Weed Science

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Key technologies and research progress of intelligent weeding robots

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Review

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Abstract

The rapid and efficient removal of weeds is currently a research hotspot. With the integration of robotics and automation technology into agricultural production, intelligent field-weeding robots have emerged. An overview of the development status of weeding robots based on bibliometric and scientific mapping methods is presented. Two key technologies of weeding robots are summarized, and the research progress of precision-spraying weeding robots, mechanical weeding robots, and thermal weeding robots with laser devices, categorized by weeding method, is reviewed. Finally, a summary and an outlook on the future development trends of intelligent field-weeding robots are provided, aiming to offer a reference for further promoting the development of weeding robots.

Introduction

As the global population continues to grow, the increasing demand for food has made improving agricultural productivity and reducing resource waste one of the key challenges in agricultural development. In traditional farming, weeds not only compete with crops for nutrients and water but also provide habitats for various pests and diseases, leading to a decline in crop yields. According to data from the United Nations Food and Agriculture Organization (FAO) in 2023, more than 8,000 species of weeds have been identified worldwide, with greater than 26% causing crop yield reductions. Given the detrimental effects of weeds, effectively controlling their growth has become a critical aspect of crop cultivation (Deng et al. 2018).

To eliminate the impact of weeds on crops, various weed control methods have been explored. Traditional manual weeding methods, such as using hoes, sickles, or push mowers, are simple to operate but have high labor intensity, low efficiency, and high costs. The effectiveness of these methods often depends on the skill level of the workers, frequently leading to missed weeds. Although mechanical weeding improves efficiency, its application in large-scale fields remains limited (Bloomer et al. 2024). Chemical herbicide spraying is highly efficient, but it can result in herbicide waste, environmental pollution, and negative impacts on non-target plants and surrounding ecosystems.

In the face of these limitations of traditional weeding methods, especially with the rapid advances in sensor technology (Shaikh et al. 2022), machine learning algorithms (Liakos et al. 2018), artificial intelligence (AI) (Sharma et al. 2023), and drone technology in the 21st century (Wen et al. 2018), intelligent field-weeding robots have emerged. These robots, equipped with advanced image processing technology and AI algorithms, use vision sensors, GPS systems, robotic arms, laser tools, and automated control systems to accurately detect, locate, and eliminate weeds without harming crops. Based on different weeding techniques, intelligent weeding robots can be classified into precision-spraying robots, mechanical weeding robots, and thermal weeding robots (Hall et al. 2017; Hu et al. 2012; Quan et al. 2021; Xing et al. 2022). Among these, laser weeding technology, which allows for precise weed removal, represents a future trend. Precision weeding, which targets only specific weeds and avoids affecting crops and soil, relies on sensor technology and AI algorithms. Unlike traditional broad-spectrum weed control methods, precision weeding significantly improves resource efficiency and reduces environmental pollution, making it especially suitable for sustainable agriculture and organic crop production. Sustainable agriculture refers to the practice of conducting agricultural production in an eco-friendly and economically viable manner to meet the current food demands while protecting the environment and natural resources. The goal is to ensure that

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future generations can continue farming. Sustainable agriculture aims to reduce overreliance on land, energy, and water resources; minimize the excessive use of chemicals and harmful substances; and promote soil health, biodiversity, and ecosystem balance.

Compared with traditional weeding methods, intelligent field-weeding robots can significantly reduce labor costs, improve weeding efficiency, and minimize environmental impacts. Precision weeding in interrow and near-row areas will be a key area for technological breakthroughs in future farmland weed control. Under the broader context of smart agriculture, intelligent field-weeding robots are becoming a research hotspot in agricultural technology. A review of key technologies and research advances in intelligent field-weeding robots will not only provide valuable insights for researchers in related fields but also offer new perspectives for the intelligent development of agricultural production.

To understand the development process of intelligent weeding robots, this study used bibliometric and scientific mapping methods (Chen et al. 2015) to analyze literature on intelligent weeding from the core Social Sciences Citation Index database of the Web of Science (WOS) platform. Keywords such as "weeding robot," "weeder," and "robot platform for weeding" were set in the search interface, covering the years 2009 to 2023, and literature types including "article," "review article," "early access," and "book chapters" were selected. After removal of irrelevant and duplicate documents, a total of 385 relevant papers were identified. The number of publications, years, and keyword co-occurrence maps, as well as country, author, and institution maps were obtained using CiteSpace 6.2.R4 (64-bit) Basic software (Xu et al. 2023).

As shown in Figure 1, the number of relevant publications has been increasing exponentially. From 2009 to 2015, the number of publications was relatively low and stable. After 2016, the number of publications increased steadily, indicating growing interest and increasing attention to the research theme of intelligent weeding.

Figure 2 shows the clustering based on keywords such as "weeding," "recognition," "deep learning," "navigation," and "weeding equipment." The colors range from blue (weakest relevance) to red (strongest relevance). The clustering was based on the two key technologies of intelligent weeding and the current development status, selecting 15 major clusters with 277 nodes and 1,114 links, resulting in a network density of 0.0291, a Q value of 0.7189 (>0.3), and a mean silhouette value of 0.8921 (>0.4), indicating a reasonable clustering structure and good homogeneity within clusters. The diagram also shows that researchers focus on deep learning technology, machine vision, and the development of weeding robots, with strong interrelations between these content areas, consistent with practical applications in production.

In recent years, researchers have optimized deep learning algorithms (Chong et al. 2023; Weyler et al. 2023) to achieve weed and crop recognition and localization within the machine vision field. They have also developed mobile robot platforms to plan navigation routes (Diao et al. 2023; Li et al. 2023c), thereby achieving automated precision weeding (Guo et al. 2023; Li et al. 2023a; Tran et al. 2023). Analysis of Figure 3 shows that institutions such as China Agricultural University (Li et al. 2023b), University of California (Su et al. 2020), Indian Council of Agricultural Research (ICAR) (Pandey et al. 2023), and Consejo Superior de Investigaciones Científicas (CSIC) (Emmi et al. 2023) have produced significant research outcomes in recent years. Scholars from the United States, such as Fennimore (Su et al. 2020; Raja et al. 2020), Slaughter (Su et al. 2020; Raja et al. 2020), and Johnson (Johnson et al. 2018); Chinese experts such as Cao (Zhang et al. 2022; Tian et al. 2021), Tian (Zhang et al. 2022; Tian et al. 2021), and Ge (Tian et al. 2021); Spanish researchers like Ribeiro Angela (Conesa-Muñoz et al. 2016) and Perez-Ruiz Manuel (Aravind et al. 2017); and scholars from Germany, India, Australia, and Japan have all made notable contributions to international research.

Overall, the field of intelligent weeding has been a focus of attention, with substantial research results from countries including the United States, China, Spain, Germany, India, Australia, and Japan. Concurrently, deep learning technology has been applied to address weed removal issues. Future research will continue to focus on the development of weeding robots.

Recognition based on machine vision is a prerequisite for effective weed removal, while navigation and localization technology determine the efficiency of precision weeding. These two aspects constitute the key technologies of intelligent weeding, as illustrated in Figure 4. This paper reviews the research status of intelligent weeding robots and summarizes the critical technologies of intelligent robots, including an overview of some public datasets. It elaborates on the research progress of intelligent weeding robots categorized by weeding methods. Finally, the paper concludes with a summary and a discussion of future development trends for intelligent weeding robots.

Research Progress of Key Technologies in Intelligent Weeding Robots

Accurately and intelligently distinguishing between weeds and crops in the field is a prerequisite for the precise weeding operations of weeding robots. Navigation and localization technology, which determines the efficiency of precision weeding, is essential. These two aspects constitute the key technologies of intelligent weeding robots (Yuan et al. 2020). This paper reviews these two key technologies.

Recognition Technologies Based on Machine Vision

Research on the recognition of farmland weeds has been extensive, with methods including manual recognition, spectral analysis, spectral imaging, infrared recognition, and machine vision recognition (Chen et al. 2013). The proportions of these recognition methods in the WOS platform are shown in Figure 5. Manual recognition is inefficient, labor-intensive, and costly, with no recent references, indicating its eventual phaseout. With the continuous advancement of science and technology, computer vision technology has gradually been applied to various fields. In the 1980s, computer vision technology began to be used in agricultural applications (Wang et al. 2001). Currently, weed recognition mainly relies on machine vision technology, and the research and development of intelligent field-weeding robots cannot be separated from machine vision technology. As shown in Figure 5, other recognition methods represent a smaller proportion and are less commonly used in actual weeding operations.

Weeds are generally found in complex field environments, and any recognition technology must apply specific characteristics to the objects being identified. Weed recognition primarily involves extracting features such as morphology, color, and texture of crops and surrounding weeds. Researchers provide these extracted features to machine learning algorithms for recognition, as shown in Figure 6, which depicts the traditional machine learning–based recognition workflow. This stage of feature extraction is referred to as manual feature recognition, which includes recognition technologies based on color, shape, texture, and spectrum. As

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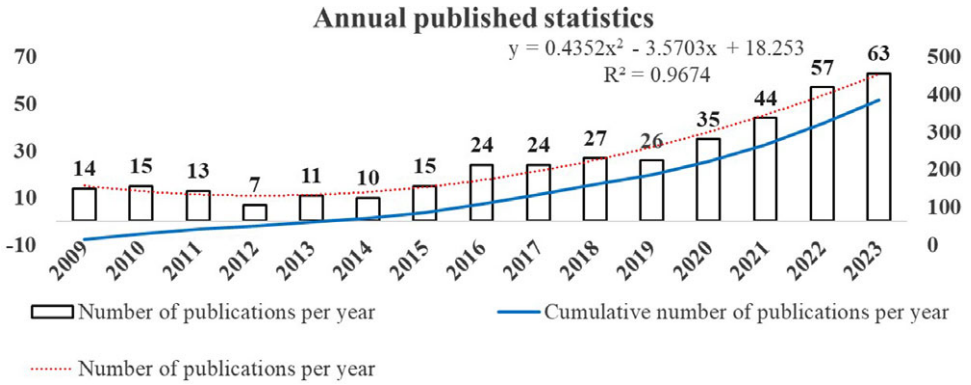


Figure 1. Annual publication volume of research literature relevant to intelligent weeding.

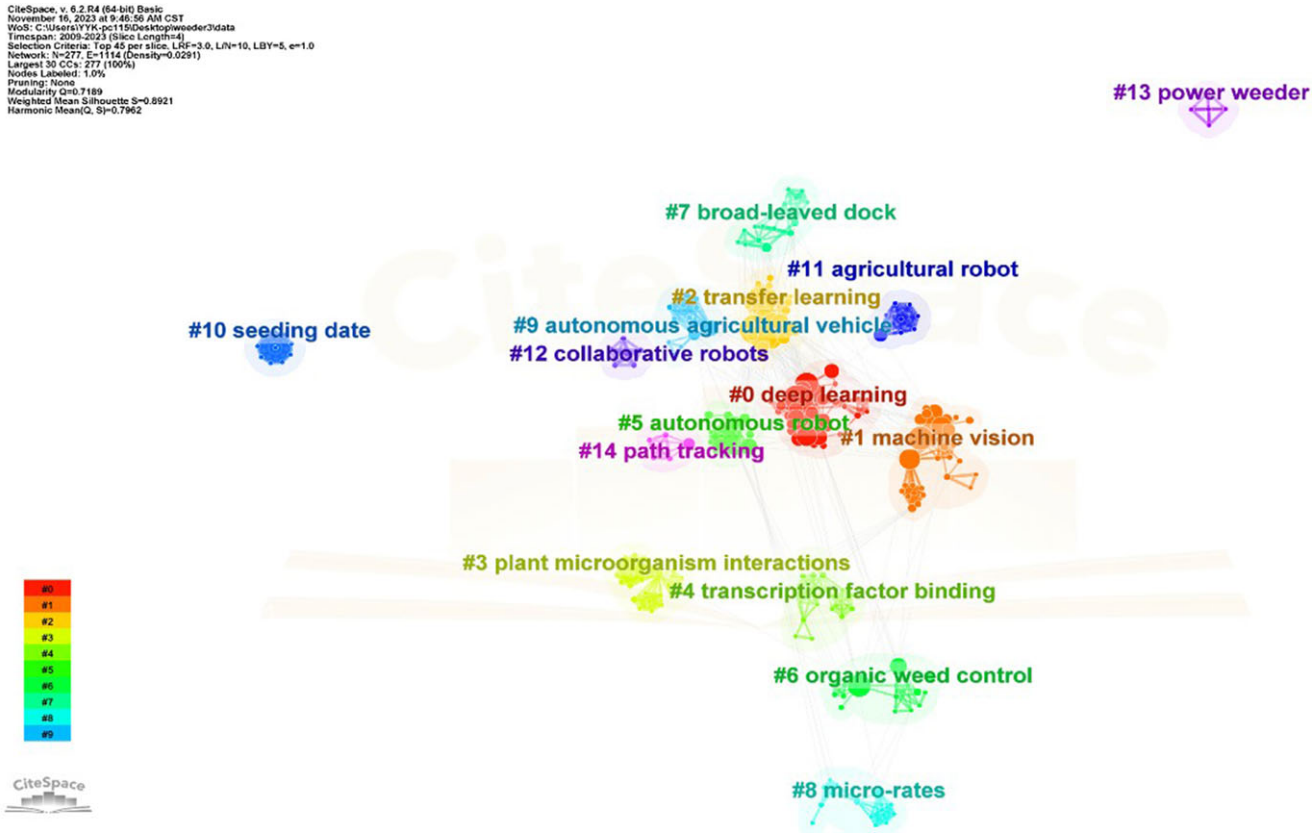


Figure 2. Co-occurrence graph of key terms.

the cost of computer hardware decreases and central processing unit (CPU) computing power increases, deep learning, which requires extensive data computation, has gradually expanded into the agricultural field. Deep learning methods extract weed features more effectively than manual feature extraction, and this stage of feature extraction is referred to as deep learning recognition technology. The following sections will detail recognition technologies based on manual features and deep learning.

Color-based Recognition

Compared with other feature-based recognition methods, color features require less computational effort and are more effective for weed detection in fields with crops that have distinctive colors. Researchers have utilized color indices to segment weeds, crops, and soil, employing recognition methods based on red–green–blue (RGB) (Chen et al. 2009; Jafari et al. 2006; Nieuwenhuizen et al. 2007), hue–saturation–value (HSV) (Hamuda et al. 2017; Miao et al. 2020), and hue–saturation–intensity (HSI) color spaces (Li et al. 2016).

In the RGB color space, the green channel contains more useful information compared with the red channel, thus requiring the integration of threshold algorithms to accomplish the segmentation task. However, it is challenging to segment plant pixels under low or bright lighting conditions in this space, whereas HSV and HSI color spaces are more robust to changes in lighting conditions.

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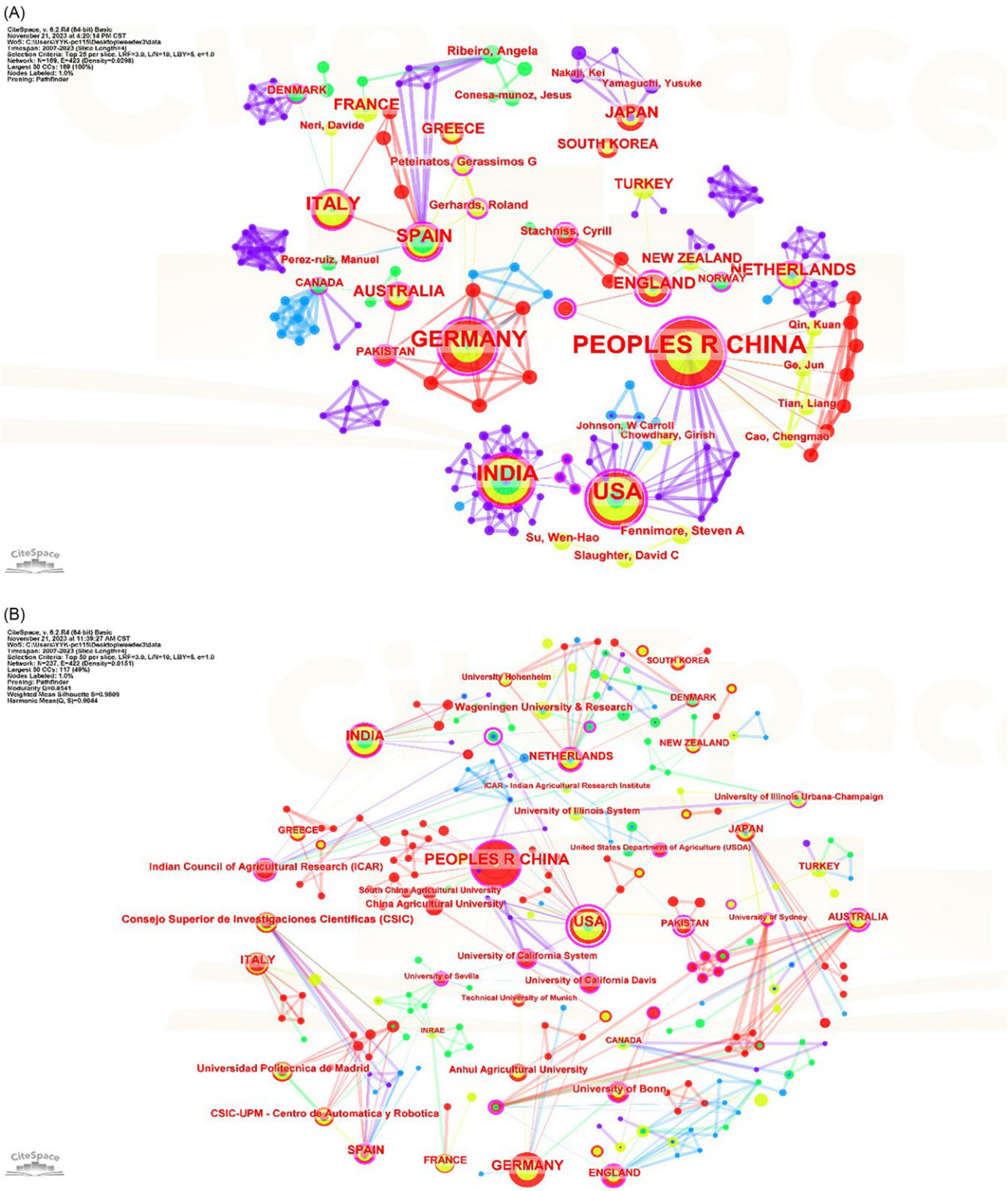


Figure 3. Research country, author, and institutional affiliation map.

This paper presents some references to color-based recognition algorithms and their recognition accuracy in Table 1.

Color features are easy to recognize and allow for quick decision making, making them suitable for real-time image processing. Additionally, ordinary cameras can meet the requirements for feature extraction, making this approach applicable to various crops and weed types. However, variations in lighting and shadows can affect recognition performance. When the colors of the plants

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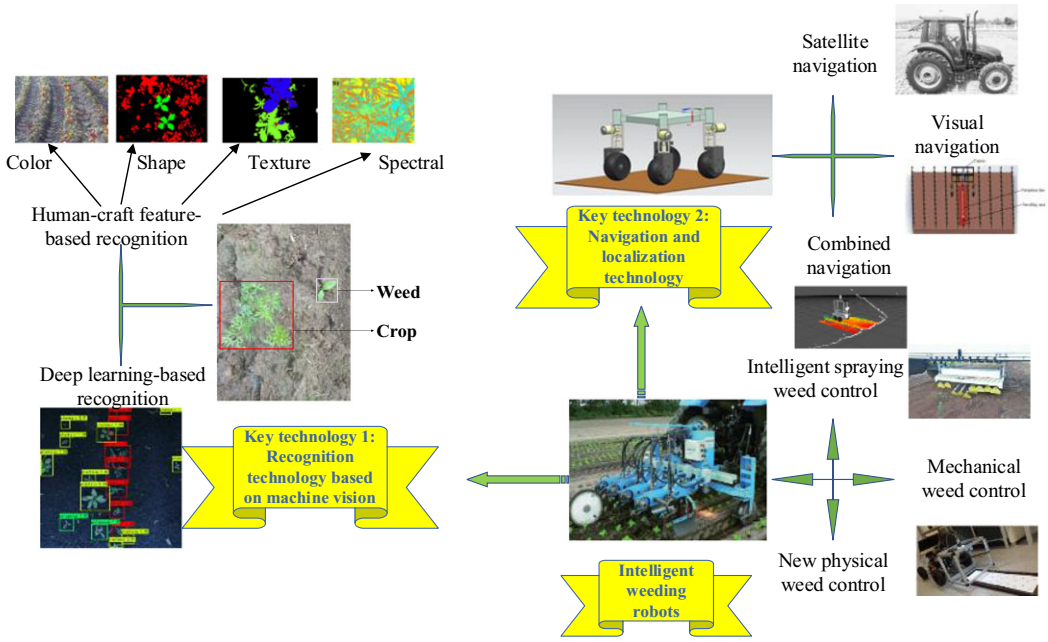


Figure 4. Key technologies of intelligent weed control.

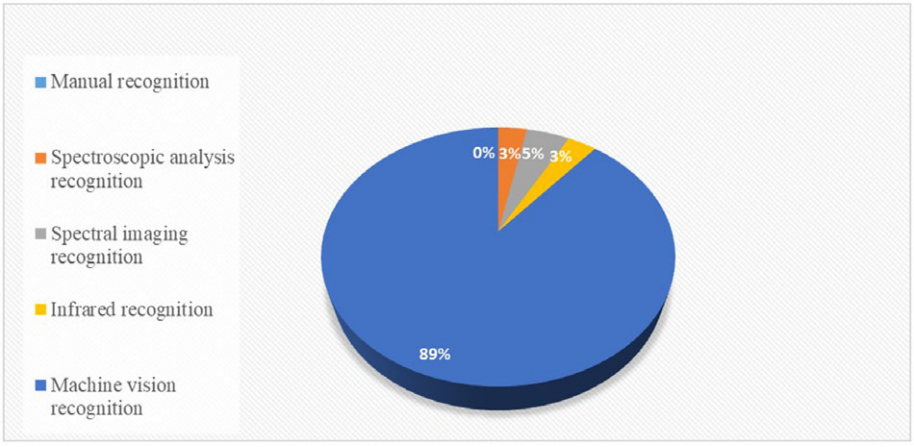


Figure 5. The proportion of references on each recognition method.



Figure 6. Recognition of traditional machine learning.

are similar, relying solely on color features may not provide satisfactory separation. To improve recognition accuracy, it is necessary to combine other features.

Shape-based Recognition

Shape features are crucial morphological characteristics in biology and play a key role in distinguishing between crops and weeds. Researchers have combined these features with machine learning algorithms, such as artificial neural networks (ANN), morphological processing algorithms, and classification algorithms like support vector machines (SVM) (Bakhshipour and Jafari 2018; Murawwat et al. 2018). Some studies have integrated shape features with other features, such as color and spectral features, utilizing a comprehensive set of morphological characteristics for analysis (Hussin et al. 2013).

Murawwat et al. (2018) applied SVM and blob analysis techniques for weed recognition. In non-occluded scenarios, the recognition accuracy reached 100%; however, in complex scenes where weeds overlap with carrot (*Daucus carota* L.) plants, the recognition accuracy dropped to 90%, as shown in the segmented image in Figure 7A. Bakhshipour and Jafari (2018) compared the performance of SVM and ANN in classifying sugar beet (*Beta vulgaris* L.) plants and weeds. SVM achieved a crop recognition accuracy of 96.67% and weed accuracy of 93.33%, while ANN

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Table 1. Color-based recognition results.

Feature	Recognition methods[a]	Crops	Recognition accuracy	Reference
Color	RGB space + Otsu automatic threshold segmentation	—	Crop row: 86.35% to 92.8%	García-Santillán et al. (2017)
	RGB space + color-depth fusion algorithm	Broccoli (*Brassica oleracea* L. var. *botrytis*), lettuce (*Lactuca sativa* L.)	Crops: 96.6%, 92.4%	Gai et al. (2020)
	RGB space + k-means clustering + adaptive neural network algorithm	Beet	Weeds: 97%/49% (different field environments)	Nieuwenhuizen et al. (2007)
	RGB space + chromaticity method	Cotton	Crop: 82.1%	Chen et al. (2009)
	RGB space + setting brightness threshold + discriminant analysis method	Beet	Crop: 88.5% Weeds: 88.1%	Jafari et al. (2006)
	HSV space + shape erosion and dilation algorithm	Broccoli	Crop: 99.04%	Hamuda et al. (2017)
	HSI space + constructing Mahalanobis distance classifier	Broccoli	Crop: 93.6%	Li et al. (2016)

[a]HSI, hue–saturation–intensity; HSV, hue–saturation–value; RGB red–green–blue.

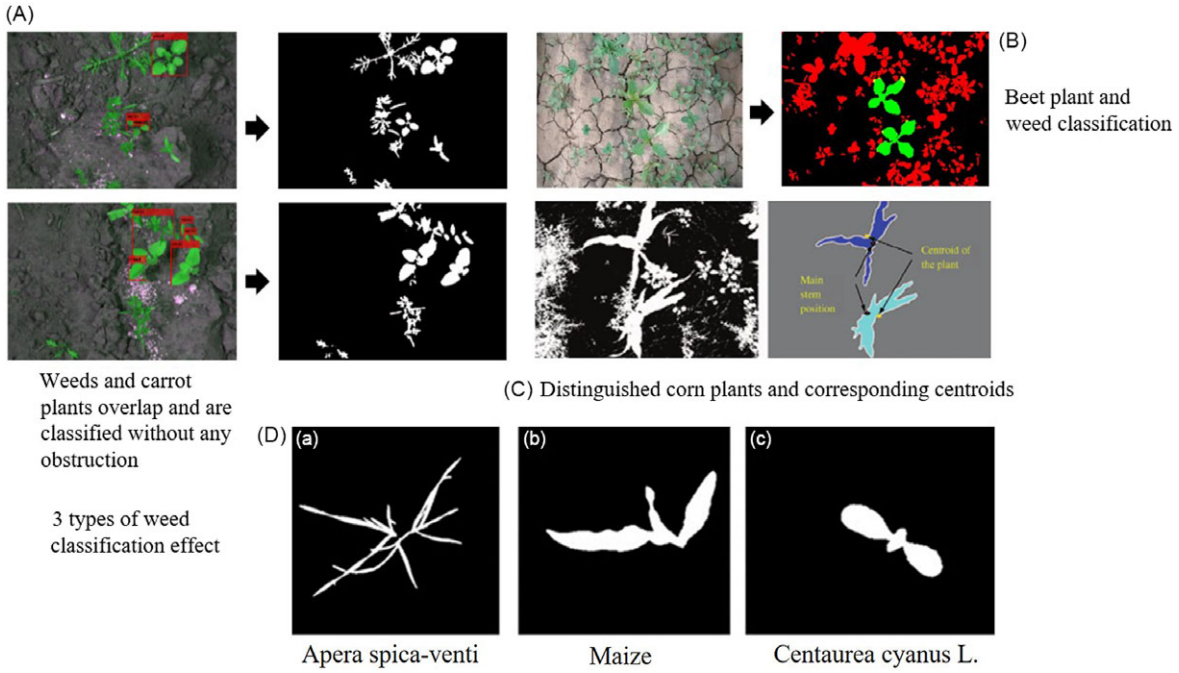


Figure 7. Classification performance based on shape features.

achieved 93.33% accuracy for crops and 92.5% for weeds. The classification results are shown in Figure 7B. An autonomous fine-tuning and feature selection using a genetic algorithm was proposed by Wong et al. (2013) and tested with the assumption that the weeds are young and non-occluded. The results show that solidity of the shapes is the most prominent feature and alone could be used to achieved 90% recognition rates. One hundred percent recognition was achieved with the combination of shape and moment invariants, as shown in the segmented image in Figure 7C. Kiani and Jafari (2012) combined discriminant analysis with back-propagation neural networks to classify maize (*Zea mays* L.) plants and weeds, achieving a maize recognition accuracy of 100% and a weed recognition accuracy of 96%, as depicted in Figure 7D.

Additionally, Jeon et al. (2011) conducted research on recognizing crops against the soil background using machine learning algorithms such as ANN, utilizing shape features to identify weeds. Li et al. (2010) employed morphological operations and distance transformation–based threshold segmentation to separate overlapping leaves. They then used the ant colony optimization algorithm and SVM classifiers for feature selection and classification, achieving a recognition accuracy of 95%.

Shape features are effective when plant leaves are intact and not overlapping. However, when there is significant overlap or damage to the leaves, extracting shape features becomes much more difficult. Furthermore, when multiple plant species with similar shapes are present in field images, classification based on shape features becomes highly complex.

Texture-based Recognition

Textural features represent the spatial arrangement of pixel grayscale levels in an image region, which are critical for recognizing objects or regions of interest in images. Researchers have used the gray-level co-occurrence matrix to extract textural features of crops and weeds (Mustafa et al. 2007; Wu et al. 2009) and employed supervised learning algorithms, such as SVM and ANN, for weed recognition. To address the challenge of significant leaf occlusion hindering effective textural feature extraction, some

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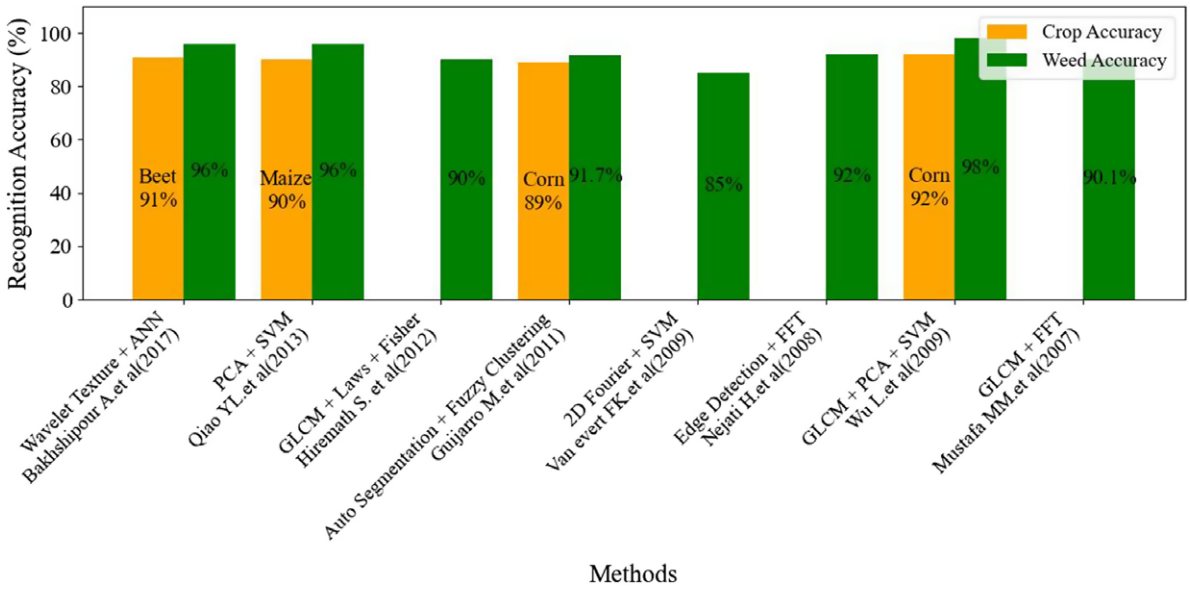


Figure 8. Texture-based crop/weed recognition accuracy. ANN, artificial neural networks; FFT, fast Fourier transform; GLCM, gray-level co-occurrence matrix; PCA, principal component analysis; SVM, support vector machines.

studies have adopted wavelet decomposition methods combined with supervised learning algorithms for recognition (Bakhshipour et al. 2017).

As shown in Figure 8, the horizontal axis represents crop/weed recognition methods based on textural features, and the vertical axis indicates the corresponding crop and weed recognition accuracy. PCA refers to principal component analysis; GLCM refers to gray-level co-occurrence matrix; and FFT refers to fast Fourier transform. The figure shows that the crop recognition accuracy across different methods ranges from 89% to 92%, and weed recognition accuracy ranges from 85% to 98%. The method by Wu et al. (2009) achieves the highest recognition accuracy. Their image-segmentation process involves converting the original color image to grayscale based on the statistical values of the red, green, and blue components. The textural features of weeds and maize seedlings are then obtained using GLCM and the statistical properties of the grayscale image histogram. These textural features are used in the classification process. PCA is employed to select textural features that contribute best to reducing spatial dimensions. SVM is used as the classification tool to identify weeds and maize seedlings in the early growth stages of a maize field. The results show that the SVM classifiers with different feature selection strategies can successfully identify weeds and maize, achieving an accuracy ranging from 92.31% to 100%.

Like shape features, the extraction of textural features is a computationally intensive image processing task. Typically, feature selection and dimensionality reduction algorithms are used to select the most contributory feature parameters for input into classifiers. Effective texture analysis requires a large amount of high-quality labeled data for training. The advantage of textural features lies in their stability when dealing with occluded leaves and in distinguishing between crops and weeds, even under varying lighting conditions.

Spectrum-based Recognition

The main challenge in classifying weeds and crops lies in their similar spectral characteristics. If the weed and crop leaf colors are different, this recognition technique can effectively distinguish them; if their colors are similar, other features such as shape must be included for efficient recognition. Researchers have used hyperspectral cameras to collect data and then integrated machine learning algorithms for recognition (Bai et al. 2013; Gao et al. 2018; Herrmann et al. 2013; Pantazi et al. 2016; Piron et al. 2008).

Gao et al. (2018) explored the feasibility of using a near-infrared snapshot mosaic hyperspectral camera for weed and maize classification. They tested random forest (RF) models to build classifiers with different spectral feature combinations, identifying an optimal RF model with 30 key spectral features. The average accuracy for corn, field bindweed (*Convolvulus arvensis* L.), *Rumex* spp., and Canada thistle [*Cirsium arvense* (L.) Scop.] was 1.0, 0.789, 0.691, and 0.752, respectively, as shown in Figure 9A. Pantazi et al. (2016) achieved optimal results with active learning by using a self-organizing map (SOM) and mixture of Gaussians (MOG) single-class classifiers. The crop recognition performance was 100% for both methods. For the MOG-based single-class classifier, the correct recognition rate for different weed species ranged from 31% to 98%. The SOM-based single-class classifier's correct recognition rate varied between 53% and 94%, as illustrated in Figure 9B. Zhao et al. (2013) proposed a multifeature weed recognition method based on multispectral imaging and data mining, in which the multifeature recognition rate was higher than single-feature recognition. The combination of spectral, textural, and fractal dimension features yielded the highest recognition accuracy of 96.3%, as depicted in Figure 9C. Bai et al. (2013) used stepwise discriminant analysis to select spectral reflectance data at four key wavelength points—710, 755, 950, and 595 nm—for precise weed recognition. By determining prior probabilities based on category size, the Bayesian discriminant function model achieved a recognition accuracy of 98.89%, enabling precise and stable weed recognition during the early growth stage of winter canola (*Brassica napus* L.), as shown in Figure 9D. Herrmann et al. (2013) used ground-level image spectroscopy data, with high spectral and spatial resolutions, for detecting annual grasses and broadleaf weeds in wheat (*Triticum aestivum* L.) fields. The image pixels were used to cross-validate partial least-squares discriminant analysis classification models. The best model was chosen by comparing the

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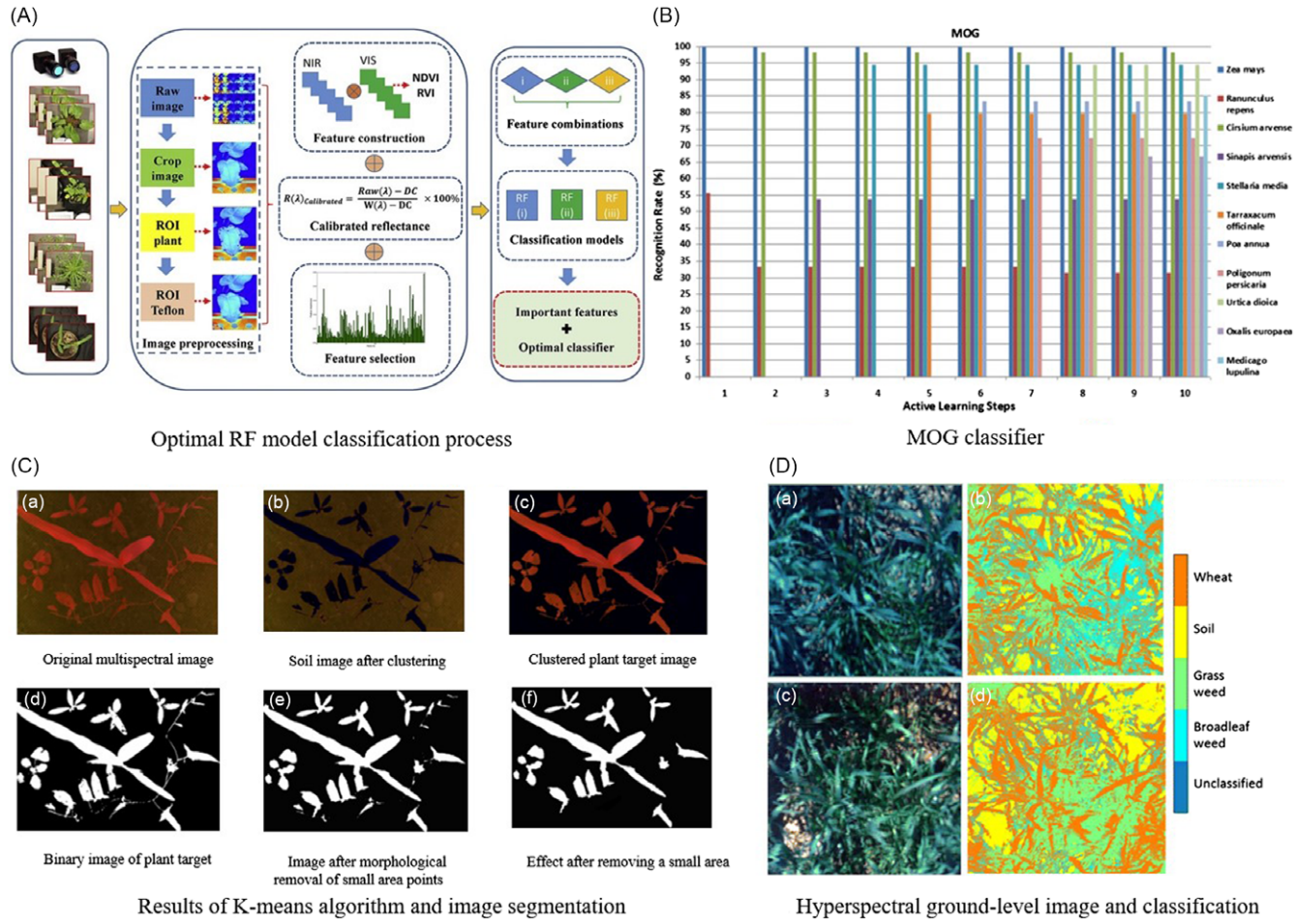


Figure 9. Classification performance based on spectral features. MOG, mixture of Gaussians; RF, Random Forest.

cross-validation confusion matrices in terms of their variances and Cohen's kappa values. This best model used four classes—broadleaf, grass weeds, soil, and wheat—and resulted in a kappa of 0.79 and total accuracy of 85%.

Hyperspectral cameras can capture subtle spectral differences between crops and weeds. However, pixel-based recognition is inefficient. Machine learning algorithms, such as SVM and RF, can be employed to build weed recognition classification models, significantly improving efficiency and accuracy in large-scale crop production. Nevertheless, these methods also face challenges, such as changing lighting conditions, the similarity of spectral features between crops and weeds, and the complexity of processing and analyzing image data.

Therefore, relying on a single feature for recognition often results in low accuracy and poor stability, as it fails to fully utilize multifeature information for recognition. It is essential to consider a combination of factors, optimize model algorithms, and integrate other agricultural technologies to achieve more accurate and reliable weed detection and management. How to optimize the fusion of features and resolve the contradiction between recognition accuracy and response time is a critical issue that needs to be addressed.

Analysis of these references and comparison of various feature-based recognition methods indicates that techniques using color, shape, texture, and spectral features can achieve high recognition rates. However, the performance of these techniques in real-time weed detection is hindered by the complex field environment, as the recognition rate depends on image acquisition methods, preprocessing methods, and the quality of feature extraction.

Deep Learning–based Recognition

Deep learning algorithms effectively avoid the subjectivity introduced by the feature extraction process in traditional machine learning methods. They can automatically extract deep features from images, offering stronger representation capabilities and unique network feature structures, thereby improving weed recognition accuracy.

On the one hand, deep learning methods can extract weed features. For instance, Peng et al. (2019) proposed a two-stage algorithm based on faster region-based convolutional neural networks integrated with feature pyramid networks, which achieved good detection performance in complex backgrounds in cotton (*Gossypium hirsutum* L.) fields. Fawakherji et al. (2019) developed a model that accurately classified crops and weeds by generating patches from binary images for robotic use. dos Santos Ferreira et al. (2017) trained a neural network using the Caffe Net architecture, achieving 97% accuracy in weed detection.

On the other hand, deep learning algorithms can directly recognize weeds. Naveed et al. (2023) proposed a novel weed detection model that can be executed on CPU systems, reducing computational costs. Some researchers have optimized deep learning algorithms for better recognition performance (Bah

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Table 2. Experimental results of deep learning algorithms.

Deep learning algorithms	Crop	Recognition accuracy	Reference
Mobile robots + YOLOv5	Vegetable	Crop: 95.7%	Zhang et al. (2023)
PC/BC-DIM	—	Crop: 94.38%	Naveed et al. (2023)
Machine vision algorithms	Tomato	Crop: 99.19%	Raja et al. (2020)
Improvements to the Xception model	Corn	Crop: 98.63%	Xu et al. (2021)
SegNet model + CNN	—	Crop: 93.58%	Bah et al. (2019)
YOLOv4 + attention mechanisms	Carrot	—	Ying et al. (2021)
Deep backbone network	Rice	Crop: 93.22%	Huang et al. (2020)
Semantic graphs and deep convolutional encoder-decoder networks for data annotation	Echinochloa crus-galli	—	Adhikari et al. (2019)
Caffe Net architecture for training neural networks	—	Weeds: 97%	dos Santos Ferreira et al. (2017)

DIM, decisive input modulation; PC, predictive coding; BC, biased computation; CNN, convolutional neural networks.

et al. 2019; Krizhevsky et al. 2017; Sun et al. 2018). Other studies have utilized one-stage object detection algorithms from the YOLO series for weed detection (Sun et al. 2024; Ying et al. 2021; Zhang et al. 2023). In deep network research, Li et al. (2023a) proposed E2CropDet, a deep learning-based crop-row detection network that achieved end-to-end detection at 166 frames s^{-1}, with a lateral deviation of 5.945 pixels in centerline extraction, surpassing semantic segmentation (7.153) and Hough transform–based methods (17.834). You et al. (2020) continuously improved a weed/crop segmentation network by integrating four additional components, reducing weed density. Some experts have achieved good recognition results in multistage algorithm design (Adhikari et al. 2019; Huang et al. 2020). Table 2 provides information on deep learning–based seedling and weed recognition technologies.

Analysis of the experimental results of recognition algorithms indicates that this technology makes weed detection and classification more accurate in complex field environments.

Traditional feature-based recognition technologies primarily focus on image-level classification, while deep learning–based recognition focuses on pixel-level classification, where each pixel is segmented and labeled as either weed or crop. In recent years, some scholars have combined deep learning methods with traditional methods, proposing solutions for different processing steps in fruit and vegetable recognition against similar color backgrounds. This demonstrates that the integration of image processing technology and deep learning technology is a significant research direction for the future.

Navigation and Localization Technologies

Navigation and localization technologies are critical for intelligent weeding. After seedling and weed recognition, accurate localization of weeds is necessary to assist intelligent weeding devices in completing real-time calculations and weeding tasks. With the continuous development of AI technology in recent years, this key technology has been increasingly researched and improved by experts and scholars. Satellite navigation, visual navigation, and integrated navigation are the most widely used, and the following sections will introduce the research and development status of these three navigation and localization technologies.

Satellite Navigation and Localization

Currently, the application of Global Navigation Satellite System (GNSS) navigation is widespread and mature. Agricultural machinery equipped with GNSS can significantly improve operation quality and efficiency in the field, although GNSS signal loss can occur in complex environments, such as dense foliage.

Examining the history of satellite navigation development, GNSS can be applied in three ways.

GPS Localization: Stoll et al. (2000) used GPS as the sole localization sensor for autonomous driving experiments, achieving a standard deviation better than 100 mm under various conditions, with a lateral deviation range of 25 to 69 mm during straight-line driving. Corpe et al. (2013) developed a GPS-based agricultural robot equipped with multiple sensors for environmental information detection, considering complex field conditions.

Real time kinematic (RTK)-GPS Localization: Kise et al. (2001) applied this localization method to a tractor control system, reducing heading response and error during trajectory-following operations. Researchers have used this method for intrarow weed control (Nørremark et al. 2012; Pérez-Ruiz et al. 2012).

RTK-DGPS Localization: Luo et al. (2009) achieved a maximum linear-tracking error of less than 0.15 m at a travel speed of 0.8 m s^{-1}, with an average tracking error of less than 0.03 m using this method. Bakker et al. (2011) conducted autonomous navigation research in sugar beet fields using an RTK-DGPS-based agricultural robot platform, achieving centimeter-level precision in field trials. Subsequently, RTK-DGPS with centimeter-level localization accuracy has been widely used in agricultural machinery navigation systems (Hu et al. 2015). Li et al. (2017) combined dual-loop steering-control technology with this navigation method, achieving a path-tracking error average of less than 1.9 cm and a standard deviation of less than 4.1 cm. Additionally, some experts have combined satellite localization technology with other navigation techniques to achieve better localization accuracy.

Visual Navigation and Localization

In the 1980s, the United Kingdom and the United States were the first to research visual navigation systems. This localization technology has been a great success, and to this day, experts and scholars continue to use visual navigation systems for precise pesticide spraying, intelligent mechanical weeding, and physical weeding, despite some drawbacks during usage. This localization technology is often used in combination with intelligent robots.

Marchant et al. (1996) developed a weeding robot based on visual navigation and localization technology using a grayscale band-pass filter. At a traveling speed of 1.6 m s^{-1}, the lateral localization error was 15.6 mm. Lee et al. (1999) developed an intelligent weeding robot based on machine vision. This robot is equipped with two cameras, one for navigation and the other for

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weed recognition. Kise et al. (2005) applied stereovision to the navigation system of agricultural vehicles in the field, enabling accurate localization of crop rows in weedy fields and guiding the tractor to travel precisely along both straight and curved lines. Zhang and Ying (2006) also proposed a field automatic navigation system based on machine vision. Meng et al. (2013) used visual navigation and localization technology and proposed a crop-row centerline detection method constrained by linear correlation coefficients, solving the problems of slow detection algorithms and susceptibility to external interference. García-Santillán et al. (2018) developed a system for detecting crop and weed rows in early growth stages of cornfields using a camera mounted at the front of a tractor, based on visual navigation and localization technology.

Some researchers have applied machine learning algorithms to visual navigation systems. Hiremath et al. (2014) proposed a vision-based navigation algorithm using particle filtering, and experiments demonstrated that this algorithm has good robustness, enabling accurate navigation in the field. Zhou et al. (2014) applied a self-learning visual navigation method to a wheeled mobile robot. Yao et al. (2016) proposed a navigation control algorithm based on binocular vision, and experiments showed that the system had a small navigation offset. Wang et al. (2019) applied deep learning algorithms to orchard environment navigation systems, extracting new orchard road navigation lines that solved issues of susceptibility to other conditions.

Li et al. (2022) proposed an Aster-U-Net model to address issues such as complex image backgrounds in visual navigation systems in both field and greenhouse environments, as well as weed and light interference. Thakur et al. (2023) published an academic work aimed at using acquired knowledge to guide the construction of practical agricultural machine vision systems. This work thoroughly examined the components of machine vision systems; investigated image acquisition, processing, and classification techniques; and explored the methods adopted by each technology. Additionally, it studied how to integrate these processes to perform various agricultural activities, such as weeding, seeding, harvesting, fruit counting, overlapping, and sorting.

Integrated Navigation and Localization

A combined navigation system typically consists of two or more subsystems based on different navigation technologies. By leveraging the error characteristics and advantages of each navigation technology, a continuously operating combined navigation system can provide continuous and comprehensive navigation parameters. In recent years, researchers have mainly employed the following three methods to achieve integrated navigation and localization functions.

First, the combination of GPS navigation technology and machine vision navigation technology has been applied to weeding systems. Francisco et al. (2005) fused these two navigation technologies with a fuzzy logic model, utilizing the relative information from vision to correct GPS errors. Bakker (2009) combined these navigation technologies in a multifunctional automatic weeding robot, enabling row navigation and herbicide spraying. Zhang et al. (2015) designed a system that integrates these two navigation technologies and uses corn crop row information captured by cameras for interrow mechanical weeding.

Second, the combination of laser navigation and inertial navigation systems has been explored. Kim et al. (2012) designed a paddy field-weeding robot based on multisensor fusion, combining laser navigation and inertial navigation systems, and achieved a maximum operational deviation of 6.2 cm.

Third, the GPS/Dead Reckoning (DR) integrated navigation system has been applied to weeding robots. Ding et al. (2006) applied a GPS/DR integrated navigation system to a weeding robot, improving the navigation accuracy and addressing the issue of signal interruptions.

Additionally, Ding et al. (2015) combined GPS localization technology with a fuzzy control navigation system. Simulation results showed that this method is feasible, with the system achieving rapid and stable performance. Currently, the most widely used integrated navigation system is the GNSS/Inertial Navigation System (INS) integrated navigation system. This system combines satellite navigation and inertial navigation technologies to achieve high-precision localization, speed measurement, attitude determination, and timing functions. Developing a highly reliable navigation system is a challenge rather than a simple task. Furthermore, some researchers have developed autonomous robots with integrated navigation and localization systems based on total stations and 2D LiDAR laser scanners for plant phenotyping studies. Reiser et al. (2018) combined a 2D laser scanner with a four-wheel autonomous robot to navigate between corn rows, achieving differential steering at a 30° downward angle and collecting concurrent timestamped data. Data fusion generated a 3D point cloud, which can be used for various applications and navigation purposes, particularly for phenotypic analysis, individual plant treatment, and precise weeding. As shown in Figure 10, the robot platform used for data collection is represented in the robot operating system (ROS) visualization tool rviz (Kam et al. 2015) during LiDAR data assembly. Reiser et al. (2019) also developed a rotary weeding implement for autonomous electric robots to address weeding between orchard and vineyard rows. This implement autonomously followed rows based on 2D LiDAR data at a forward speed of 0.16 m s^{-1} and a working depth of 40 mm. In the future, the combination of autonomous navigation and weeding can improve weeding quality and reduce power consumption.

It should be noted that high-precision GPS and increasingly popular LiDAR technology provide new options for field-weeding robot navigation systems. Combining machine vision with GPS or LiDAR to design efficient weeding robot navigation systems could be a significant trend in future developments.

Establishing Public Datasets

Images of crops and weeds are generally required to be acquired and processed in real time, with cameras mounted on mobile robots operating in the field. Most datasets comprise RGB images of crops and weeds taken with high-resolution digital cameras from around the world, with some datasets containing information on multiple weed species. Table 3 introduces the sources and contents of the obtained public datasets.

Progress in Research on Intelligent Weeding Robots

Precision spraying and physical weeding are currently the mainstream methods for intelligent weeding. This section reviews intelligent spraying weeding robots, mechanical weeding robots, and thermal weeding robots, focusing on these two weeding methods.

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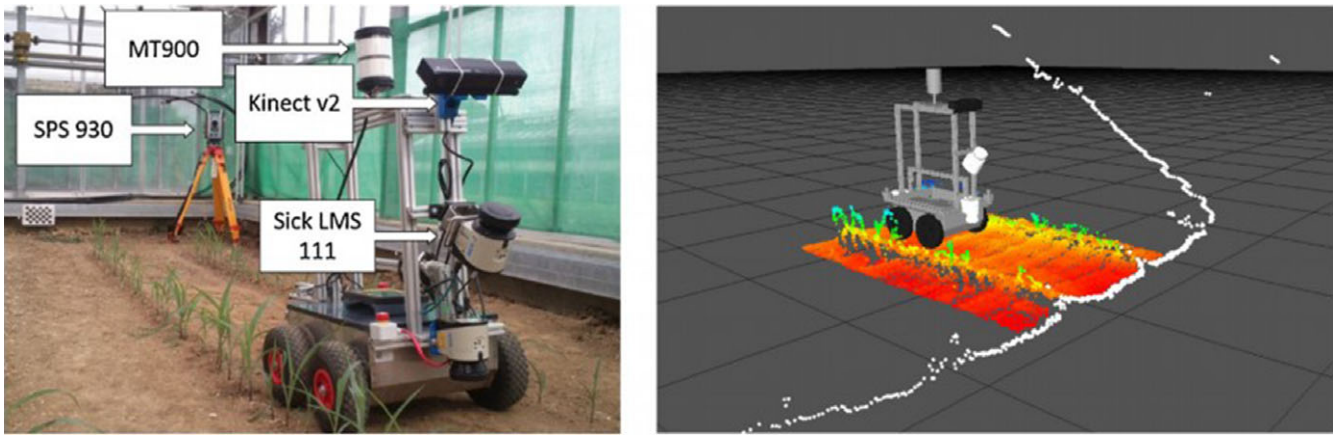


Figure 10. Robot platform (left) and data visualization (right). Kinect v2, a sensor (Microsoft n.d., Redmond, WA, USA); MT900, machine target prism (Trimble n.d., Sunnyvale, CA, USA); Sick LMS111, 2D-LiDAR laser scanner (SICK n.d., Waldkirch, Germany); SPS 930, universal total station (Trimble).

Table 3. Public datasets.

Classifications	Description of the dataset	Source	Reference
Applied to deep learning models	Annotated carrot and weed image dataset	https://github.com/cwfid/dataset	Haug et al. (2015)
	Six publicly available datasets containing 22 different plant species	—	Dyrmann et al. (2016)
	Image dataset of sugar beet and weeds	https://www.ipb.uni-bonn.de/2018/10/	Chebrolu et al. (2017)
	Crop and weed image dataset with 7,853 annotations, including 6 food crops and 8 weeds, totaling 1,118 images	https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7305380/	Sudars et al. (2020)
	A dataset of plant and weed images was from 47 different species. The data originated from Denmark and contains 315,038 plant objects representing 64,292 individuals, totaling 7,590 RGB images	https://gitlab.au.dk/AUENG-Vision/OPPD	Leminen Madsen et al. (2020)
Based on different industrial cameras	Point-and-shoot industrial cameras	https://vision.eng.au.dk/leaf-counting-dataset/	Teimouri et al. (2018)
	Multispectral camera	Carrots: https://lcas.lincoln.ac.uk/nextcloud/index.php/s/RYni5xngnEZEFkR Onions: https://lcas.lincoln.ac.uk/nextcloud/index.php/s/e8uiyrogObAPtcN	Bosilj et al. (2020)
Includes a large number of images	CNU Weed Dataset containing 21 weed species from 5 families, totaling 208,477 weed images	https://www.sciencedirectcom/science/article/pii/S0168169919319799#s0025.	Trong et al. (2020)
	GrassClover image dataset containing 31,600 unlabeled and 8,000 synthetic datasets for red clover (Trifolium pratense L.), white clover (*Trifolium repens* L.), and other related weeds	https://vision.eng.au.dk/grass-clover-dataset/	Skovsen et al. (2019)
Standardized weed data sets	ImageNet		Deng et al. (2009)
	MS COCO		Lin et al. (2014)
Others	DeepWeeds dataset evaluating encoder–decoder architecture to distinguish crops from weeds	DeepWeeds: https://github.com/AlexOlsen/DeepWeeds	Olsen et al. (2019)
	Carrot–weed dataset	https://github.com/lameski/rgbweeddetection	Lameski et al. (2017)
	Corn, lettuce, and weed datasets	https://github.com/zhangchuanyin/weed-datasets	Jiang et al. (2020)
	Plant Seedling dataset containing 12 different plant species.	https://www.kaggle.com/vbookshelf/v2-plant-seedlings-dataset	Giselsson et al. (2017)

Precision-Spraying Weeding Robots

The Smart Sprayer combines sensors, AI algorithms, and automated control systems to optimize the use of pesticides and herbicides. In the late 20th century, Lee et al. (1999) developed a prototype robot for precision herbicide spraying on tomato (*Solanum lycopersicum* L.) plants based on a machine vision system, achieving real-time identification accuracy of 73.1% for tomatoes and 68.85% for weeds. Åstrand and Baerveldt (2002) developed an autonomous agricultural robot for mechanical weed control in outdoor environments, utilizing a grayscale vision system. This system could detect crop-row structures and guide the robot with an accuracy of ±2 cm. It also employed a color-based vision system capable of identifying single crops among weeds, allowing the robot to manage weeds within crop rows.

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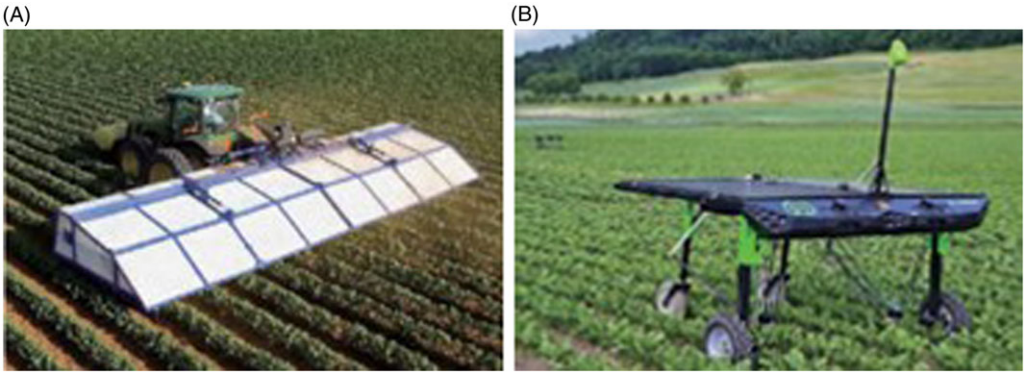


Figure 11. Precision-spraying robots.

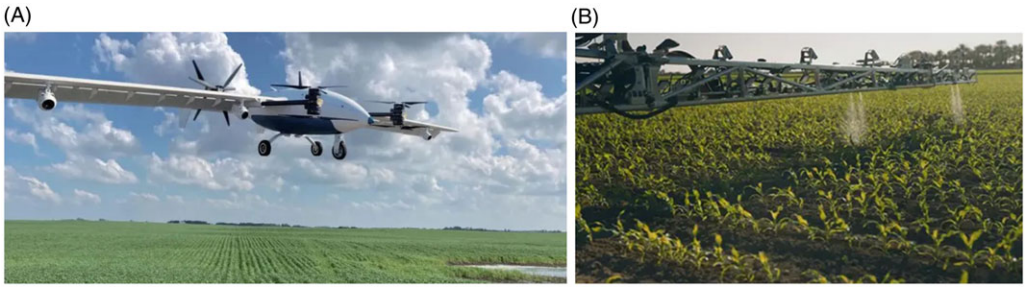


Figure 12. Drone weeding and weeding robots.

Subsequent designs focused on site-specific weed management for smart sprayers. Hussain et al. (2020) designed a variable-rate smart sprayer that achieved the highest accuracy using the YOLOv3-tiny model, it was able to save 43% spraying liquid during weeds and simulated diseased plant detection experiments. Partel et al. (2019) developed a low-cost spraying system that utilized AI and YOLOv3 for weed recognition and classification, with an NVIDIA GTX 1070 GPU achieving 71% accuracy in detecting and locating weed species. Upadhyay et al. (2024) designed and developed a YOLOv4-based smart spraying system, achieving an average effective spray rate of 93.33%, with 100% precision and a recall rate of 92.8% in indoor experiments. In contrast, field trials showed a slightly lower spray rate of 90.6%, while maintaining 95.5% precision and an 89.47% recall rate.

The See and Spray robot (Commercial promotion can be traced back to 2021) developed by John Deere combines a vision system with a precision-spraying system, achieving an identification accuracy of greater than 98%. It classifies weeds and crops using vision technology. Powered by tractors, it can operate continuously for long periods, working up to 12 h in large-scale crop fields such as cotton and soybean [*Glycine max* (L.) Merr.], covering 200 ha d^{-1} at 16 km hr^{-1}. This robot reduces herbicide usage by 50-90%, significantly minimizing environmental impact (Figure 11A).

Figure 11B is the Greeneye Technology weeding robot (Gained widespread attention, can be traced back to 2021), whose core technology is its AI-based selective spraying system (SSP). It uses onboard cameras to capture real-time field images. Combined with deep machine learning algorithms, the system accurately identifies and locates various types of weeds, enabling selective spraying on each plant. Compared with traditional weeding methods, SSP reduces herbicide usage by greater than 87% on average.

The SprayBox robot (Earliest appearance can be traced back to 2022), developed by Verdant Robotics, is equipped with 50 nozzles and a sophisticated computer system that integrates computer vision and machine vision technology. It targets individual weeds and crops at a rate of 20 times per second, spraying herbicides or fertilizers with millimeter precision. The system can spray up to 1.52 ha h^{-1} and identify and process more than 500,000 plants, reducing chemical herbicide usage by approximately 95% compared with traditional spraying techniques. It has been scaled for use in carrot cultivation.

On the other hand, demand-driven spraying (DoD) is a novel approach that applies calculated doses of herbicides to target weeds. Utstumo et al. (2018) used DoD technology to apply 5.3 µg of glyphosate per droplet, reducing herbicide usage 10-fold. Spaeth et al. (2024) reported savings of 10% to 55% in herbicide usage through weed recognition using digital image processing technology. Liu et al. (2021) integrated a deep learning model and a variable-rate sprayer for targeted weed control, with VGG-16 demonstrating the best performance, achieving an F1 score of 0.88 in weed classification, and 86% of weed targets were completely sprayed under actual field conditions. Jin et al. (2023) presented a smart sprayer system with ResNet, achieving F1 scores of 92% or higher, enabling precise weed control in dormant bermudagrass [*Cynodon dactylon* (L.) Pers.] grass lawns.

These systems improve weed and crop identification accuracy, allowing for targeted herbicide application. EcoRobotix, a Swiss company, developed a solar-powered weeding robot (Earliest appearance can be traced back to 2017) that applies machine vision, GPS, and other sensors to autonomously track crop rows and detect weeds with 95% accuracy. It then uses a parallel robotic arm to quickly and precisely spray small doses of herbicide directly onto weeds, reducing pesticide usage by 20 times (Figure 12A).

The integration of remote sensing technology has undoubtedly enhanced the efficiency of precision spraying. Gerhards et al. (2022) used airborne and ground-based remote sensing technology

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to gather weed information and applied multifeature fusion technology to identify weeds, enabling precise herbicide application. The combination of sensors and drone technology effectively improves identification efficiency. Figure 12B shows the Precision AI Weeding Drone (Earliest appearance can be traced back to 2022), equipped with 0.5-mm-resolution cameras capable of distinguishing weeds in a short time and accurately spraying them with herbicides.

The application of smart sprayers in global agriculture is rapidly expanding. Precision-spraying equipment combined with AI technology provides farmers with efficient, low-consumption solutions. In addition to reducing chemical herbicide usage, these systems can increase crop yields and reduce soil and water contamination. As AI models continue to improve, smart sprayers are becoming adaptable to different crop types and climate conditions, providing greater flexibility and accuracy in real-world applications.

The soil and water pollution caused by excessive use of herbicides and the pesticide residues on cultivated crops have become hidden dangers to human health. The machine vision subsystem cannot distinguish between plants with similar characteristics, resulting in misidentification and thus misspraying. During weeding operations, small-sized weeds may later regenerate in the targeted spraying area. Although the position error caused by the change in the nozzle angle can be reduced through calibration, key factors such as the sensitivity and stability of the servomotor still need to be considered. When the robot turns, it reduces the speed of the vehicle, while the flow of chemicals remains unchanged, making it easier for weeds to develop resistance at the place where the machine turns. The best time to apply herbicides is when the weed canopy is still developing. Once missed, the weeds can tolerate larger doses of herbicides, and this timing is elusive. In addition, the realization of further precision-spraying technology requires a high investment cost, and future technological improvements need to reduce costs.

Public concerns about the relationship between chemical herbicides and food safety, farm worker health, biodiversity, and the environment in general have renewed interest in alternative weed control measures, primarily physical weed control methods. The subsequent sections will review intelligent weeding robots that utilize physical weeding methods.

Mechanical Weeding Robots

In the past century, the commercialization of interrow mechanical weeding technology was limited due to the continued dominance of cost-effective chemical weeding methods, leading to low market demand for expensive intelligent interrow mechanical weeding equipment. However, recent advances in domestic electronic information, automatic control, and AI technologies have spurred extensive research into interrow mechanical weeding by researchers, driving the emergence of intelligent interrow mechanical weeding equipment. Table 4 details the mechanical weeding robot actuators and their characteristics.

Mechanical weeding robots face challenges in removing interrow weeds and eliminating perennial weeds. Low accuracy in weed and crop identification and positioning increases the risk of crop damage during the weeding process, necessitating further optimization of identification and positioning algorithms. High-efficiency weeding operations can cause severe soil disturbance, damaging crops. Therefore, the design must strike a balance between operational speed, reducing costs, and minimizing crop damage. Different soil conditions present varying levels of resistance, requiring weeding devices to adapt to different types of soil to reduce operational resistance. For example, heavy clay soils often result in poor weeding and soil fragmentation effects. Mechanical weeding also demands rapid tool movement, meaning the hardware needs to have a higher response speed. After completion of weeding tasks, weed entanglement between the weeding components can affect efficiency, so further optimization of these components is necessary.

Thermal Weeding Robots

Modern physical weeding methods include flame weeding, laser weeding, steam weeding, infrared radiation weeding, and hot-water weeding, with laser weeding being the latest invention among thermal weeding methods.

Laser weeding is an effective physical weeding method that involves emitting high-energy laser beams at weeds over a short period, directly transferring thermal energy to selectively heat plant material, causing the moisture within plant cells to rise and inhibiting weed growth. The penetration of specific-wavelength laser radiation into tissues, the thermal effects within irradiated tissues, and the associated damage mechanisms are critical for the successful laser control of weeds. Hoki (2000) irradiated young rice (*Oryza sativa* L.) plants with lasers of different wavelengths (532 and 1,064 nm), discovering effect and dose–effect relationships that were neither uniform nor consistent. Targeting stems can be challenging for some weed species. Mathiassen et al. (2006) studied the effects of lasers on the apical meristems of certain weed species at the cotyledon stage using a handheld system under three different potted weed conditions, testing two lasers and two spot sizes, and applying different energy doses by varying irradiation times.

In recent years, laser weeding technology has increasingly relied on the overall regulation of laser weeding equipment. Xiong et al. (2017) designed a prototype robot for indoor performance testing, achieving a hit rate of 97% with a laser penetration speed of 30 mm s^{-1} and a dwell time of 0.64 s $weed^{-1}$. Considering the high dynamic advantages of parallel mechanisms (PM), Wang et al. (2022) proposed a novel laser weeding frame based on a two-degrees-of-freedom, five-rotation parallel mechanical arm for dynamic laser weeding. Fatima et al. (2023) designed a lightweight, deep learning–based commercial autonomous laser weeding robot weed detection system (Figure 13A). LaserWeeder, a weeding robot developed by Carbon Robotics (n.d.) in the United States (Commercial promotion can be traced back to 2022), uses lasers instead of herbicides. Combined with AI and visual technology, it achieves a recognition accuracy of 99%. Consuming about 30 kWh d^{-1}, it can work continuously for 8 to 10 h per charge, with a range of 1.5 to 3 km h^{-1}, depending on the weed density. The CO_2 laser module array emits once every 50 ms with an accuracy of 3 mm and can perform laser weeding on 8 targets at the same time. It can handle 6 to 8 ha d^{-1}, and the laser system can handle up to 100 weeds s^{-1} without the need for chemical agents, making it particularly suitable for organic farmland that needs to avoid chemical residues (Figure 13B). The WeedBot Laser Weeder (Earliest appearance can be traced back to 2022) (n.d.), developed by the European-based company WeedBot (n.d.), is designed for organic farming and high-precision weeding scenarios, ensuring healthy crop growth. It precisely targets weeds and eliminates them with lasers, with a recognition accuracy of greater than 98%. Battery-powered, it consumes around 25 kWh d^{-1} and can work

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Table 4. Characteristics of mechanical weeding implementations.

Mechanical actuators	Specificities	Reference
Rotary nylon brush	Suitable for removing small grass; horizontal weeding between rows, vertical weeding between rows and between plants	Melander (1997) Fogelberg et al. (1999)
Claw tooth	High assembly accuracy required; rotation required to avoid seedlings; damage rate to seedlings < 8%.	Hu et al. (2012)
Weed whacker	Uses laser sensors and motor control to avoid seedlings along the sine wave; seedling damage rate of 23.7%	Cordill and Grift (2011)
Oscillating hoe shovel	Cam swing rod swings to avoid seedlings; can incorporate GPS localization technology	Wang et al. (2021)
Rotating hoe shovel	Good mechanical properties; seedling damage rate of 4.54%	Quan et al. (2021)
Eight-claw style	Taking the distance between the weeding blade teeth and the crop as the threshold, seedling damage rate <10%	Chen et al. (2010)
In-line weeding knife	Utilization of machine vision technology for the detection of seedling position information and the control of the movement trajectory of the hoe	Pérez-Ruiz et al. (2014)
Rotary-press type	Based on real-time detection by ultrasonic sensors, avoids seedlings through hydraulic means	Saber et al. (2015)
Notched disk knife type	Knife setting and crop rotation weeding via traverse mechanism	Garford (n.d.); Tillett et al. (2008)
Spring-tooth type	Simple structure; causes damage to crops in the seedling stage	Midtiby et al. (2012)
Finger weeding knife	Applicable to small areas and soft soil conditions to remove weeds	Riemens et al. (2007)
Comb type	Corn seedling avoidance during the intertillage period, one-way intermittent rotation movement	Jia et al. (2018)
Oscillating hoe	Using cameras to determine crop positions and achieve weeding between plants	Frank Poulsen Engineering (n.d.)

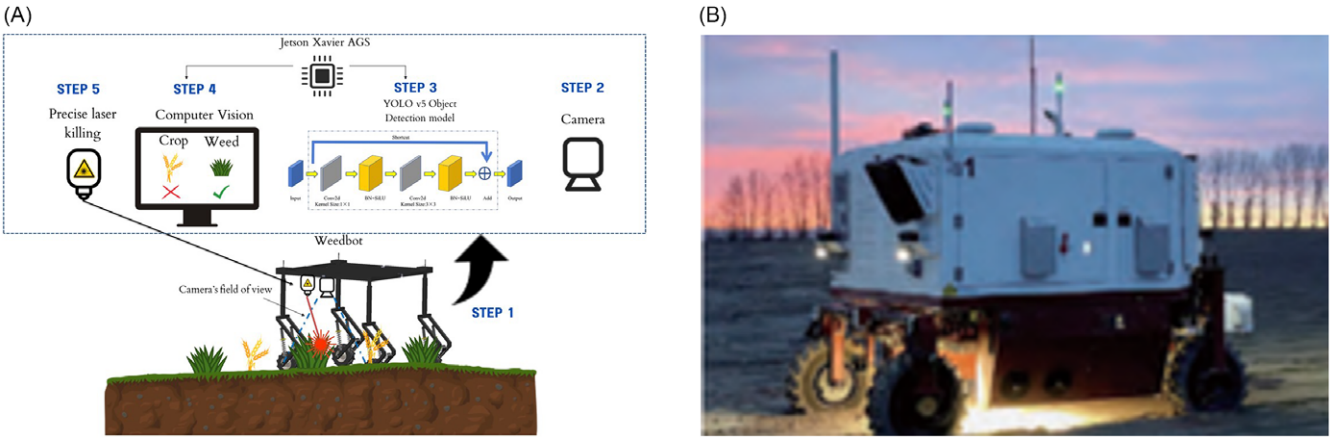


Figure 13. Laser weeding robots.

continuously for 8 h, covering 1.5 to 2 km h^{-1} and processing approximately 10 ha d^{-1}, depending on terrain and weed density.

Additional references for laser weeding machines are listed in Table 5. Analysis of Table 5 reveals that the organic combination of laser generators and mechanical arms has been a research focus for laser weeding machines. Some scholars have also conducted research on laser generators. Notably, in recent years, more experts and scholars have focused on the whole-machine aspects of weeding machines.

The accuracy of weed centroid positioning is often inadequate, impacting the precision of weeding operations. The diversity in weed species and shapes makes detection challenging, leading to potential misidentifications. Robots may also miss some weeds, affecting the overall weeding effectiveness. During laser weeding, there is a risk of crop damage, especially when positioning is inaccurate. Optimizing laser energy usage and improving energy efficiency are significant technical challenges. Laser weeding may also cause reflection issues, increasing safety risks, and care must be taken to ensure that reflections do not harm crops or surrounding equipment. These challenges represent key technological hurdles for the future development of laser weeding robots. Future progress must address improvements in recognition accuracy, operational efficiency, environmental impact, and energy utilization across these systems.

Discussion

In the rapid development of smart agriculture today, intelligent weeding equipment, as an important component of intelligent agricultural machinery, is bound to undergo further reconstruction and upgrades with the promotion of new production operation models and the introduction of advanced intelligent technologies.

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Table 5. Circuit design and characteristics of laser weeding device.

Main circuit design or components	Specificities	Reference
Conveyor + two-axis deflector	This laser weeder uses a stereo camera to identify plants and simulates a moving vehicle to destroy weeds.	Nadimi et al. (2009)
Laser generator + robotic arm	This laser weeder uses a robotic arm to aim a laser beam at weeds with little error.	Ge et al. (2013)
Four-degree-of-freedom parallel mechanism	The 3UPS-RPU (The novel 3UPS-RPU PM is composed of three UPS-type active legs and one RPUtype active leg) parallel mechanism is synchronized in real time during the panning motion; there are no sudden changes or breakpoints during the motion.	Wang et al. (2016)
Mobile platform + camera + laser pointer	This weeder used a two-degree-of-freedom laser beam to simulate static laser weeding in the laboratory and proposed a new weeding path planning algorithm.	Xiong et al. (2017)
Two-axis deflector for mirrors + lenses	This weeder was unable to achieve stable performance requirements and was affected by complex field conditions.	Rakhmatulin et al. (2020)
A novel laserweeding gimbal is proposed based on a two-degree-offreedom 5-revolute rotational parallel manipulator to perform a dynamic intrarow laser weeding operation.	For dynamic laser weeding, the average error in accuracy was 0.62 mm, and the dynamic weeding efficiency was about 0.72 s per weed with a dwell time of 0.64s.	Wang et al. (2022)
Tracked mobile platform + weed recognition module + robotic arm + laser generator	The feasibility of blue-light laser as a non-contact weed control tool was verified with an average detection rate of 92.45% and 88.94% for corn seedlings and weeds, respectively, and an average seedling injury rate of 4.68%.	Zhu et al. (2022)

Smart agriculture refers to the use of advanced technologies such as the Internet of Things (IoT), AI, big data, sensors, and robotics to enhance the efficiency, productivity, and sustainability of agricultural operations. It involves data-driven decision making, precision agriculture techniques, and real-time monitoring to optimize crop management, reduce resource waste, and improve farm management systems. Smart agriculture focuses on increasing yields, minimizing environmental impact, and enabling automation and remote control of agricultural processes.

Although weeding robots are still in the prototype development stage, companies like FarmWise (n.d.) and Carbon Robotics (n.d.) are gradually moving toward commercialization. This section reviews two major technical issues of weeding robots—weed detection and vision-based navigation—as well as mainstream weeding robots. Currently, intelligent weeding still requires in-depth research in the following areas.

Optimization of Recognition Algorithms and Precision Weeding Efficiency

To further improve the operational efficiency of intelligent weeding, advanced deep learning technologies need to be optimized, including data augmentation, feature extraction, attention mechanisms, and model simplification. These improvements are essential to address the challenges in recognizing overlapping stems or leaves between weeds and crops. Additionally, data annotation, particularly the labeling of massive weed datasets, deserves more attention. Researchers must enhance the robustness and generalization of deep learning algorithms. Reinforcement learning and transfer learning algorithms can be used to achieve better results with less data.

The recognition of crop and weed characteristics such as color, shape, texture, and spectral features still requires an integrated approach combining novel image processing techniques and AI. Current algorithms face complexity and long processing times, and future optimization is needed to overcome these drawbacks.

The emergence of new physical weeding technologies, such as laser weeding, offers a promising outlook for intelligent weeding. Intelligent weeding devices need to be closely integrated with AI technology, using different combinations of navigation technologies for different application scenarios, to further address the challenge of weed removal in interrow regions. The performance of various intelligent weeding equipment developed for different weed-handling conditions must be further improved to enhance operational efficiency. For instance, small- and medium-sized weeding robots need to improve in terms of cooperative operation, autonomy, and human–machine coordination.

Intelligent Sensing and Equipment Generalization

The operation of sensors is required for navigation data, image recognition data, and more. In recent years, multimodal sensors, such as visual, infrared, and ultrasonic sensors, have seen rapid development, providing valuable assistance in obtaining comprehensive and real-time information from complex field environments. Future research should further explore multisensor fusion technology, machine vision, field navigation technology, and multidisciplinary integration to achieve intelligent sensing functions. Through intelligent sensing, efficient identification and location of crops and weeds can be realized, enabling intelligent weeding.

With the extensive application of AI, intelligent weeding devices are also evolving toward wide-area operations, group intelligence, and multifunctional operations. For example, equipment for sowing, weeding, and fertilization can be quickly swapped. The generalization of robotic platforms can lower production costs. Additionally, an open-platform structure with compatibility will significantly increase operational efficiency. Intelligent weeding systems may also integrate crop disease and pest monitoring for pesticide management and, through intelligent sensing of crop growth and maturity, facilitate automated fertilization and harvesting.

Integration of Agricultural Machinery and Agronomy

In some countries, a few fields have already achieved a leveled furrow environment suitable for intelligent weeding equipment.

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Considerations for optimal interrow spacing and leveled furrows can reduce crop and weed occlusion and clustering, which lowers the complexity of deep learning networks and facilitates the application of intelligent weeding technologies. Through integration of agricultural machinery and agronomy, the weeding environment can be improved and operational efficiency increased. Rational close planting, intercropping, and mixed cropping can fully utilize solar energy and spatial structure, enhancing crop growth while controlling weed density and damage.

Further Integration of Drone Technology

The development of agricultural drones provides new solutions for smart agriculture and represents a major trend in agricultural equipment development. Drones have natural advantages, such as obtaining ultra–high resolution images at low altitudes, which allows for the detailed observation of crops and weeds. In addition, drones generate vast amounts of imagery during aerial photography, providing datasets for training and applying deep learning algorithm models. Equipped with different sensors and perception systems, drones can capture spectral information from crops and weeds, which, combined with machine learning algorithms, significantly improves weed identification accuracy. Drones also offer flexibility in scheduling flights and can generate digital surface models with 3D measurements. Currently, drones are widely used in field weed identification and intelligent spraying. Future integration of sensor, deep learning, communication, and drone technologies can achieve higher weed identification efficiency.

Integration of 5G, Digital Twin Technology, and IoT Technologies

The integration of 5G, IoT, and digital twin technologies is rapidly driving weed control robots toward becoming smarter and more efficient. This convergence not only enhances the performance and decision-making capabilities of robots but also provides precise and visualized operational support for agricultural management, contributing to the overall intelligence level of farming operations.

Digital twin technology creates a digital replica of the physical weed control robot, enabling full life-cycle management through virtual–physical interaction. By building digital models that correspond to the physical robot and the farm environment, digital twins provide real-time status monitoring, simulation optimization, and predictive maintenance. In a virtual environment, robots can simulate path planning and weed control strategies to optimize paths, reduce energy consumption, and ensure crops are not damaged. Monitoring through the digital twin model allows real-time simulation and analysis of the operational status of the robot's components. By combining historical data and algorithms, the system can predict when the robot may experience failure, enabling timely preventive maintenance and reducing downtime. Simultaneously, the farm environment, crop conditions, and the robot's actual working status can be visually displayed. Operators can monitor the robot's work process via a virtual interface, offering remote guidance and adjustments.

IoT facilitates the intelligent scheduling of weed control tasks and supports decision making by integrating climate conditions and weed growth patterns with agronomy to determine the optimal weeding time. Weed control robots can connect to sensors installed in the field, such as soil moisture, weather, and crop growth status sensors, to collect environmental and crop condition data. These data enable robots to more accurately identify weed growth areas and optimize weeding strategies. Under the IoT framework, basic data processing for weeding tasks can be handled by edge computing devices (e.g., local servers), while more complex analyses and model inference tasks are transferred to the cloud for computation. Through IoT networks, farm management systems can monitor the status of the weed control robots (battery life, mechanical wear, software condition, etc.) in real time and carry out equipment scheduling, fault alarms, and automatic maintenance when necessary.

With its ultra-low latency, 5G technology ensures real-time remote operation of weed control robots over large farmlands, even supporting cross-regional control of multiple robots working in collaboration. Multiple weed control robots can share data via 5G networks to perform coordinated operations, avoiding repeated weeding or missed weeds, thereby improving efficiency. This technology supports real-time data transmission from robots using high-definition cameras or other sensors (e.g., LiDAR, depth cameras), enabling a central system to analyze and make decisions regarding weed control.

The integration of 5G, IoT, and digital twin technologies significantly enhances the real-time performance and decision-making capabilities of weed control robots, enabling them to operate with higher precision and efficiency in complex farm environments. This reduces the risk of damaging crops or missing weeds. These technologies empower weed control robots with intelligent perception, remote control, and autonomous decision-making capabilities, supporting large-scale farm operations where robots can collaborate intelligently, achieving unmanned and automated weeding operations. Through continuous data collection and feedback, robotic systems can optimize their operational processes in different environments and crop conditions, providing personalized and precise weeding services.

However, these integrated smart field-weeding robots also face risks and challenges. The vast amount of data involved raises security and privacy concerns, necessitating robust cybersecurity measures. The interoperability between different IoT devices and systems is also a challenge, requiring the establishment of common standards and protocols. Furthermore, managing the complexity of these weeding robot systems and ensuring scalability will require ongoing innovation and investment.

Moreover, for specific target users, that is, non-technical personnel, the operation should be sufficiently safe and simple to facilitate quick user adoption and proficient operation. After-sales and technical support services should also be provided in the later stages.

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References

Adhikari SP, Yang H, Kim H (2019) Learning semantic graphics using convolutional encoder–decoder network for autonomous weeding in paddy. Front Plant Sci 10:1404

Aravind KR, Purushothaman R, Manuel Pérez-Ruiz (2017) Task-based agricultural mobile robots in arable farming: A review. SJAR 15:e02R01

Åstrand B, Baerveldt AJ (2002) An agricultural mobile robot with vision-based perception for mechanical weed control. Auton Robot 13:21–35

https://doi.org/10.1017/wsc.2024.95 Published online by Cambridge University Press

Bah MD, Hafiane A, Canals R (2019) CRowNet: deep network for crop row detection in UAV images. IEEE Access 8:5189–5200
Bai J, Xu Y, Wei XH (2013) Weed identification from winter rape at seeding stage based on spectrum characteristics analysis. Trans Chinese Soc Agric Eng 29:128–134
Bakhshipour A, Jafari A (2018) Evaluation of support vector machine and artificial neural networks in weed detection using shape features. Comput Electron Agric 145:153–160
Bakhshipour A, Jafari A, Nassiri SM, Zare D (2017) Weed segmentation using texture features extracted from wavelet sub-images. Biosyst Eng 157:1–12
Bakker T (2009) An Autonomous Robot for Weed Control: Design, Navigation and Control. Wageningen, Netherlands: Wageningen University and Research. 149 p
Bakker T, van Asselt K, Bontsema J (2011) Autonomous navigation using a robot platform in a sugar beet field. Biosyst Eng 109:357–368
Berge TW, Goldberg S, Kaspersen K, (2012) Towards machine vision based site-specific weed management in cereals. Comput Electron Agric 81:79–86
Bloomer DJ, Harrington KC, Ghanizadeh H, James TK (2024) Robots and shocks: emerging non-herbicide weed control options for vegetable and arable crop. NZ J Agric Res 67:81–103
Blue River Technology (n.d.) Home page. https://bluerivertechnology.com/our-products. Accessed: May 15, 2024
Bosilj P, Aptoula E, Duckett T, Cielniak G (2020) Transfer learning between crop types for semantic segmentation of crops versus weeds in precision agriculture. J Field Robot 37:7–19
Carbon Robotics (n.d.) Home page. https://carbonrobotics.com. Accessed: May 15, 2024
Chebrolu N, Lottes P, Schaefer A, Winterhalter W, Burgard W, Stachniss C (2017) Agricultural robot dataset for plant classification, localization and mapping on sugar beet fields. Int J Rob Res 36:1045–1052
Chen SR, Shen BG, Mao HP (2009) Copperleaf herb detection from cotton field based on color feature. Trans Chinese Soc Agric Mach 40:149–152
Chen SR, Zhang PJ, Yin DF (2010) Control system of eight claw intra-row mechanical weeding device based on LabVIEW. Trans Chinese Soc Agric Eng 26:234–237
Chen SR, Zou HD, Wu RM (2013) Identification for weedy rice at seeding stage based on hyper-spectral imaging technique. Trans Chinese Soc Agric Mach 44:253–257, 163
Chen Y, Chen CM, Liu ZY (2015) The methodology function of CiteSpace mapping knowledge domains. Studies in Science of Science 2:242–253
Chong YL, Weyler J, Lottes P, Behley J, Stachniss C (2023) Unsupervised generation of labeled training images for crop-weed segmentation in new fields and on different robotic platforms. IEEE Robot Autom Lett 8: 5259–5266
Conesa-Muñoz J, Valente J, Del Cerro J, Barrientos A, Ribeiro A (2016) A multi-robot sense-act approach to lead to a proper acting in environmental incidents. Sensors 16:1269
Cordill C, Grift T (2011) Design and testing of an intra-row mechanical weeding machine for corn. Biosyst Eng 110:247–252
Corpe SJO, Tang L, Abplanalp P (2013) GPS-guided modular design mobile robot platform for agricultural applications. Pages 806–810 *in* 2013 Seventh International Conference on Sensing Technology (ICST), Wellington, New Zealand, December 3–5, 2013
Deng J, Dong W, Socher R, Li LJ, Li K, Fei-Fei L (2009) Imagenet: a large-scale hierarchical image database. Pages 248–255 *in* 2009 IEEE Conference on Computer Vision and Pattern Recognition, Miami, FL, June 20–25, 2009
Deng XW, Qi L, Ma X (2018) Recognition of weeds at seeding stage in paddy fields using multi-feature fusion and deep belief networks. Trans Chinese Soc Agric Eng 34:165–172
Diao Z, Guo P, Zhang B, Zhang D, Yan J, He Z, Zhao S, Zhao C (2023) Maize crop row recognition algorithm based on improved UNet network. Comput Electron Agric 210:107940
Ding W, Ge ZY, Lu ZZ (2015) The design of GPS assembled with fuzzy control in navigation system of field robot. JAMR 37:109–112
Ding Y, Qiu BJ, Zhou N (2006) Research of mowing robot GPS/DR navigation system. J Agri Mech Res 68–71
dos Santos Ferreira A, Freitas DM, da Silva GG (2017) Weed detection in soybean crops using ConvNets. Comput Electron Agric 143:314–32
Dyrmann M, Karstoft H, Midtiby HS (2016) Plant species classification using deep convolutional neural network. Biosyst Eng 151:72–80
EcoRobotix (n.d.) Home page. https://ecorobotix.com/en. Accessed: May 15, 2024
Emmi L, Fernández R, Gonzalez-de-Santos P, Francia M, Golfarelli M, Vitali G, Sandmann H, Hustedt M, Wollweber M (2023) Exploiting the internet resources for autonomous robots in agriculture. Agriculture 13:1005
FarmWise (n.d.) Home page. https://www.farmwise.io. Accessed: June 1, 2024
Fatima HS, ul Hassan I, Hasan S (2023) Formation of a lightweight, deep learning-based weed detection system for a commercial autonomous laser weeding robot. Applied Sci 13:3997
Fawakherji M, Youssef A, Bloisi D, Pretto A, Nardi D (2019) Crop and weeds classification for precision agriculture using context-independent pixel-wise segmentation. Pages 146–152 *in* 2019 Third IEEE International Conference on Robotic Computing (IRC), Naples, Italy, February 25–27, 2019
Fogelberg F, Kritz G (1999) Intra-row weeding with brushes on vertical axes-factors influencing in-row soil height. Soil Tillage Res 50:149–157
Francisco RM, Han SF, Wei JT (2005) Fuzzy logic model for sensor fusion of machine vision and gps in autonomous navigation[C]//ASABE paper 051156:1–20
Frank Poulsen Engineering (n.d.) Home page. http://www.visionweeding.com. Accessed: June 1, 2024
Gai J, Tang L, Steward BL (2020) Automated crop plant detection based on the fusion of color and depth images for robotic weed control. J Field Robot 37:35–52
Gao JF, Nuyttens D, Lootens P, He Y, Pieters JG (2018) Recognising weeds in a maize crop using a random forest machine-learning algorithm and near-infrared snapshot mosaic hyperspectral imagery. Biosyst Eng 170:39–50
García-Santillán I, Guerrero JM, Montalvo M (2018) Curved and straight crop row detection by accumulation of green pixels from images in maize fields. Precis Agric 19:18–41
García-Santillán ID, Montalvo M, Guerrero JM (2017) Automatic detection of curved and straight crop rows from images in maize fields. Biosyst Eng 156:61–79
Garford (n.d.) Robocrop Inrow Weeder. https://garford.com/products/robocrop-inrow-weeder. Accessed: May 15, 2024
Ge ZY, Wu WW, Yu YJ (2013) Design of mechanical arm for laser weeding robot. Appl Mech Mater 347:834–838
Gerhards R, Andujar SD, Hamouz P (2022) Advances in site-specific weed management in agriculture—a review. Weed Res 62:123–133
Giselsson TM, Jørgensen RN, Jensen PK, Dyrmann M, Midtiby HS (2017) A public image database for benchmark of plant seedling classification algorithms. arXiv 1711:05458
Greeneye Technology (n.d.) Home page. https://greeneye.ag. Accessed: June 1, 2024
Guijarro M, Pajares G, Riomoros I (2011) Automatic segmentation of relevant textures in agricultural images. Comput Electron Agric 75:75–83
Guo Z, Goh HH, Li X, Zhang M, Li Y (2023) WeedNet-R: a sugar beet field weed detection algorithm based on enhanced RetinaNet and context semantic fusion. Front Plant Sci 14:1226329
Hall D, Dayoub F, Kulk J (2017) Towards unsupervised weed scouting for agricultural robotics. Pages 5223–5230 *in* 2017 IEEE International Conference on Robotics and Automation (ICRA), Singapore, May 29, to June 3, 2017
Hamuda E, Mc Ginley B, Glavin M (2017) Automatic crop detection under field conditions using the HSV colour space and morphological operations. Comput Electron Agric 133:97–107
Haug S, Ostermann J (2015) A crop/weed field image dataset for the evaluation of computer vision based precision agriculture tasks. Pages 105–116 *in* Agapito L, Bronstein M, Rother C, eds. Computer Vision—ECCV 2014 Workshops. ECCV 2014. Lecture Notes in Computer Science 8928. Cham, Switzerland: Springer
Herrmann I, Shapira U, Kinast S (2013) Ground-level hyperspectral imagery for detecting weeds in wheat fields. Precis Agric 14:637–659

https://doi.org/10.1017/wsc.2024.95 Published online by Cambridge University Press

Hiremath S, van der Heijden G, Van Evert FK (2012) The role of textures to improve the detection accuracy of Rumex obtusifolius in robotic systems. Weed Res 52:430–440
Hiremath S, Van Evert FK, ter Braak C (2014) Image-based particle filtering for navigation in a semi-structured agricultural environment. Biosyst Eng 121:85–95
Hoki M (2000) Fundamental study of laser application for weed and pest control effect of laser emissions on rice plant leaves. Trans Chinese Soc Agric Mach 62:98–103
Hu JT, Gao L, Bai XP (2015) Review of research on automatic guidance of agricultural vehicles. Trans Chinese Soc Agric Eng 31:1–10
Hu L, Luo XW, Yan YA (2012) Development and experiment of intra-row mechanical weeding device based on trochoid motion of claw tooth. Trans Chinese Soc Agric Eng 28:10–16
Huang SP, Wu SH, Sun C, Ma X, Jiang Yu, Qi L (2020) Deep localization model for intra-row crop detection in paddy field. Comput Electron Agric 169:105203
Hussain N, Farooque AA, Schumann AW, McKenzie-Gopsill A, Esau T, Abbas, F, Acharya B, Zaman Q (2020) Design and development of a smart variable rate sprayer using deep learning. Remote Sens. 12 (24) :4091
Hussin NAC, Jamil N, Nordin S (2013) Plant species identification by using scale invariant feature transform (SIFT) and grid based colour moment (GBCM). Pages 226–230 *in* 2013 IEEE Conference on Open Systems (ICOS), Kuching, Malaysia, December 2–4, 2013
Hyyti H, Kalmari J, Visala A (2013) Real-time detection of young spruce using color and texture features on an autonomous forest machine. Pages 1–8 *in* 2013 International Joint Conference on Neural Networks (IJCNN), Dallas, TX, August 4–9, 2013
Jafari A, Mohtasebi SS, Jahromi HE (2006) Weed detection in sugar beet fields using machine vision. Biosyst Eng 8:602–605
Jeon HY, Tian LF, Zhu H (2011) Robust crop and weed segmentation under uncontrolled outdoor illumination. Sensors 11:6270–6283
Jia HL, Li SS, Wang G (2018) Design and experiment of seedling avoidable weeding control device for intertillage maize (*Zea mays* L.). Trans Chinese Soc Agric Eng 34:15–22
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
Jin XJ, Liu T, Zhe Y, Xie JC, Bagavathiannan M, Hong XW, Xu ZW, Chen X, Yu JL, Chen Y (2023) Precision weed control using a smart sprayer in dormant bermudagrass turf, Crop Prot 172:106302
John Deere (n.d.) Sense and Act. https://about.deere.com/en-us/our-company-and-purpose/technology-and-innovation/sense-and-act. Accessed: June 1, 2024
Johnson III WC, Luo X (2018) Cool-season weed control using ammonium nonanoate and cultivation in organic Vidalia® sweet onion production. Weed Technol 32:90–94
Kam HR, Lee SH, Park T, Kim CH (2015) Rviz: a toolkit for real domain data visualization. Telecommun Syst 60:337–345
Kiani S, Jafari A (2012) Crop detection and localization in the field using discriminant analysis and neural networks based on shape features. J Agric Sci Technol 14:755–765
Kim GH, Kim SC, Hong YK (2012) A robot platform for unmanned weeding in a paddy field using sensor fusion. Pages 904–907 *in* 2012 IEEE International Conference on Automation Science and Engineering (CASE), Seoul, Korea (South), August 20–24 2012
Kise M, Noguchi N, Ishii K (2001) Development of the agricultural autonomous tractor with an RTK-GPS and a fog. IFAC Proc Vol 34:99–104
Kise M, Zhang Q, Más FR (2005) A stereovision-based crop row detection method for tractor-automated guidance. Biosyst Eng 90:357–367
Krizhevsky A, Sutskever I, Hinton GE (2017) ImageNet classification with deep convolutional neural networks. Commun ACM 60:84–90
Lameski P, Zdravevski E, Trajkovik V, Kulakov A (2017) Weed detection dataset with RGB images taken under variable light conditions. Pages 112–119 *in* Trajanov D, Bakeva V, eds. ICT Innovations 2017. Communications in Computer and Information Science. Volume 778. Cham, Switzerland: Springer
Lee WS, Slaughter DC, Giles DK (1999) Robotic weed control system for tomatoes. Precis Agric 1:95–113
Leminen Madsen S, Mathiassen SK, Dyrmann M, Laursen MS, Paz LC, Jørgensen RN (2020) Open plant phenotype database of common weeds in Denmark. Remote Sens 12:1246
Liakos KG, Busato P, Moshou D, Pearson S, Bochtis D (2018) Machine learning in agriculture: a review. Sensors 18:2674
Li D, Li B, Kang S, Feng H, Long S, Wang J (2023a) E2CropDet: an efficient end-to-end solution to crop row detection. Expert Syst Appl 227:120345
Li H, Quan L, Guo Y, Pi P, Shi Y, Lou Z, Jiang W, Sun D, Yang Y, Xu W (2023b) Improving agricultural robot patch-spraying accuracy and precision through combined error adjustment. Comput Electron Agric 207:107755
Li JL, Su WH, Zhang HY, Peng Y (2023c) A real-time smart sensing system for automatic localization and recognition of vegetable plants for weed control. Front Plant Sci 14:1133969
Li N, Grift TE, Yuan T (2016) Image processing for crop/weed discrimination in fields with high weed pressure. Paper 162460475 *in* 2016 ASABE Annual International Meeting.. St Joseph, MI: American Society of Agricultural and Biological Engineers
Li X, Su J, Yue Z (2022) Adaptive multi-ROI agricultural robot navigation line extraction based on image semantic segmentation. Sensors 22:7707
Li XF, Zhu W, Ji B (2010) Shape feature selection and weed recognition based on image processing and ant colony optimization. Trans Chinese Soc Agric Eng 26:178–182
Li YJ, Zhao ZX, Huang PK (2017) Automatic navigation system of tractor based on DGPS and double closed-loop steering control. Trans Chinese Soc Agric Mach 48:11–19
Lin TY, Maire M, Belongie S, Hays J, Perona P, Ramanan D, Dollar P, Zitnick CL (2014) Microsoft coco: common objects in context. Pages 740–755 *in* Fleet D, Pajdla T, Schiele B, Tuytelaars T, eds. Computer Vision—ECCV 2014. Lecture Notes in Computer Science 8693. Cham, Switzerland: Springer
Liu J, Abbas I, Noor RS (2021) Development of deep learning-based variable rate agrochemical spraying system for targeted weeds control in strawberry crop. Agronomy 11:1480
Luo XW, Zhang ZG, Zhao ZX (2009) Design of DGPS navigation control system for Dongfanghong X-804 tractor. Trans Chinese Soc Agric Eng 25:139–145
Lv J, Xu H, Xu L, Zou L, Rong H, Yang B (2022) Recognition of fruits and vegetables with similar-color background in natural environment: a survey. J Field Robot 39:888–904
Marchant JA (1996) Tracking of row structure in three crops using image analysis. Comput Electron Agric 15:161–179
Mathiassen SK, Bak T, Christensen S, Kudsk P (2006) The effect of laser treatment as a weed control method. Biosyst Eng 95:497–505
Melander B (1997) Optimization of the adjustment of a vertical axis rotary brush weeder for intra-row weed control in row crops. J Agric Eng Res 68: 39–50
Meng QK, Liu G, Zhang M (2013) Crop rows detection based on constraint of liner correlation coefficient. Trans Chinese Soc Agric Mach 44:216–223
Miao ZH, Yu XY, Xu MH (2020) Automatic weed detection method based on fusion of multiple image processing algorithms. Smart Agric 2:103–115
Midtiby HS, Giselsson TM, Jørgensen RN (2012) Estimating the plant stem emerging points (PSEPs) of sugar beets at early growth stages. Biosyst Eng 111:83–90
Murawwat S, Qureshi A, Ahmad S (2018) Weed detection using SVMs. Eng Technol Appl Sci Res 8:2412–2416
Mustafa MM, Hussain A, Ghazali KH (2007) Implementation of image processing technique in real time vision system for automatic weeding strategy. Pages 632–635 *in* 2007 IEEE International Symposium on Signal Processing and Information Technology, Giza, Egypt, December 15–18, 2007
Nadimi ES., Andersson KJ., Jorgensen RN., Maagaard J, Mathiassen S, Christensen S (2009) Designing, modelling and controlling a novel autonomous laser weeding system. Pages 299–303 *in* Seventh World Congress on Computers in Agriculture Conference Proceedings, Reno, Nevada, June 22–24, 2009

https://doi.org/10.1017/wsc.2024.95 Published online by Cambridge University Press

Naveed A, Muhammad W, Irshad MJ (2023) Saliency-based semantic weeds detection and classification using UAV multispectral imaging. IEEE Access 11:11991–12003

Nejati H, Azimifar Z, Zamani M (2008) Using fast Fourier transform for weed detection in corn fields. Pages 1215–1219 *in* 2008 IEEE International Conference on Systems, Man and Cybernetics, Singapore, October 12–15, 2008

Nieuwenhuizen AT, Tang L, Hofstee JW (2007) Colour based detection of volunteer potatoes as weeds in sugar beet fields using machine vision. Precis Agric 8:267–278

Nørremark M, Griepentrog HW, Nielsen J (2012) Evaluation of an autonomous GPS-based system for intra-row weed control by assessing the tilled area. Precis Agric 13:149–162

Olsen A, Konovalov DA., Philippa B, Ridd P, Wood JC, Johns J, Banks W, Girgenti B, Kenny O, Whinney J (2019) DeepWeeds: a multiclass weed species image dataset for deep learning. Sci Rep 9:2058

Özlüoymak ÖB (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

Pandey HS, Tiwari GS, Sharma AK (2023) Design and development of an e-powered inter row weeder for small farm mechanization: e-powered inter row weeder for small farm mechanization. J Sci Indust Res 82: 671–682

Pantazi XE., Moshou D, Bravo C (2016) Active learning system for weed species recognition based on hyperspectral sensing. Biosyst Eng 146:193–202

Partel V, Kakarla SC, Ampatzidis Y (2019) Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence. Comput Electron Agric 157:339–350

Peng MX, Xia JF, Peng H (2019) Efficient recognition of cotton and weed in field based on Faster R-CNN by integrating FPN. Trans Chinese Soc Agric Eng 35:202–209

Pérez-Ruiz M, Slaughter DC, Fathallah FA (2014) Co-robotic intra-row weed control system. Biosyst Eng 126:45–55

Pérez-Ruiz M, Slaughter DC, Gliever CJ (2012) Automatic GPS-based intra-row weed knife control system for transplanted row crops. Comput Electron Agric 80:41–49

Piron A, Leemans V, Kleynen O (2008) Selection of the most efficient wavelength bands for discriminating weeds from crop. Comput Electron Agric 62:141–148

Precision AI (n.d.) Home page. https://www.precision.ai. Accessed: June 1, 2024

Qiao YL, He DJ, Zhao CY (2013) Corn field weeds recognition based on multi-spectral images and SVM. JAMR 35:30–34

Quan LZ,Zhang JY, Jiang W (2021) Development and experiment of intra-row weeding robot system based on protection of maize root system. Trans Chinese Soc Agric Mach 52:115–123

Raja R, Nguyen TT, Slaughter DC, Fennimore SA (2020) Real-time robotic weed knife control system for tomato and lettuce based on geometric appearance of plant labels. Biosyst Eng 194:152–164

Rakhmatulin I, Andreasen C (2020) A concept of a compact and inexpensive device for controlling weeds with laser beams. Agronomy 10:1616

Reiser D, Sehsah ES, Bumann O (2019) Development of an autonomous electric robot implement for intra-row weeding in vineyards. Agriculture 9:18

Reiser D, Vazquez AM, Paraforos DS (2018) Iterative individual plant clustering in maize with assembled 2D LiDAR data. Comput Ind 99:42–52

Riemens MM., Groeneveld RMW, Lotz LAP (2007) Effects of three management strategies on the seedbank, emergence and the need for hand weeding in an organic arable crop system. Weed Res 47:442–451

Sabanci K, Aydin C (2017) Smart robotic weed control system for sugar beet. J Agric Sci Technol 19:73–83

Saber M, Lee WS, Burks TF (2015) Performance and evaluation of intra-row weeder ultrasonic plant detection system and pinch-roller weeding mechanism for vegetable crops. Paper 152188868 *in* 2015 ASABE Annual International Meeting. St Joseph, MI: American Society of Agricultural and Biological Engineers

Shaikh FK, Karim S, Zeadally S, Nebhen J (2022) Recent trends in internet-of-things-enabled sensor technologies for smart agriculture. IEEE Internet Things J 9:23583–23598

Sharma S, Verma K, Hardaha P (2023) Implementation of artificial intelligence in agriculture. JCCE 2:155–162

Skovsen S, Dyrmann M, Mortensen AK, Laursen MS, Gislum R, Eriksen J, Farkhani, S, Karstoft H, Jorgensen RN (2019) The GrassClover image dataset for semantic and hierarchical species understanding in agriculture. Pages 2676–2684 *in* 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), Long Beach, CA, June 16–17, 2019

Small Robot Co (n.d.) Home page. https://smallrobotco.com Accessed: June 1, 2023

Spaeth M, Sökefeld M, Schwaderer P, Gauer ME, Sturm DJ, Delatrée CC, Gerhards R (2024) Smart sprayer a technology for site-specific herbicide application. Crop Prot 177:106564

Stoll A, Dieter KH (2000) Guidance of a forage harvester with GPS. Precis Agric 2:281–291

Su WH, Fennimore SA, Slaughter DC (2020) Development of a systemic crop signalling system for automated real-time plant care in vegetable crops. Biosyst Eng 193:62–74

Sudars K, Jasko J, Namatevs I, Ozola L, Badaukis N (2020) Dataset of annotatedfood crops and weed images for robotic computer vision control. Data in Brief 31:105833

Sun H, Liu T, Wang J, Zhai D, Yu J (2024) Evaluation of two deep learning-based approaches for detecting weeds growing in cabbage. Pest Manag Sci 80:2817–2826

Sun J, He XF, Tan WJ (2018) Recognition of crop seedling and weed recognition based on dilated convolution and global pooling in CNN. Trans Chinese Soc Agric Eng 34:159–165

Swain KC, Nørremark M, Jørgensen RN (2011) Weed identification using an automated active shape matching (AASM) technique. Biosyst Eng 110: 450–457

Teimouri N, Dyrmann M, Nielsen PR, Mathiassen SK, Somerville GJ, Jørgensen RN (2018) Weed growth stage estimator using deep convolutional neural networks. Sensors 18:1580

Thakur A, Venu S, Gurusamy M (2023) An extensive review on agricultural robots with a focus on their perception systems. Comput Electron Agric 212:108146

Tian L, Cao C, Qin K, Fang L, Ge J (2021) Design and test of post-seat weeding machine for paddy. IJABE 14:112–122

Tillett ND, Hague T, Grundy AC (2008) Mechanical within-row weed control for transplanted crops using computer vision. Biosyst Eng 99: 171–178

Tran D, Schouteten JJ, Degieter M, Krupanek J, Jarosz W, Areta A, Emmi L, De Steur H, Gellynck X (2023) European stakeholders' perspectives on implementation potential of precision weed control: the case of autonomous vehicles with laser treatment. Precis Agric 24:2200–2222

Trong VH, Gwang HY, Vu DT, Jin-young K (2020) Late fusion of multimodal deep neural networks for weeds classification. Comput Electron Agric 175:105506

Upadhyay A, Sunil GC, Zhang Y, Koparan C, Sun X (2024) Development and evaluation of a machine vision and deep learning-based smart sprayer system for site-specific weed management in row crops: an edge computing approach. J Agric Food Chem 18:101331

Utstumo T, Urdal F, Brevik A (2018) Robotic in-row weed control in vegetables. Comput Electron Agric 154:36–45

Van Evert FK, Polder G, Van Der Heijden G (2009) Real-time vision-based detection of *Rumex obtusifolius* in grassland. Weed Res 49:164–174

Verdant Robotics (n.d.) Sharpshooter Precision Application System. https://www.verdantrobotics.com. Accessed: June 10, 2024

Wang M, Leal-Naranjo JA, Ceccarelli M (2022) A novel two-degree-of-freedom gimbal for dynamic laser weeding: design, analysis, and experimentation. IEEE/ASME Trans Mechatronics 27:5016–5026

Wang Y, Liu B, Xiong LY (2019) Research on generating algorithm on orchard road navigation line based on deep learning. J Hunan Agri Univ (Natural Sciences) 45:674–678

Wang N, Zhang N, Dowell FE, Sun Y, Peterson DE (2001) Design of an optical weed sensor using plant spectral characteristics. Trans ASAE 44:409

https://doi.org/10.1017/wsc.2024.95 Published online by Cambridge University Press

Wang S, Su DBLG, Wang ZM (2021) Design and experiments of the cam rod intra-row weeding device for lettuce farm. Trans Chinese Soc Agric Eng 37:34–44

Wang XL, Huang J, Zhao DJ, Guo HH, Li CJ (2016) Kinematics and statics analysis of a novel 4-DOF parallel mechanism for laser weeding robot. INMATEH Agric Eng 50:29–38

WeedBot (n.d.) Home page. https://weedbot.eu. Accessed: September 10, 2024

Wen S, Zhang Q, Deng J, Lan Y, Yin X, Shan J (2018) Design and experiment of a variable spray system for unmanned aerial vehicles based on PID and PWM control. Appl Sci 8:2482

Weyler J, Läbe T, Magistri F, Behley J, Stachniss C (2023) Towards domain generalization in crop and weed segmentation for precision farming robots. IEEE Robot Autom Lett 8:3310–3317

Wong WK, Chekima A, Ahmad IOB (2013) Genetic algorithm feature selection and classifier optimization using moment invariants and shape features. Pages 55–60 *in* 2013 1st International Conference on Artificial Intelligence, Modelling and Simulation, Kota Kinabalu, Malaysia, December 3–5, 2013

Wu L, Wen Y (2009) Weed/corn seedling recognition by support vector machine using texture features. Afr J Agric Res 4:840–846

Wu LL, Liu JY, Wen YX (2009) Weed identification method based on SVM in the corn field. Trans Chinese Soc Agric Eng 40:162–166

Xing QS, Ding SM, Xue XY (2022) Research on the development status of intelligent field weeding robot. Trans Chinese Soc Agric Eng 43:173–181

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

Xu YL, He R, Zhai YT (2021) Weed identification method based on deep transfer in field natural environment. J Jilin Univ Eng Technol Ed 51: 2304–2312

Xu Y, Deng Y (2024) Exoskeleton-assisted walking rehabilitation for spinal cord injury: CiteSpace analysis of research hotspots. Chinese J. Tissue Eng. Res 28:5403

Yao H, Zhang Z (2016) Research of camera calibration based on genetic algorithm BP neural network. Pages 350–355 *in* 2016 IEEE International Conference on Information and Automation (ICIA), Ningbo, China, August 1–3, 2016

Ying BY, Xu YC, Zhang S (2021) Weed detection in images of carrot fields based on improved YOLOv4. Traitement du Signal 38:341–348

You J, Liu W, Lee J (2020) A DNN-based semantic segmentation for detecting weed and crop. Comput Electron Agric 178:105750

Yuan HB, Zhao ND, Cheng, M (2020) Review of weeds recognition based on image processing. Trans Chinese Soc Agric Eng 51:323–334

Zhang FM, Ying YB (2005) Review of machine vision research in agricultural vehicle guidance. Trans Chinese Soc Agric Eng 36:133–136

Zhang M, Xiang M, Wei S (2015) Design and implementation of a corn weeding-cultivating integrated navigation system based on GNSS and MV. Trans Chinese Soc Agric Eng 46:8–14

Zhang WK, Sun H, Chen XK (2023) Research on weed detection in vegetable seedling fields based on the improved YOLOv5 intelligent weeding robot. J Graph 44:346–356

Zhang Y, Tian L, Cao C, Zhu C, Qin K, Ge J (2022) Optimization and validation of blade parameters for inter-row weeding wheel in paddy fields. Front Plant Sci 13:1003471

Zhao CY, He DJ, Qiao YL (2013) Identification method of multi-feature weed based on multi-spectral images and data mining. Trans Chinese Soc Agric Eng 29:192–198

Zhou J, Chen Q, Liang Q (2014) Vision navigation of agricultural mobile robot based on reinforcement learning. Trans Chinese Soc Agric Eng 45: 53–58

Zhu H, Zhang Y, Mu D, Bai L, Zhuang H, Li H (2022) YOLOX-based blue laser weeding robot in corn field. Front Plant Sci 13:1017803

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