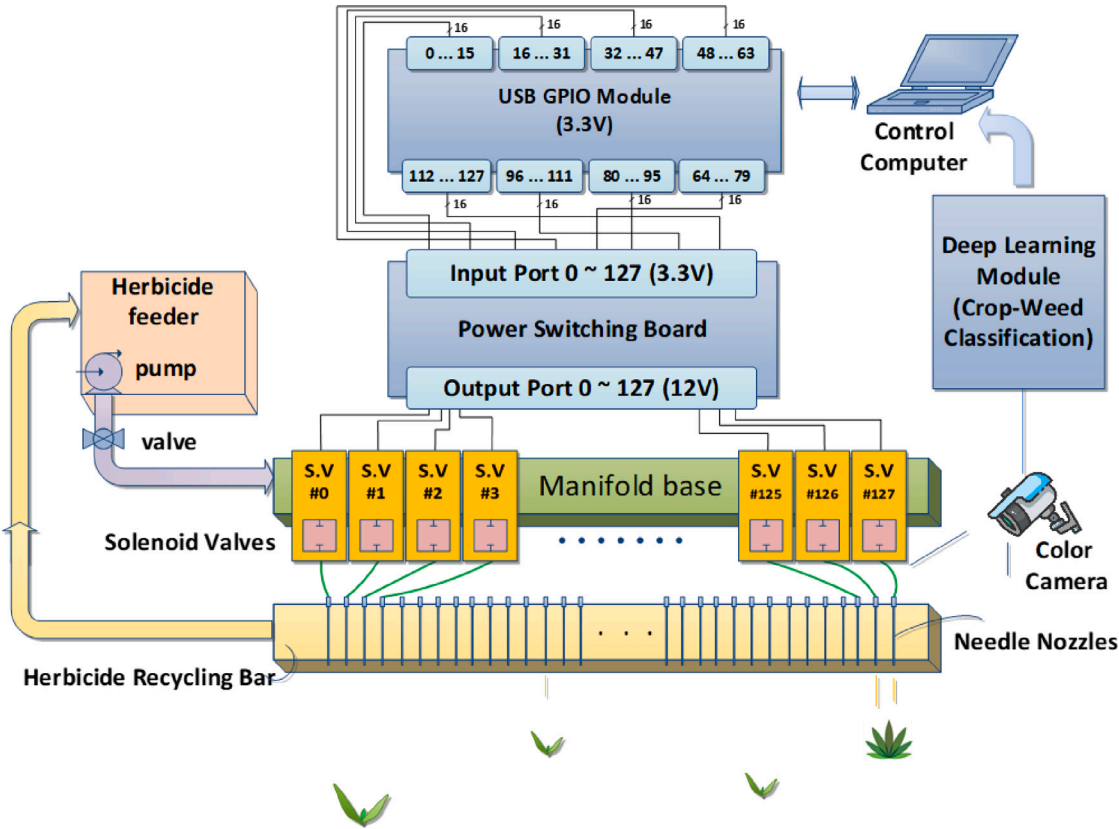


Fig. 3. Configurations of the proposed pin-precision parallel weeding machine.

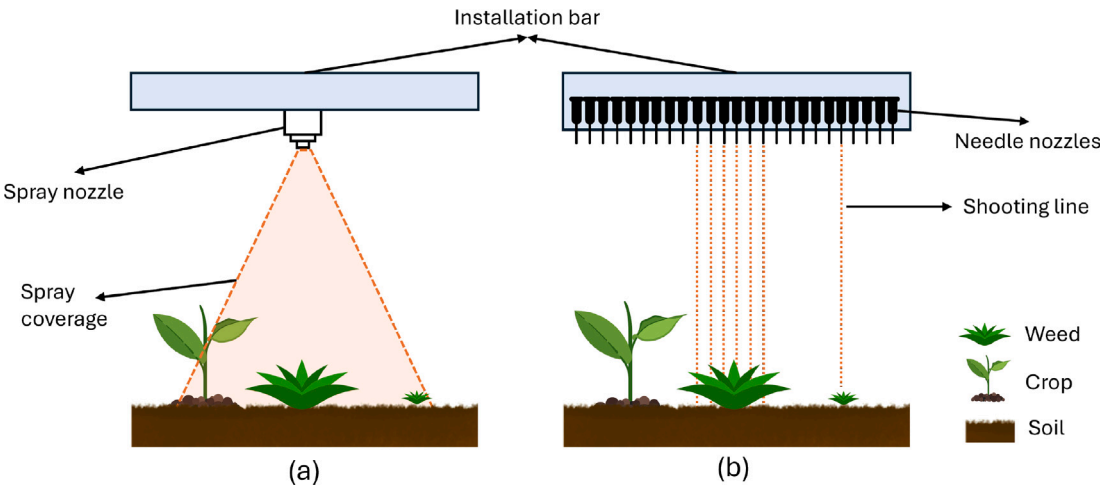


Fig. 4. Comparison between spray-based nozzle (a) and needle-based nozzle (b) for herbicide application.

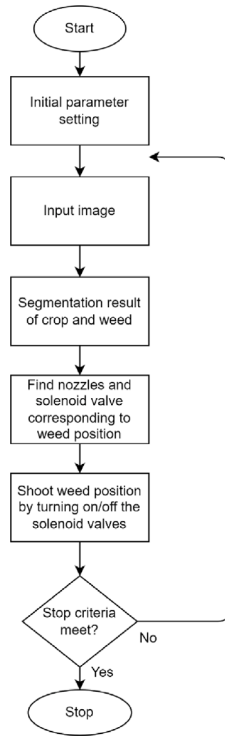


Fig. 5. Flow diagram of weeding procedure with the proposed weeding machine.

optimal nozzles to target the detected weeds. Moreover, the control unit can adjust the timing of herbicide discharge based on the machine's movement speed, ensuring precise application.

Aiming to the above task, the machine is installed such that the needle nozzles are oriented vertically towards the ground, maintaining a distance of approximately 170 mm above the ground, targeting the weeds. Additionally, the camera is positioned to monitor the immediate front direction, along with the end of the weeding needle nozzles.

For more details, Fig. 5 illustrates the flow diagram of the weeding procedure of the proposed weeding machine. Before commencing the process of weeding, fundamental parameter values for the weeding process, such as nozzle height and the movement speed of the weeding machine, need to be established. The proposed weeding machine incorporates several components for herbicide passage, including a solenoid valve that introduces a certain delay in activation. Consequently, it becomes imperative to perform preemptive shooting prior to the target weeds reaching the point of hitting with the nozzle. The predefined shooting positions on the image are termed "herbicide shooting lines", and their placement ahead of the nozzle is contingent on the machine's speed or the nozzle's elevated height. The nozzle height and the information about the weeding machine's speed entered during the initialization process, are used to determine the positions of these shooting lines.

Following parameter configuration, the camera system is activated and calibrated to capture images that include both crops and weeds, as well as the needle nozzles, as illustrated in Fig. 6. This careful calibration ensures accurate field coverage and enhances the precision of subsequent steps.

Subsequent to image acquisition, crop and weed regions are identified through inference using a pre-trained deep learning model. The covering range of the image recognition is from the nozzle position in the image to some more area above the herbicide shooting line. The identified crops and weeds in the region are then tracked for their trajectories, and when the center of a weed region aligns with the herbicide shooting line, the nearest needle nozzle is activated to

dispense herbicide. An approach for determining the closest needle nozzle to the center of the aforementioned weed region could be by overlaying the nozzle area of the image onto the herbicide shooting line for position comparison.

The quantity of herbicide dispensed during the aforementioned process is determined based on the size of the recognized weed and can be adjusted via the activated duration of the solenoid valve. Moreover, regions recognized as crops undergo individual assessment, and solenoid valves positioned in locations that pose potential crop damage are deactivated to prevent herbicide-induced harm to the crops.

2.3. Vision-based shooting

When targeting individual weeds for herbicide spraying in the weeding machine, some delays occur due to several factors: the time taken for the solenoid valve to open, the herbicide's passage through the narrow hose, and the time required for it to travel through the nozzle and air to reach the weeds. During this delay, the target weeds continue to move, making it difficult to calculate or measure the delay time accurately.

In this study, instead of calculating or measuring the delay in time, we propose an accurate and straightforward Vision-based hitting method by converting the delay into pixel units and shooting the herbicide. Fig. 7 illustrates our proposed shooting mechanism.

Let the transition time from the solenoid being off to on be t_{sol} , the delay time for the herbicide to pass through the hose be t_{hose} , and the time for the herbicide to fly through the air to hit the target by t_{flight} . The total delay time t_d is calculated as:

$$t_d = t_{sol} + t_{hose} + t_{flight} \quad (9)$$

Let the speed of the Weeding machine be V_M , the distance equivalent to the delay time is given by:

$$L_d = V_M t_d \quad (10)$$

Assuming that the distance value is known, if the target object is approaching the shooting position in front of the nozzle by L_d , which is the equivalent distance to the delay time t_d , the herbicide can hit the target exactly. However, there is no easy way to measure the time value t_d to compute L_d .

Fortunately, since the hitting error of the herbicide is proportional to the pixel displacement of the image between the actual herbicide hitting position and the target object, it is straightforward to regard this displacement as a distance value.

Measuring displacement in the presented image is also straightforward. Specifically, the method involves experimentally shooting herbicide onto a target object positioned directly beneath the valve, and subsequently, recording the displacement of the hitting position due to the time delay of the weeding machine. This displacement is measured on the image during the calibration period.

To achieve accurate hitting, the weeding machine and camera are installed, and the Weeding machine is aligned perpendicular to its direction of travel. The solenoid valves for shooting the herbicide is positioned at the bottom of the video as shown in Fig. 6.

It is noted that the delaying distance value is not measured in actual distance but is converted into pixel distance (number of pixels) in the image, making it a straightforward and accurate method.

2.4. Recycling of leaked herbicide for micro solenoid valves

The proposed weeding machine utilizes small-diameter injection needle nozzles, similar to those used in medical applications, which are connected to solenoid valves via hoses. These needle nozzles offer distinct characteristics:

- They enable the discharge of a fine, direct water stream, ideal for targeted herbicide application.

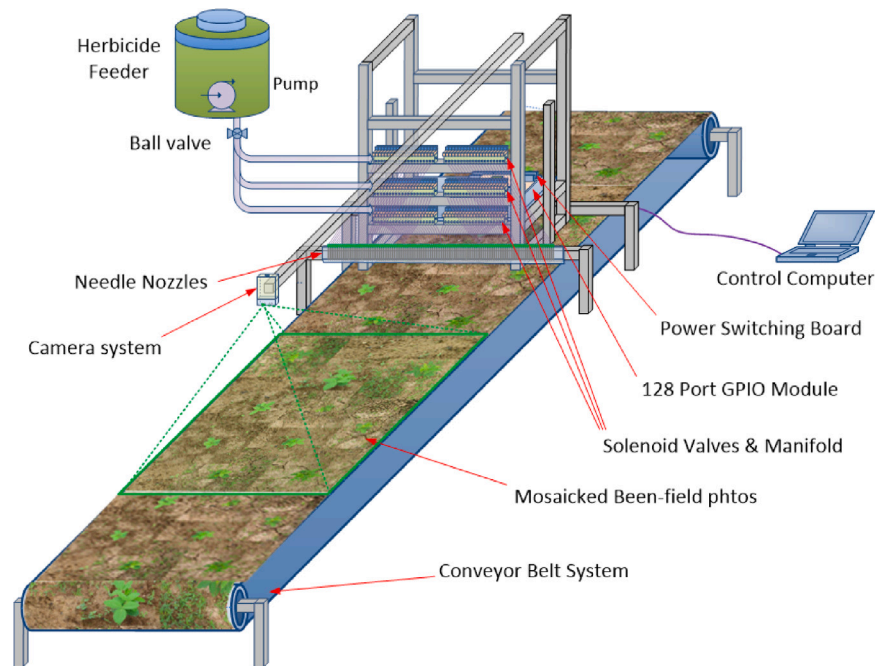


Fig. 6. Operational architecture of the proposed weeding machine.

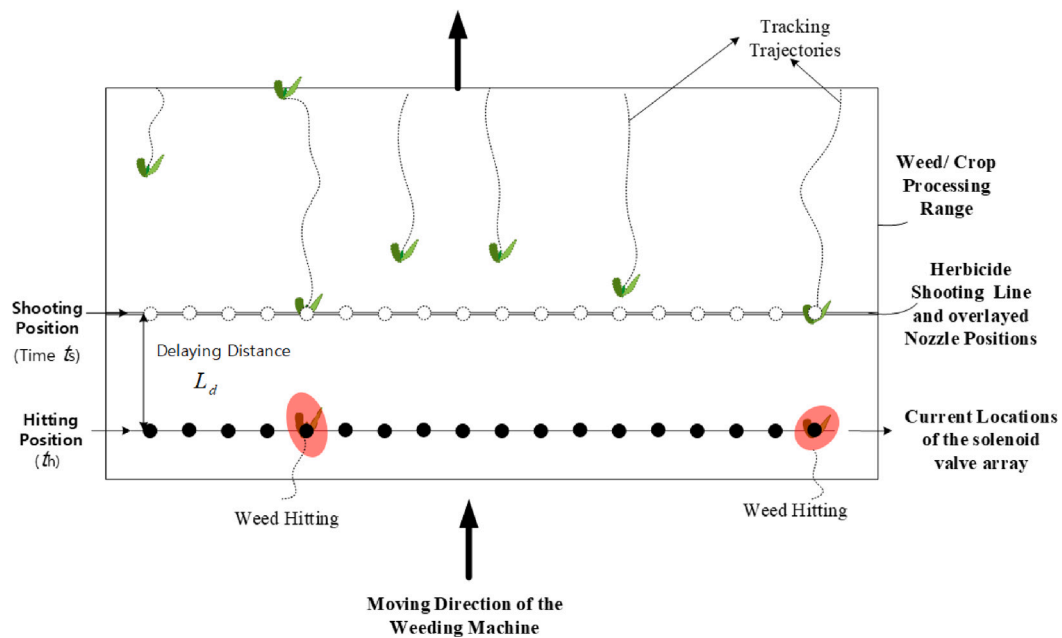


Fig. 7. Illustration of the proposed shooting mechanism.



Fig. 8. Visualization of water gradually emerging from the needle nozzle.

- The herbicide flow rate through the needle nozzle is directly proportional to both the water pressure and spray duration, allowing for precise control over the amount applied.

Given the design of the proposed weeding machine, the use of multiple needle nozzles is necessary to achieve effective coverage. Solenoid valves are essential for controlling the herbicide flow within the spatial limitations of the machine. The solenoid valves used are normally closed, meaning that without an activation command, they remain in an off state. However, when the valve is closed, it relies solely on the force of a small spring to prevent leakage, which may result in some herbicide seeping out. This leakage is exacerbated by residual herbicide in the hoses after the valve is shut off, leading to unintended spraying at improper times or locations, potentially damaging crops. Despite this issue, solenoid valves are crucial for achieving precision weeding.

To address the leakage issue associated with solenoid valves, the proposed solution leverages the differential adhesion forces between a metal plate and the surface tension of the water. The leaked herbicide adheres to the cutting surface of the needle due to the heteromaterial adhesion force between the needle nozzle and the liquid (Kistler and Scriven, 1994). Surface tension plays a role in forming the herbicide into rounded droplets, which, as illustrated in Fig. 8, do not immediately fall to the ground. Due to the significant adhesion force between the liquid and the metal surface of the needle, relatively large droplets remain attached.

This phenomenon inspired a solution to enhance the adhesion force further. The idea involves separating the leaked droplets from the fast and fine stream of liquid produced by the solenoid valve control. While the leaked water grows into a larger droplet and flows down along a wall placed near the cutting surface of the needle, the controlled stream from the solenoid valve proceeds directly to the target weed.

The proposed solution introduces an aluminum plate bar positioned near the needle's cutting surface to exploit heteromaterial adhesion forces. The herbicide gathering plate bar creates a small angle with the needle as shown in Fig. 9, allowing the leaked liquid to adhere to the plate. As the contact area of the liquid on the plate is larger than on the needle, the adhesion force on the plate is stronger, thus capturing more of the leaked herbicide. This design prevents unwanted herbicide from reaching the ground and ensures that the spraying mechanism maintains precision.

Fig. 10 illustrates the growth and movement of a water droplet caused by leakage, flowing along a surface positioned adjacent to the needle's cutting edge. As the droplet accumulates and increases in size, it reaches a critical point where the portion adhered to the needle's tip detaches due to its weight and the lack of additional support for growth.

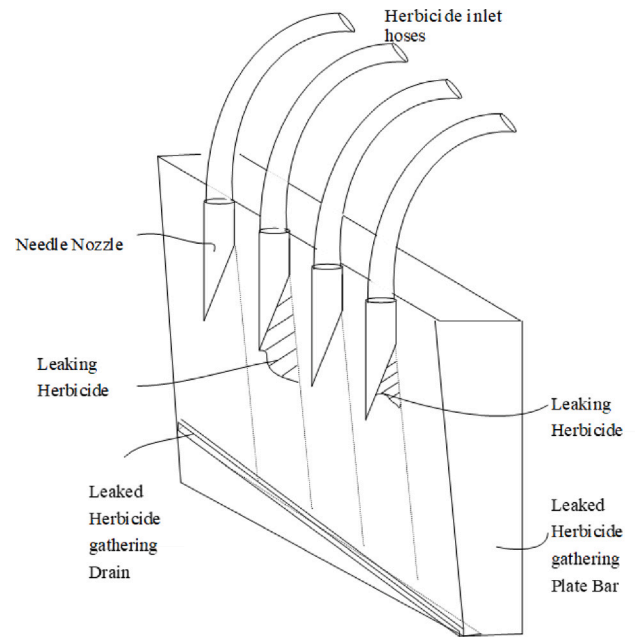


Fig. 9. Recycling module for leaked herbicide, constructed using an aluminum plate bar for enhanced efficiency and environmental sustainability.

However, the droplet continues to adhere to the larger collection plate due to sustained adhesion forces, which are facilitated by the broader surface area of the plate in contact with the liquid.

Consequently, the water droplet detaches from the needle and descends along the collection plate, enabling the possibility of recycling the herbicide. In contrast, when high-pressure water is discharged through the needle nozzle, the targeted herbicide stream is projected with sufficient force to bypass the collection plate entirely. This allows for a rapid, linear application of herbicide without interference from the gathering plate, ensuring precise and efficient delivery to the target weeds. This mechanism highlights an effective strategy to mitigate leakage while maintaining the precision of high-pressure herbicide application.

3. Results

3.1. Experiment setup

We cultivate an experimental bean land of 600 m² without weeding for the entire growth period. We captured a total of 1500 still-cut images approximately every 3 days, showing the co-growth of beans and weeds. There are several types of weeds appeared in our dataset, such as various type of broad leaves, various type of sedges, and various type of grasses, all of which are comprehensively categorized and exemplified in Ilyas et al. (2025). Additionally, we recorded 10 video clips to verify the discrimination capability between crops and weeds while moving.

Among the captured images, we performed semantic segmentation labeling to represent the shape of objects in 1500 images. We classified objects in the images into three classes: crops (beans), weeds (all weeds), and background. For the semantic segmentation labeling, we manually drew the shapes of crops, while for many types of weeds, we used color thresholding and grouped all weeds into one class. Out of these images, 1050 frames were used for training, and the remaining 450 images were kept for testing. For the learning process, we designed the neural network based on Section 2.1 and implemented them based on the PyTorch Framework. The training was conducted on two graphical processing units (GPUs) RTX3090 24 GB. In all

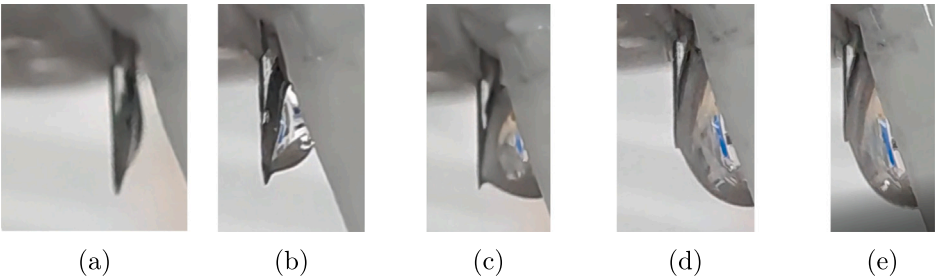


Fig. 10. Illustration of a water droplet expanding due to leakage and flowing along a surface positioned adjacent to the needle's cutting edge.

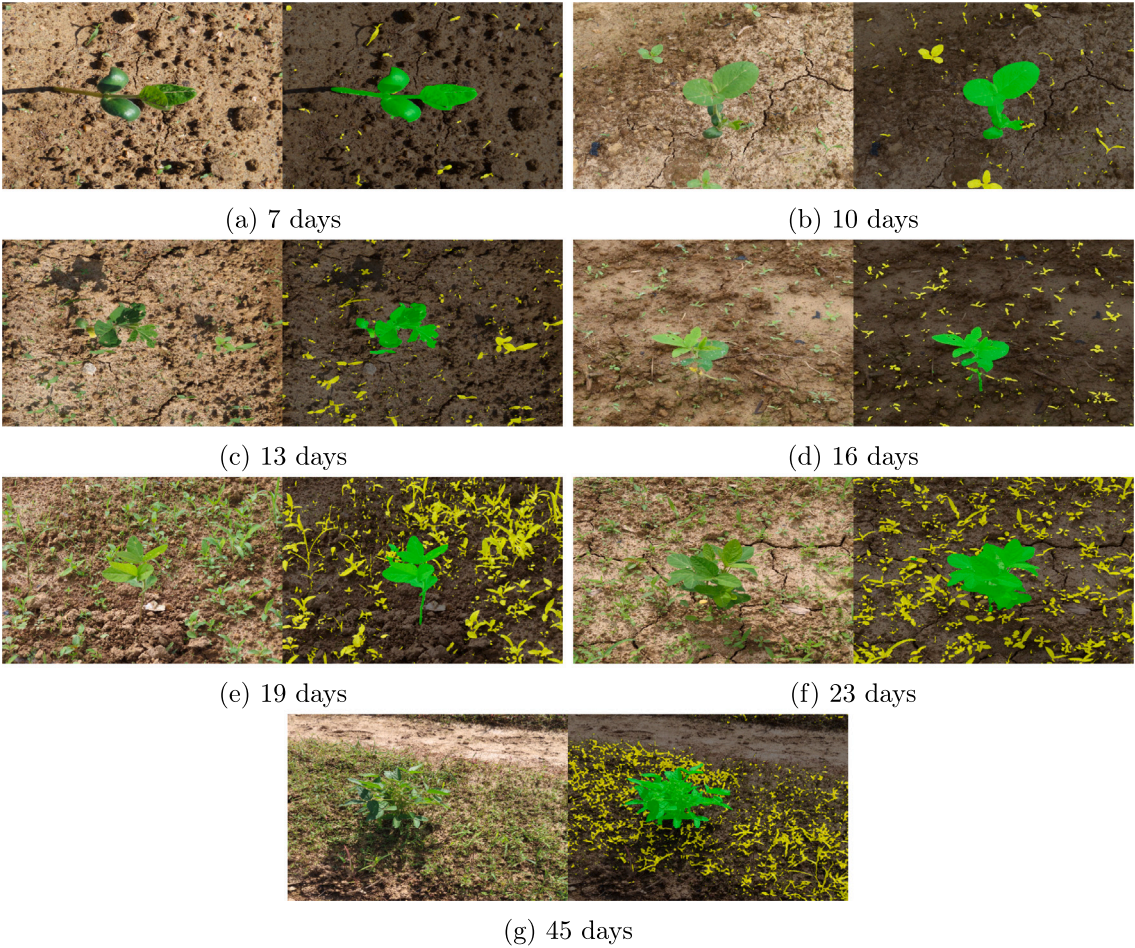


Fig. 11. Segmentation results across different growth stages of beans and weeds. Each pair of images shows the input image on the left, with the corresponding segmentation output overlaid on the right.

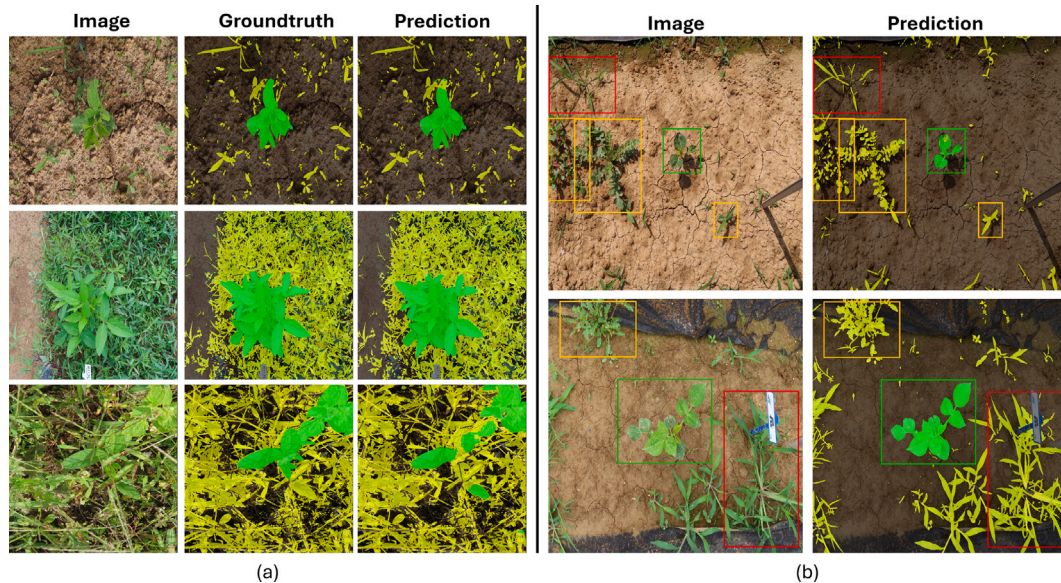


Fig. 12. Qualitative results of crop and weeds segmentation across varying densities and diverse field environments. (a) The images depict the original input, ground truth, and detection results under different weed densities. (b) Example of different weed types present in the test set. Green boxes represent crop (red bean), orange boxes denote various types of broadleaf weeds, and red boxes indicate different types of grasses. Best observed in color for optimal visualization.



Fig. 13. Medical needles used as nozzles in the proposed weeding machine, with corresponding model names and internal diameters: 21G (0.51 mm), 24G (0.30 mm), 26G (0.24 mm), and 30G (0.15 mm).

laboratory-based weeding experiments, pure water was utilized in place of herbicide to maintain a safe testing environment. Furthermore, for real-time inference during operation, a notebook computer embedded with an Nvidia RTX 3060 GPU with 16 GB of memory was utilized to execute predictions and generate commands for the solenoid valves' opening and closing mechanisms. The notebook computer was connected to the weeding machine via a USB interface to a GPIO module, enabling precise communication and control over the solenoid valve mechanisms for optimal weeding performance. This setup provided the necessary computational power and efficiency required for real-time decision-making in the weeding system.

3.2. Crops and weeds detection

The performance evaluation results on the proposed neural network are 88.6% mIoU (the mean of intersection over Union) for the segmentation of the crops, and for the weeds, it was 90.9% IoU, indicating precise segmentation. Note that the accuracy measure in mIoU of the segmentation is much more challenging than that of the bounding box which is used in most of the other works (Redmon and Farhadi, 2018;

Rezatofighi et al., 2019; Zou et al., 2023). We chose segmentation-based detection over the bounding box approach to accommodate precision weed control in our innovative weeding machine's design, focusing on the accurate targeting of individual leaf-level weeds.

Some samples of the semantic segmentation results are shown in Fig. 11. Each left images are the original test image, and the right ones are the results of semantic segmentation, which are the overlaid images by the classified segmentation results on the original test images. The yellow areas represent weeds, while the green areas are crops as seen in Fig. 11. The segmentation accurately delineates the areas of crops and weeds at the pixel level. Notably, even as the plant's shape changes with its growing stage, the model accurately classifies the plants. For instance, for 7-day-old plants, it correctly classifies the stem parts that are closer to brown rather than green as part of the crop. Similarly, for 45-day-old plants, it precisely classifies the weeds located within the plant shadow in the lower-left corner of the image. In all the images shown in Fig. 11, even the small weeds that are difficult to identify visually are accurately classified without altering their shapes. During the process of preparing the training dataset, extracting weeds through image processing yielded more sophisticated results compared to training with manually labeled data.

Fig. 12a illustrates input images across three different crop and weeds densities, highlighting the performance of the proposed method under varying field conditions. In the top row (Fig. 12a), where weed density is low, our method accurately detects both classes, with only a minor misdetection in the upper area of the crop. This demonstrates the method's precision even in low weeds density environment. In the middle sample (Fig. 12a), featuring a more advanced crop growth stage with a higher density of weeds, the proposed method continues to perform with high precision, accurately segmenting both crop and weeds despite the increased complexity. Ability to maintain accurate detection in dense weed environments is a strong indication of the method's robustness in challenging field conditions. Bottom row of Fig. 12a presents a more complex scenario with significant overlap between crop and weeds, where both have grown extensively. Despite the increased difficulty, the proposed method successfully detects the crop, though with a slight under-detection of a small portion. This scenario reflects one of the more challenging samples in our dataset, underscoring the complexity of the test set and the capability of our model to handle intricate scenes. Additionally, this image (Fig. 12a)

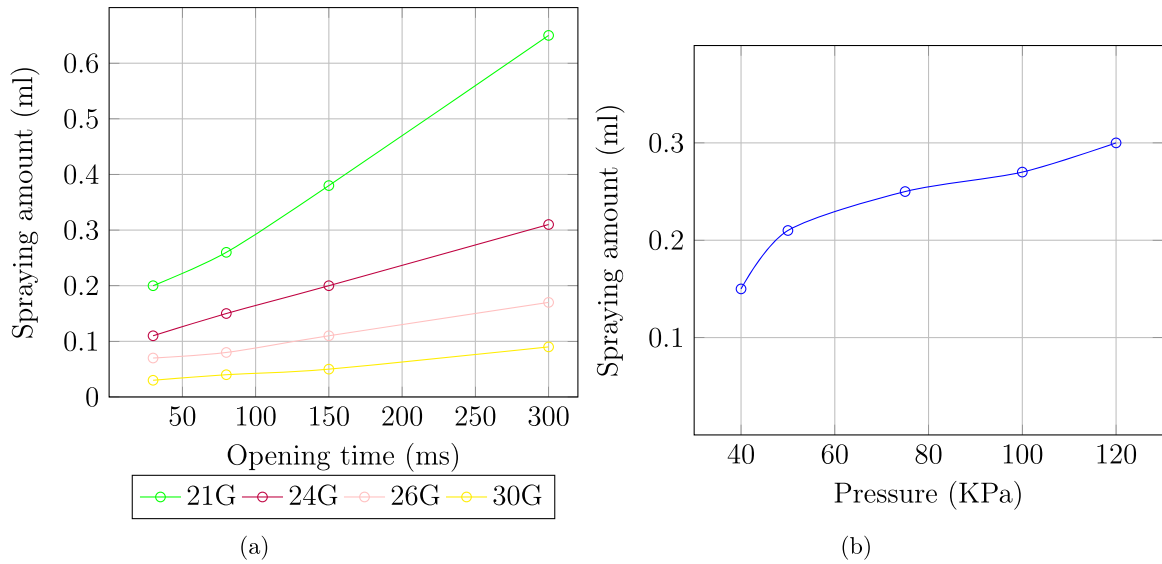


Fig. 14. (a) Graph depicting the spraying amount from medical needles of varying size, using a consistent pressure (90KPa) based on solenoid valve opening time. (b) Graph showing the spray amount from a 21G needle nozzle for different pressure of water during a 30 ms solenoid valve opening time.

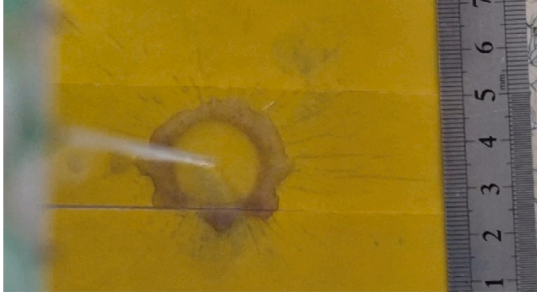


Fig. 15. Photo capturing a test shooting of water using the proposed weeding machine. The fine water stream extends from the left side to the center of the circle. (Height from the ground: 17 cm).

was taken at a closer distance compared to the other samples, demonstrating the method's robustness in addressing varying scales within the input data.

In addition, in Fig. 12b, both broadleaf weeds and grasses are present within the detection boxes, manually annotated for visualization purposes. Despite the diversity of weed types—categorized as a single class in the training data—the proposed Spray-Net effectively differentiates between crop and weeds, including various broadleaves and grasses. This result reinforces the method's generalization capability and robustness in handling diverse weed types across different field conditions, proving the effectiveness of the proposed solution.

We conducted an experiment using video clips to assess the model's capability to distinguish between crop and weeds in real-time, aiming to verify its operational feasibility on the weeding machine. The test utilized video clips recorded at a walking speed of approximately 0.5 km/h in a bean field. The model achieved a performance of 89.7% mIoU at a processing speed of 28 frames per second (fps), demonstrating accurate crop and weed identification. A video clip displaying the crop-weed classification at a reduced resolution is available in the supplementary data (see Supplementary A).

3.3. Ablation study examining the impact of different loss function configurations

To validate the effectiveness of composite loss function in training our deep learning model, an ablation study was conducted. Table 1

Table 1

Ablation study of various loss function combinations, with bolded values indicating the highest mIoU scores achieved. Results are reported as mIoU percentages for the crop and weed classes.

$\mathcal{L}_{mask}$	$\mathcal{L}_{flow}$	$\mathcal{L}_{smooth}$	Crop %	Weed %
✓	✗	✗	76.56	78.41
✗	✓	✗	81.42	82.57
✓	✓	✗	86.56	89.14
✓	✓	✓	88.60	90.90

presents the results of this study, showing how different combinations of loss functions impact the mean Intersection over Union (mIoU) for crop and weed segmentation. The mask consistency loss ($\mathcal{L}_{mask}$) is pivotal for enforcing pixel-level alignment between predicted and ground truth labels, thereby ensuring mask accuracy. However, relying solely on $\mathcal{L}_{mask}$ results in diminished spatial coherence, yielding the lowest mIoU at 74.81. This is because $\mathcal{L}_{mask}$ focuses exclusively on individual pixel accuracy, neglecting spatial dependencies across the image.

To counteract this, the addition of the flow consistency loss ($\mathcal{L}_{flow}$) ensures that spatial relationships between neighboring pixels are preserved. By propagating flow fields over foreground regions, $\mathcal{L}_{flow}$ enhances the network's ability to maintain spatial coherence, essential for accurately distinguishing complex regions. However, $\mathcal{L}_{flow}$ on its own falls short in distinguishing object boundaries, as it merely enforces flow field consistency without focusing on pixel accuracy.

The synergistic combination of $\mathcal{L}_{mask}$ and $\mathcal{L}_{flow}$ significantly boosts performance, raising mIoU from 74.81 to 89.14, as these functions complement each other by balancing pixel-wise accuracy and spatial coherence. Further refinement is achieved with the introduction of the smoothness loss ($\mathcal{L}_{smooth}$), which minimizes abrupt transitions at class boundaries. This is particularly beneficial in agricultural contexts where crop and weed boundaries are often indistinct. Consequently, the model achieves its highest mIoU of 90.9, underscoring the critical role of smooth boundary predictions in enhancing segmentation accuracy and robustness in real-world scenarios.

To determine the optimal weighting of these loss components, we performed a two-stage grid search strategy over the parameters α , β , and γ , which control the contributions of $\mathcal{L}_{smooth}$, $\mathcal{L}_{flow}$, and $\mathcal{L}_{mask}$, respectively. The initial stage comprised a coarse search using an equal-weighting scheme, wherein we set $\alpha = \beta = \gamma \in \{0.2, 0.4, 0.6, 0.8, 1.0\}$.

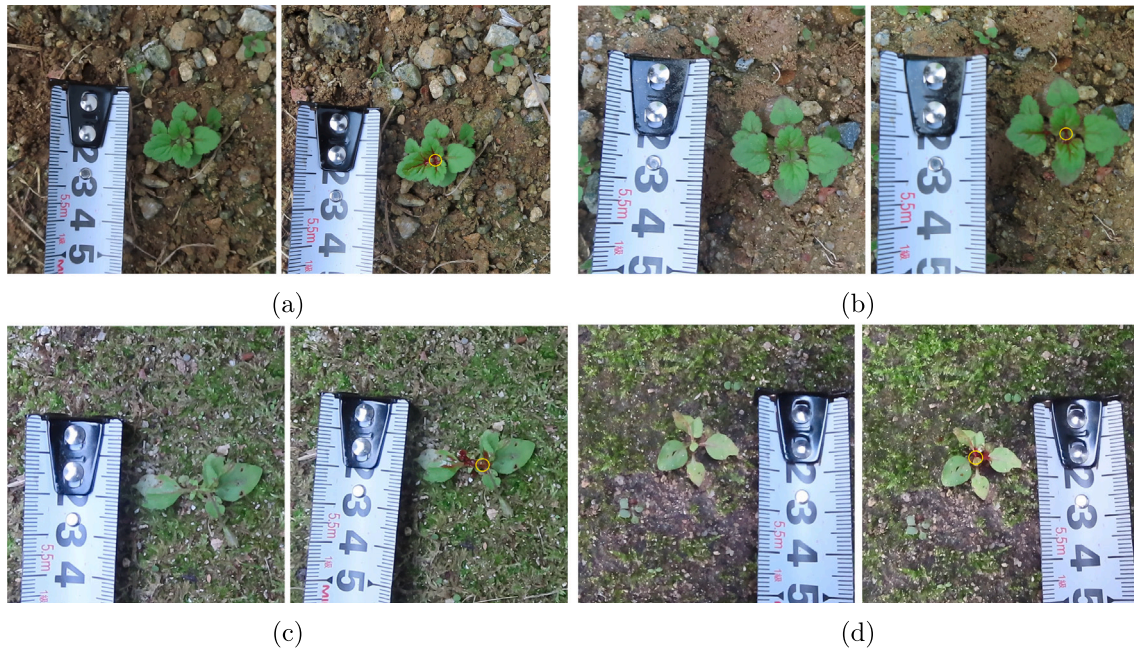


Fig. 16. Efficacy of herbicide application using the proposed needle nozzle system. The left-side images depict the weeds in their pre-application state, while the right-side images show the post-application effects on the targeted weed areas. The yellow circle indicates the shooting point.

Table 2

Ablation study on the hyperparameters (α , β , γ) used in the loss function as defined in Eq. (8) using a two-stage grid search strategy. Bolded values highlight the highest mIoU scores achieved. Results are reported as mIoU percentages for the crop and weed classes.

(a) Coarse search: $\alpha = \beta = \gamma$					
$\alpha = \beta = \gamma$	0.2	0.4	0.6	0.8	1.0
Crop (%)	75.00	80.50	79.20	81.70	85.90
Weed (%)	77.01	80.30	85.10	84.80	82.73

(b) Fine search: $\beta = 1.0$, varying α , γ			
α	γ	Crop (%)	Weed (%)
0.4	0.6	88.60	90.90

to delimit a feasible region of interest. As presented in Table 2, the best equal-weight configuration was achieved at $\alpha = \beta = \gamma = 0.4$. Building upon this result, the second stage involved a finer-grained search with an emphasis on flow consistency, motivated by prior findings that highlight its critical role in preserving object boundaries in semantic segmentation tasks (Li et al., 2024; Ding et al., 2020). In this phase, we fixed $\beta = 1.0$ and independently varied α and γ across the set 0.2, 0.4, 0.6, 0.8, 1.0. This refinement yielded the global optimum at $(\alpha, \beta, \gamma) = (0.4, 1.0, 0.6)$, as detailed in Table 2. Composite loss functions that combine regional (mask) and boundary/structure (flow and smoothness) terms have been shown to improve segmentation accuracy and visual coherence in similar domains. In particular, mask consistency losses enforce pixel-wise fidelity (Long et al., 2015), flow-based terms enhance boundary alignment and capture local texture variations (Dosovitskiy et al., 2015), and smoothness regularization reduces spurious predictions at object borders (Ronneberger et al., 2015). Our two-stage search aligns with best practices in hyperparameter tuning for multi-term objectives (Smith and Topin, 2019).

3.4. Densely positioned needle nozzles evaluation

Medical needles, as illustrated in Fig. 13, were employed for the nozzles of our proposed weeding machine. Fig. 14(a) presents a graph

depicting the amount of water sprayed over time using various needle sizes at a pressure of 90 KPa. As the needle size increases numerically, the corresponding needle diameter decreases, leading to a reduced volume of liquid sprayed. This evaluation demonstrates the machine's controllability, where solenoid valve opening times can be precisely managed to adjust spray output. For our experiments, we selected a 21G needle, which delivers a relatively high spray volume, to visually demonstrate the spraying mechanism. The 21G needle was chosen due to its ability to deliver an optimal amount of herbicide, unlike smaller needles that produce insufficient spray to effectively target and kill weeds. This selection underscores the machine's capacity to achieve precise herbicide application tailored to specific operational requirements.

Additionally, Fig. 14(b) illustrates the relationship between water pressure and the amount of water sprayed during a 30 ms solenoid valve opening. As anticipated, the amount of sprayed water increases with higher water pressure. This trend highlights the direct correlation between pressure and spray volume, suggesting that adjustments in water pressure can be effectively used to control the herbicide application rate in precision weeding applications.

Moreover, Fig. 15 displays a photo capturing the water shooting test conducted with the proposed weeding machine. The fine water stream, marked by a white line extending from the left to the center of the circle, maintains a diameter of approximately 2–3 mm until it reaches the ground, illustrating the precision of the spray mechanism. Fig. 16 further presents experimental results illustrating herbicide dispersion on live weeds. In this setup, the nozzle plate was positioned 170 mm above ground, with a standardized 30 ms valve opening to emulate realistic operational conditions where rapid, precise application is critical due to the robot's continuous movement. For this experiment, the machine is targeting the growing points of weeds utilizing one of our previous works, the weed growing point detection technique in Arsa et al. (2023). To enhance visibility, red ink was mixed with the herbicide. The yellow circles in the right-side images in Fig. 16 indicate the shooting points, aligned precisely with the weeds' growing points. Post-application, the impacted regions display a reddish tint, verifying herbicide dispersion at the intended target sites. The results demonstrate that the needle nozzle delivers an optimal quantity of herbicide—neither excessive nor insufficient—without spillage onto

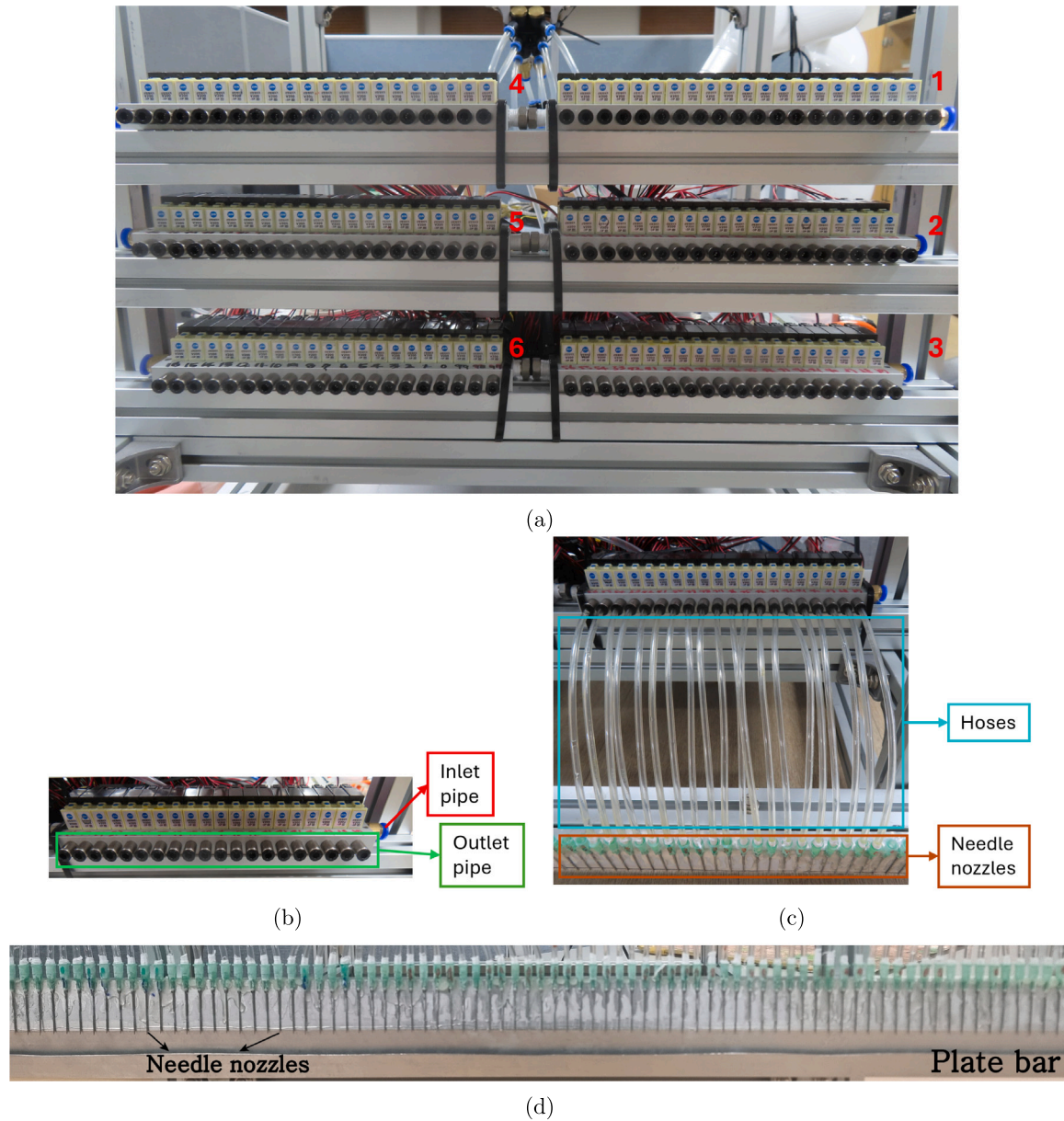


Fig. 17. Solenoid valves for herbicide shooting in the proposed weeding machine. (a) The configuration and arrangement of the solenoid valves within the machine's manifold. The numbers indicating the arrangement number of manifolds. (b) A single solenoid valve manifold, comprising an inlet and outlet pipe for herbicide intake and discharge, respectively. (c) Each outlet pipe is connected to needle nozzles via hoses, facilitating precise herbicide application. (d) The Needle nozzles and leaked herbicide recycling plate bar developed in this study.

Table 3

Comparison of wasted herbicide before and after installation of the recycling bar.

Number of Solenoids	Before the Bar Installation	After the Bar Installation
128	3.84 cc/min	0.05 cc/min

the surrounding soil. This precise targeting confirms the efficiency of the needle nozzle approach in minimizing herbicide waste and environmental impact while ensuring effective weed control.

3.5. Investigation on the features of solenoids and the plate bar to recycle droplet of herbicide

The proposed weeding machine is built upon a modular architecture comprising three core components: the solenoid valve, hose, and nozzle. This configuration not only streamlines the manufacturing process but also enhances scalability, making it suitable for commercial production through the simple replication of these essential elements.

In the proposed weeding machine, an array of 128 needle nozzles is employed, each spaced approximately 9 mm apart, as illustrated in Fig. 17(d). Given the large number of nozzles, compact solenoid valves are utilized, as seen in Fig. 17(b). These valves rely on small springs to maintain a normally closed state, but the limited strength of these springs can lead to herbicide leakage. Furthermore, residual herbicide drops often remain in the hoses and valves post-application, posing a risk of unintended crop exposure.

To address this, the system incorporates an aluminum plate bar adjacent to the needle nozzles, leveraging heteromaterial adhesion forces to facilitate the collection and recycling of leaked herbicide. This plate bar is strategically angled to enhance the adhesion effect, as shown in Fig. 17(d). With this configuration, the majority of leaked herbicide that would otherwise be wasted is effectively gathered and recycled, as demonstrated by the results presented in Table 3. This approach not only mitigates potential crop damage from herbicide residue but also contributes to a more sustainable weeding operation by minimizing chemical waste.

To install 128 solenoids, several manifolds are required. The solenoid valve and its manifold module used for herbicide shooting control are shown in Fig. 17(a). Specifically, six manifolds are strategically arranged as illustrated in Fig. 17(a), organized into two columns. Each solenoid manifold contains an inlet pipe connected to the herbicide storage and 20 outlet pipes (Fig. 17(b)), each linked to a needle nozzle via hoses (Fig. 17(c)). This configuration ensures precise and efficient herbicide delivery, optimizing the system's performance for targeted application.

3.6. Time delay in herbicide shooting

As described in Section 2.3, when an herbicide shoot-out command is issued to a solenoid valve, a significant amount of time is required until the herbicide strikes the target weed. Measurement of this time delay accurately is not an easy task. In this study, a vision-based method is introduced to correct the shooting time of miss-hitting targets. The proposed idea is to set a shooting line before the nozzle.

Therefore, as the speed of the weeding machine increases, the shooting line should be set upper place of the image. The position of this shooting line determined in this way shows an almost linearly increasing pattern with speed as shown in Fig. 18. To perform weeding, the value from Fig. 18 should be used as the shooting line accordingly based on the speed. However, if the camera position or the nozzle position of the weeding machine changes, the shooting line should be re-adjusted.

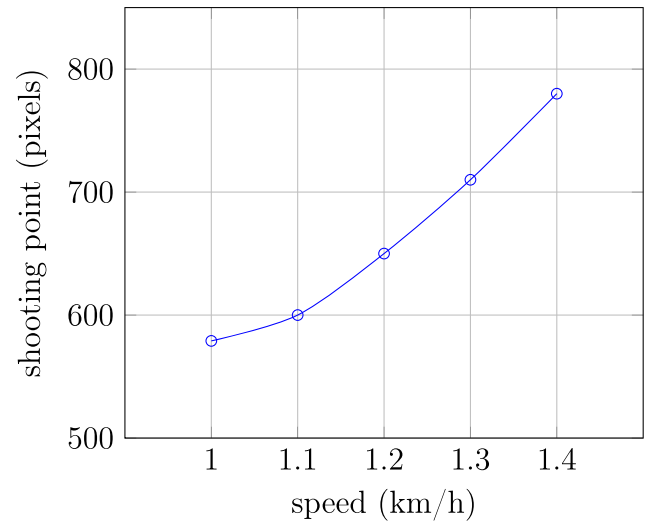


Fig. 18. Shooting point for different speed (pixels ahead of needle nozzles).

Table 4

Detection, false positive rate, hitting accuracy for bean and weeds.

Criteria	Crop (bean)(%)	All Weeds(%)
Detection IoU	88.6	90.9
False Positive Rate	10.8	8.4
Hitting accuracy	–	86.1

3.7. Performance of the integrated weeding machine

Fig. 19(a) illustrates a side view of the proposed pin precision weeding machine prototype, with dimensions measuring $540 \times 540 \times 900$ mm and a plate bar width of 1200 mm. To evaluate the integrated performance of crop and weed recognition alongside the herbicide spraying system, a comprehensive experiment was conducted. In this setup, color photographs of an open bean field were moved to simulate real-world conditions, approximating the actual movement of the weeding machine over crops. This dynamic arrangement allowed the machine to recognize weed targets within the images and then spray water over identified areas, effectively emulating operational scenarios. Fig. 19(b) illustrates the experimental configuration, designed to closely replicate real-field conditions and enable a thorough evaluation of the weeding machine's performance.

In this experimental scenario, photograph printing and video capturing are additionally required, which leads to significant degradation of image quality. This image degradation handicap makes the experimental setting to be more challenging than that of the real open-field scenario. Under these challenging circumstances, we conducted weed eradication experiments. The color-printed images using the mosaic method of image augmentation are transported at a velocity of 0.6 km/h while capturing video for recognition and subsequent water shot out onto selected weeds.

The results presented in Table 4, which include weed recognition rates and hitting accuracy, provide a comprehensive assessment of the system's performance. Detection and hitting accuracies were calculated based on frame-by-frame analysis of recorded video clips. Notably, the false positive rate for crop detection is 10.8%, attributable to instances where small portions of the crop remain visible to the camera after crossing the hitting line, leading to misclassification as weeds. This phenomenon, illustrated in Fig. 20, underscores a critical limitation of

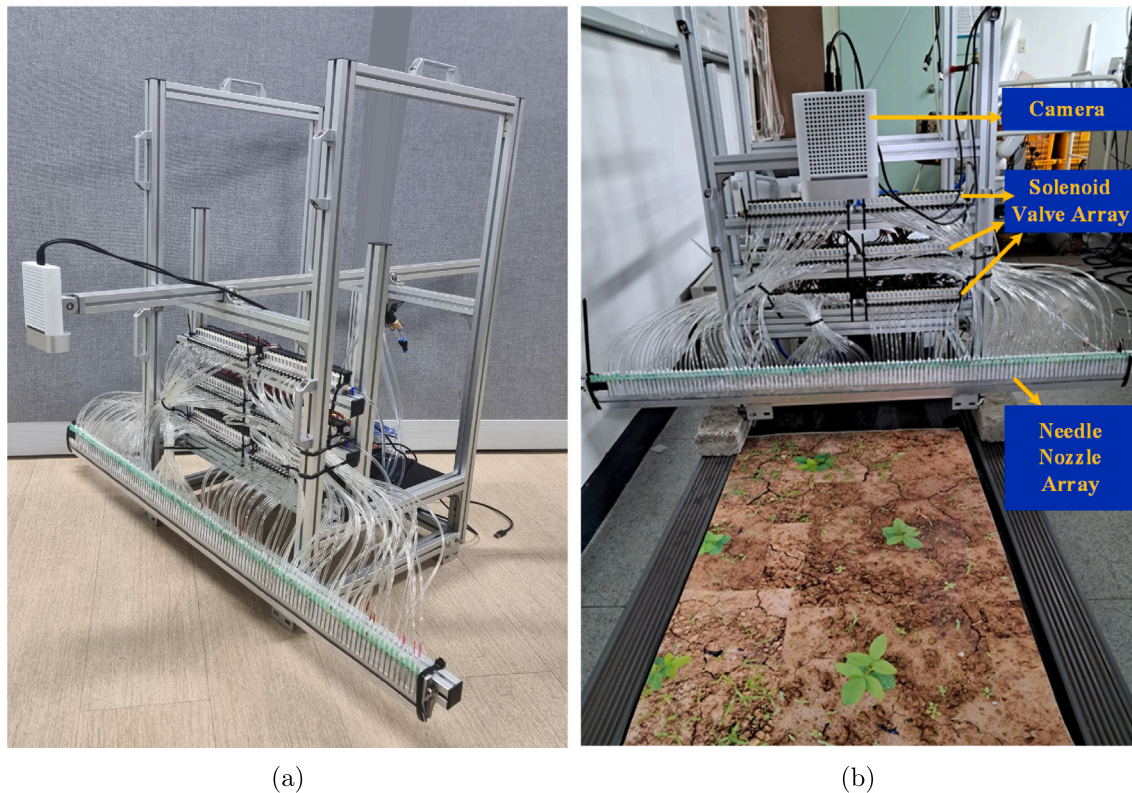


Fig. 19. Images of the proposed weeding machine prototype: (a) pin-precision parallel weeding machine prototype at 45-degree angle. (b) Experimental setup illustrating the operational configuration for the weeding machine.

the neural network, which fails to capture sufficient distinctive features for accurate crop segmentation when only small fragments are visible. Conversely, when crops are fully within the camera's view, particularly in critical regions for shooting and hitting, detection accuracy remains consistently high. This observation underscores the system's reliability in ideal conditions and suggests that crops can be effectively avoided during herbicide application.

On the weed detection side, the false positive rate stands at 8.4%. A notable limitation of the system is its inability to detect very small weeds (see Fig. 20), which impacts overall detection performance. Despite potential losses due to errors in crop-weed recognition, this weeding machine provides a substantial advantage in agricultural management by enabling robotic operation, which eliminates the need for costly labor.

Furthermore, Fig. 21 shows a shooting moment by the water stream of the proposed needle nozzle-based weeding machine. It can be observed that several water streams are shooting only over weeds, avoiding crops. The duration of these shootings is very short, around 30 ms. This demonstrates that the system can accurately distinguish between crops and weeds, allowing the herbicide to be sprayed only on the weeds and not on the crops.

4. Conclusion

Precision Weed control is one of the most vexing and challenging tasks in agriculture, and herbicide application has proven to be an effective method of weeding. However, excessive herbicide usage causes significant environmental harm. Nevertheless, the herbicide application still relies on the conventional wide-spreading methods which were developed originally for the purpose of pest/insect control.

Fortunately, recent developments in artificial intelligence and robotic technology enable us to realize an ideal weeding machine with minimal environmental impact and high efficiency.

This study aimed to achieve the development of an advanced weeding machine by combining fine needle nozzles with artificial intelligence and robotic technology. In the weeding test, the proposed neural networks show 88.6% detection mIoU for beans and 90.9% for weeds, and 86.1% of hitting accuracy of herbicide in a lab experimental setting at a moving speed of 0.6 km/h. Moreover, the proposed weeding machine, which differs from conventional broadcasting weeding by adopting a single needle nozzle-based weeding approach, can lead to a pioneering weeding machine of deep learning-based pin precision parallel weeding. Theoretically, the maximum speed of weeding can reach 4266 weeds/s (128 nozzles, 30 m s/shooting).

The needle nozzles possess the ability to deliver herbicide with extreme fineness and form a linear stream, enabling precise weeding while avoiding crops. Additionally, since the nozzles' positions in the plate bar are fixed, there is no increase in the inaccuracy of retargeting and the time consumption due to nozzle movement. Furthermore, the use of 128 nozzles in parallel ensures extremely high-speed weeding operation. Though the current version of the weeding machine is a stand-alone type, it has been designed to be set on mobile robots easily.

While the proposed weeding machine presents several advantages, there remain critical challenges that must be addressed. Specifically, difficulties arise in maintaining precise targeting when the machine operates at higher speeds or when navigating uneven furrow surfaces, where vibrations can significantly impair accuracy. These limitations highlight areas for improvement in future research and development.

Finally, it is worth to be noted that we do not call the proposed weeding machine as a weeding robot yet because it does not have moving capability now. Once it is setting on a general purpose mobile robot, it will become a weeding robot system.

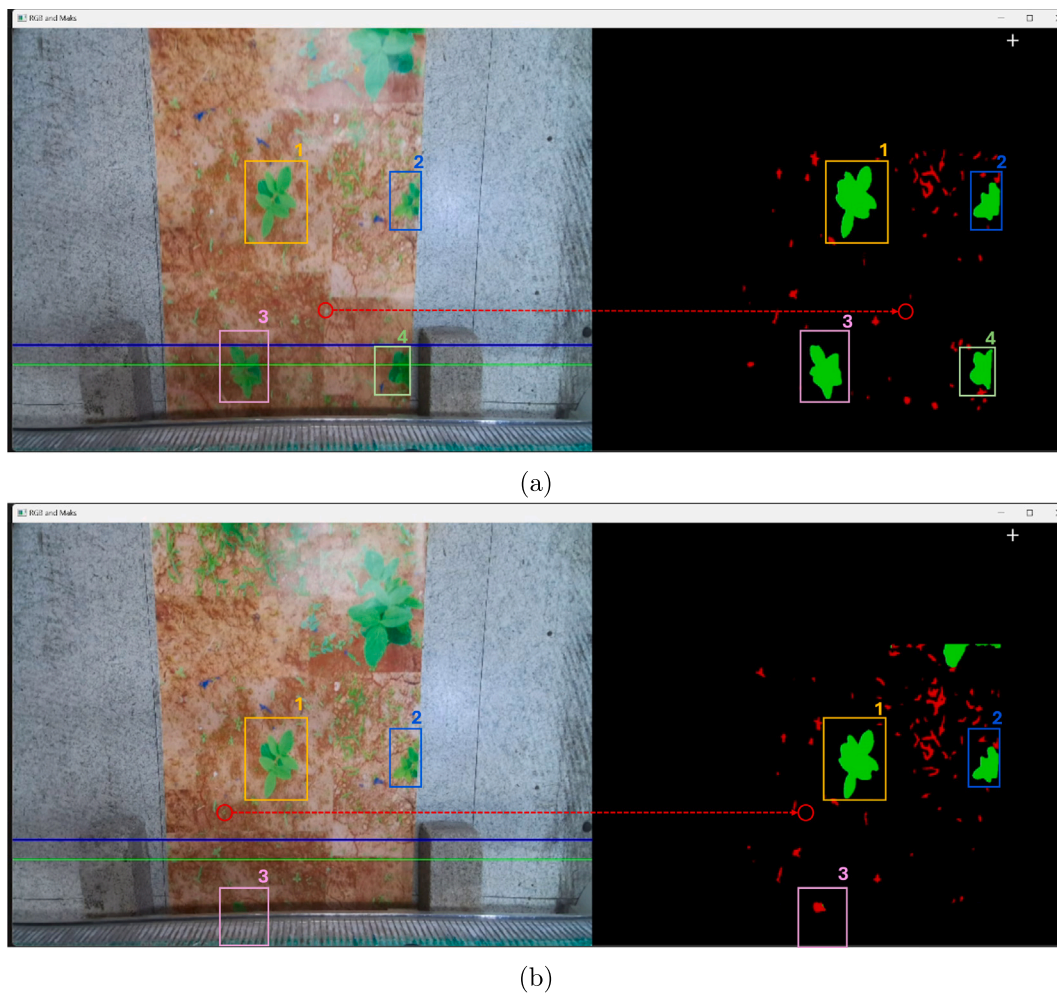


Fig. 20. Real-time detection results from our recorded experiment: (a) Frame 1640 and (b) Frame 1710. The colored boxes with numbers indicate individual crop instances. Crops that are fully visible in the frame are correctly classified. In (b), crop number 3 is only partially visible and is mistakenly classified as a weed due to insufficient identifiable features. The small red circle on the left marks a small weed that appears in the frame, and the dashed arrow points to the corresponding prediction, showing that this weed was not detected. Note that green and red colors represent crops and weeds, respectively.

CRediT authorship contribution statement

Hyungjun Jin: Writing – original draft, Visualization, Methodology, Investigation, Data curation. **Dewa Made Sri Arsa:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Data curation. **Talha Ilyas:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Data curation. **Jong-hoon Lee:** Validation, Investigation. **Okjae Won:** Resources, Data curation. **Seok-Hwan Park:** Validation, Supervision, Conceptualization. **Kumar Sandesh:** Visualization, Investigation. **Sang Cheol Kim:** Validation, Supervision, Funding acquisition, Conceptualization. **Hyongsuk Kim:** Writing – review & editing, Writing – original draft, Validation, Supervision, Funding acquisition, Conceptualization.

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.

Acknowledgments

This work was partly supported by the Institute of Information & Communications Technology Planning & Evaluation(IITP)-Innovative Human Resource Development for Local Intellectualization program grant funded by the Korea government(MSIT) (IITP-2025-RS-2024-00439292, 5%) and the Basic Science Research Program through the National Research Foundation of Korea (NRF), South Korea grant funded by the Ministry of Education, Taiwan (No. RS-2019-NR040079, 45%), funded by the Korea government(MSIT) (No. RS-2024-00347768, 50%)

Appendix A. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.compag.2025.110990>.

Data availability

Data will be made available on request.



Fig. 21. Shooting moment of the proposed system. See the complete moment on Supplementary B.

References

- Aarathi, R., Harini, S., 2018. A survey of deep convolutional neural network applications in image processing. *Int. J. Pure Appl. Math.* 118, 185–190.
- Aloysius, N., Geetha, M., 2017. A review on deep convolutional neural networks. In: 2017 International Conference on Communication and Signal Processing. ICCSP, IEEE, pp. 0588–0592.
- Arsa, D.M.S., Ilyas, T., Park, S.H., Won, O., Kim, H., 2023. Eco-friendly weeding through precise detection of growing points via efficient multi-branch convolutional neural networks. *Comput. Electron. Agric.* 209, 107830.
- Berenstein, R., Edan, Y., 2017a. Automatic adjustable spraying device for site-specific agricultural application. *IEEE Trans. Autom. Sci. Eng.* 15 (2), 641–650.
- Berenstein, R., Edan, Y., 2017b. Human-robot collaborative site-specific sprayer. *J. Field Robot.* 34 (8), 1519–1530.
- Chen, L.C., Papandreou, G., Kokkinos, I., Murphy, K., Yuille, A.L., 2017. Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs. *IEEE Trans. Pattern Anal. Mach. Intell.* 40 (4), 834–848.
- Chen, L.C., Papandreou, G., Kokkinos, I., Murphy, K., Yuille, A.L., 2018. DeepLab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFs. *IEEE Trans. Pattern Anal. Mach. Intell.* 40 (4), 834–848. <http://dx.doi.org/10.1109/TPAMI.2017.2699184>.
- Cui, J., Zhang, Y., Chen, H., Zhang, Y., Cai, H., Jiang, Y., Ma, R., Qi, L., 2025. CSWin-MBConv: A dual-network fusing CNN and transformer for weed recognition. *Eur. J. Agron.* 164, 127528.
- Ding, M., Wang, Z., Zhou, B., Shi, J., Lu, Z., Luo, P., 2020. Every frame counts: Joint learning of video segmentation and optical flow. In: Proceedings of the AAAI Conference on Artificial Intelligence, vol. 34, (07), pp. 10713–10720.
- Dosovitskiy, A., Fischer, P., Ilg, E., Hausser, P., Hazirbas, C., Golkov, V., Van Der Smagt, P., Cremers, D., Brox, T., 2015. FlowNet: Learning optical flow with convolutional networks. In: Proceedings of the IEEE International Conference on Computer Vision. pp. 2758–2766.
- Faiçal, B.S., Freitas, H., Gomes, P.H., Mano, L.Y., Pessin, G., de Carvalho, A.C., Krishnamachari, B., Ueyama, J., 2017. An adaptive approach for UAV-based pesticide spraying in dynamic environments. *Comput. Electron. Agric.* 138, 210–223.
- Firkat, E., An, F., Peng, B., Zhang, J., Mijit, T., Ahat, A., Zhu, J., Hamdulla, A., 2023. FGSeg: Field-ground segmentation for agricultural robot based on LiDAR. *Comput. Electron. Agric.* 211, 107965.
- Guo, T., Dong, J., Li, H., Gao, Y., 2017. Simple convolutional neural network on image classification. In: 2017 IEEE 2nd International Conference on Big Data Analysis. ICBDA, IEEE, pp. 721–724.
- He, K., Zhang, X., Ren, S., Sun, J., 2016. Deep residual learning for image recognition. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. pp. 770–778.
- Hizatate, T., Noguchi, N., 2023. Work schedule optimization for electric agricultural robots in orchards. *Comput. Electron. Agric.* 210, 107889.
- Hong, S.W., Zhao, L., Zhu, H., 2018. SAAS, a computer program for estimating pesticide spray efficiency and drift of air-assisted pesticide applications. *Comput. Electron. Agric.* 155, 58–68.
- Howard, A.G., 2014. Some improvements on deep convolutional neural network based image classification. In: 3rd International Conference on Learning Representations.
- Ilyas, T., Arsa, D.M.S., Ahmad, K., Lee, J., Won, O., Lee, H., Kim, H., Park, D.S., 2025. CWD30: A new benchmark dataset for crop weed recognition in precision agriculture. *Comput. Electron. Agric.* 229, 109737.
- Ilyas, T., Lee, J., Won, O., Jeong, Y., Kim, H., 2023. Overcoming field variability: unsupervised domain adaptation for enhanced crop-weed recognition in diverse farmlands. *Front. Plant Sci.* 14, 1234616.
- Jeon, H.Y., Tian, L.F., 2009. Direct application end effector for a precise weed control robot. *Biosyst. Eng.* 104 (4), 458–464.
- Jiang, H., Zhang, C., Qiao, Y., Zhang, Z., Zhang, W., Song, C., 2020. CNN feature based graph convolutional network for weed and crop recognition in smart farming. *Comput. Electron. Agric.* 174, 105450.
- Kistler, S., Scriven, L., 1994. The teapot effect: sheet-forming flows with deflection, wetting and hysteresis. *J. Fluid Mech.* 263, 19–62.
- LeCun, Y., Kavukcuoglu, K., Farabet, C., 2010. Convolutional networks and applications in vision. In: Proceedings of 2010 IEEE International Symposium on Circuits and Systems. IEEE, pp. 253–256.
- Lee, J., Kim, D., Ponce, J., Ham, B., 2019. Sfnets: Learning object-aware semantic correspondence. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 2278–2287.
- Li, Y., Guo, Z., Shuang, F., Zhang, M., Li, X., 2022. Key technologies of machine vision for weeding robots: A review and benchmark. *Comput. Electron. Agric.* 196, 106880.
- Li, H., Quan, L., Guo, Y., Pi, P., Shi, Y., Lou, Z., Jiang, W., Xia, F., Sun, D., Yang, Y., et al., 2023. Improving agricultural robot patch-spraying accuracy and precision through combined error adjustment. *Comput. Electron. Agric.* 207, 107755.
- Li, X., Zhang, J., Yang, Y., Cheng, G., Yang, K., Tong, Y., Tao, D., 2024. Sfnets: Faster and accurate semantic segmentation via semantic flow. *Int. J. Comput. Vis.* 132 (2), 466–489.
- Liu, N., Yuan, Y., Wan, L., Huo, H., Fang, T., 2018. A comparative study for contour detection using deep convolutional neural networks. In: Proceedings of the 2018 10th International Conference on Machine Learning and Computing. pp. 203–208.
- Long, J., Shelhamer, E., Darrell, T., 2015. Fully convolutional networks for semantic segmentation. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. pp. 3431–3440.
- Luck, J., Pitla, S., Shearer, S., Mueller, T., Dillon, C., Fulton, J., Higgins, S., 2010. Potential for pesticide and nutrient savings via map-based automatic boom section control of spray nozzles. *Comput. Electron. Agric.* 70 (1), 19–26.
- Ma, R., Hu, H., Xing, S., Li, Z., 2020. Efficient and fast real-world noisy image denoising by combining pyramid neural network and two-pathway unscented Kalman filter. *IEEE Trans. Image Process.* 29, 3927–3940.
- Ma, R., Li, S., Zhang, B., Fang, L., Li, Z., 2022. Flexible and generalized real photograph denoising exploiting dual meta attention. *IEEE Trans. Cybern.* 53 (10), 6395–6407.
- Ma, R., Zhang, Y., Zhang, B., Fang, L., Huang, D., Qi, L., 2024. Learning attention in the frequency domain for flexible real photograph denoising. *IEEE Trans. Image Process.*
- Midtby, H.S., Mathiasen, S.K., Andersson, K.J., Jørgensen, R.N., 2011. Performance evaluation of a crop/weed discriminating microsprayer. *Comput. Electron. Agric.* 77 (1), 35–40.
- Milioto, A., Lottes, P., Stachniss, C., 2018. Real-time semantic segmentation of crop and weed for precision agriculture robots leveraging background knowledge in CNNs. In: 2018 IEEE International Conference on Robotics and Automation. ICRA, IEEE, pp. 2229–2235.
- Noh, H., Hong, S., Han, B., 2015. Learning deconvolution network for semantic segmentation. In: Proceedings of the IEEE International Conference on Computer Vision. pp. 1520–1528.
- Özlüoymak, Ö.B., 2022. Development and assessment of a novel camera-integrated spraying needle nozzle design for targeted micro-dose spraying in precision weed control. *Comput. Electron. Agric.* 199, 107134. <http://dx.doi.org/10.1016/j.compag.2022.107134>, URL <https://www.sciencedirect.com/science/article/pii/S0168169922004513>.
- Rai, N., Zhang, Y., Ram, B.G., Schumacher, L., Yellavajjala, R.K., Bajwa, S., Sun, X., 2023. Applications of deep learning in precision weed management: A review. *Comput. Electron. Agric.* 206, 107698.
- Redmon, J., Farhadi, A., 2018. YoloV3: An incremental improvement. *arXiv preprint arXiv:1804.02767*.
- Rezatofighi, H., Tsai, N., Gwak, J., Sadeghian, A., Reid, I., Savarese, S., 2019. Generalized intersection over union: A metric and a loss for bounding box regression. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 658–666.

- Ronneberger, O., Fischer, P., Brox, T., 2015. U-net: Convolutional networks for biomedical image segmentation. In: Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich, Germany, October 5–9, 2015, Proceedings, Part III 18. Springer, pp. 234–241.
- Ruigrok, T., van Henten, E.J., Kootstra, G., 2023. Improved generalization of a plant-detection model for precision weed control. *Comput. Electron. Agric.* 204, 107554.
- Shen, X., Tian, X., He, A., Sun, S., Tao, D., 2016. Transform-invariant convolutional neural networks for image classification and search. In: Proceedings of the 24th ACM International Conference on Multimedia. pp. 1345–1354.
- Smith, L.N., Topin, N., 2019. Super-convergence: Very fast training of neural networks using large learning rates. In: Artificial Intelligence and Machine Learning for Multi-Domain Operations Applications, vol. 11006, SPIE, pp. 369–386.
- Underwood, J.P., Calleija, M., Taylor, Z., Hung, C., Nieto, J., Fitch, R., Sukkarieh, S., 2015. Real-time target detection and steerable spray for vegetable crops. In: Proceedings of the International Conference on Robotics and Automation: Robotics in Agriculture Workshop, Seattle, WA, USA. pp. 26–30.
- Xiao, K., Ma, Y., Gao, G., 2017. An intelligent precision orchard pesticide spray technique based on the depth-of-field extraction algorithm. *Comput. Electron. Agric.* 133, 30–36.
- Xiong, Y., Ge, Y., Liang, Y., Blackmore, S., 2017. Development of a prototype robot and fast path-planning algorithm for static laser weeding. *Comput. Electron. Agric.* 142, 494–503.
- Young, S.L., Giles, D.K., 2013. Targeted and microdose chemical applications. In: Automation: The Future of Weed Control in Cropping Systems. Springer, pp. 139–147.
- Zhang, X., Guo, Y., Yang, J., Li, D., Wang, Y., Zhao, R., 2022. Many-objective evolutionary algorithm based agricultural mobile robot route planning. *Comput. Electron. Agric.* 200, 107274.
- Zhao, D., Zhao, Y., Wang, X., Zhang, B., et al., 2016. Theoretical design and first test in laboratory of a composite visual servo-based target spray robotic system. *J. Robot.* 2016.
- Zhenyang, G., Wangwang, W., Yingjie, Y., Ruiqing, Z., 2013. Design of mechanical arm for laser weeding robot. *Coordinates* 244 (29.2), 271–7.
- Zou, Z., Chen, K., Shi, Z., Guo, Y., Ye, J., 2023. Object detection in 20 years: A survey. *Proc. IEEE*.
- Zou, K., Liao, Q., Zhang, F., Che, X., Zhang, C., 2022. A segmentation network for smart weed management in wheat fields. *Comput. Electron. Agric.* 202, 107303.