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Key technologies and research progress of intelligent weeding robots

Hong Xu[1], Tianhua Li[1,*], Xianwei Hou[2], Huarui Wu[3], Guoying Shi[1], Yang Li[1], Guanshan Zhang[1]

[1]College of Mechanical and Electronic Engineering, Shandong Agricultural University, Taian 271018, China
[2]Shandong Provincial Agricultural Machinery Technology Extension Station, Jinan 250013, China
[3]Information Technology Research Center, Beijing Academy of Agriculture and Forestry Sciences, Beijing 100097,China

Author for correspondence: Tianhua Li; Email: nygczdh@163.com

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. The development status of weeding robots is overviewed based on bibliometric and scientific mapping methods. Secondly, the two key technologies of weeding robots are summarized. Then, the research progress of precision spraying weeding robots, mechanical weeding robots, and thermal weeding robots with laser devices, categorized by their weeding methods, 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.

Keywords: field navigation, machine vision, weeds, 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 over 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 advancements 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 future generations can continue farming. Sustainable agriculture aims to reduce over-reliance on land, energy, and water resources, minimize the excessive use of chemicals and harmful substances, and promote soil health, biodiversity, and ecosystem balance.

Compared to traditional weeding methods, intelligent field weeding robots can significantly reduce labor costs, improve weeding efficiency, and minimize environmental impacts. Precision weeding in inter-row 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 advancements 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 database SSCI 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 2009-2023, and literature types including "Article," "Review Article," "Early Access," and "Book Chapters" were selected. After removing irrelevant and duplicate documents, a total of 385 relevant papers were identified. Using CiteSpace 6.2.R4(64-bit) Basic software(Xu et al. 2023), the number of publications, years, and keyword co-occurrence maps, as well as country, author, and institution maps were obtained.6

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 rising 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 1114 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. 2023), thereby achieving automated precision weeding(Guo et al. 2023; Li et al. 2023; Tran et al. 2023). Analysis of Figure 3 shows that institutions such as China Agricultural University(Li et al. 2023), 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 , Slaughter and Johnson; Chinese experts such as Cao C., Tian L., and Ge J.; Spanish researchers like Ribeiro Angela and Perez-ruiz Manuel; 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.

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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 phase-out. 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 have 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 the cost of computer hardware decreases and 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 to 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 RGB (Chen et al. 2009; Nieuwenhuizen et al. 2007; Jafari et al. 2006), HSV (Hamuda et al. 2017; Miao et al. 2020), and HSI color spaces (Li et al. 2016).

In the RGB color space, the green channel contains more useful information compared to 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. 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 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 A et al. 2018; Murawwat S 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. 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 plants, the recognition accuracy dropped to 90%, as shown in the segmented image in Figure 7a Bakhshipour et al. compared the performance of SVM and ANN

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in classifying sugar beet plants and weeds. SVM achieved a crop recognition accuracy of 96.67% and weed accuracy of 93.33%, while ANN 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 Genetic algorithm (GA) was proposed by Wong et al. and tested with the assumption that the weeds are young and non-occluded. The results show that solidity of the shapes are the most prominent feature and alone could be used to achieved 90% recognition rates. 100 % Recognition was achieved with the combination of shape and moment invariants, as shown in the segmented image in Figure 7c Kiani et al. combined Discriminant Analysis with Backpropagation Neural Networks (BPNN) to classify maize 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. 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. employed morphological operations and distance transformation-based threshold segmentation to separate overlapping leaves. They then used the Ant Colony Optimization (ACO) 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

Texture 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 texture features of crops and weeds (Mustafa MM et al. 2007; Wu LL 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 texture feature extraction, some studies have adopted wavelet decomposition methods combined with supervised learning algorithms for recognition (Bakhshipour A et al. 2017).

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As shown in Figure 8, the horizontal axis represents crop/weed recognition methods based on texture 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; 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. 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 texture features of weeds and maize seedlings are then obtained using GLCM and the statistical properties of the grayscale image histogram. These texture features are used in the classification process. PCA is employed to select texture 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 texture 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 texture 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 must be combined for efficient recognition, such as shape. Researchers have used hyperspectral cameras to collect data and then integrated machine learning algorithms for recognition (Bai J et al. 2013; Gao JF et al. 2018; Herrmann I et al. 2013; Pantazi XE et al. 2017; Piron A et al. 2008).

Gao et al. explored the feasibility of using a Near-Infrared (NIR) 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

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with 30 key spectral features. The average accuracy for corn (*Zea mays* L.), 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. 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. proposed a multi-feature weed recognition method based on multispectral imaging and data mining, where the multi-feature recognition rate was higher than single-feature recognition. The combination of spectral, texture, and fractal dimension features yielded the highest recognition accuracy of 96.3%, as depicted in Figure 9c Bai et al. 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 oilseed rape, as shown in Figure 9d Herrmann et al. 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 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 Kappa of 0.79 and total accuracy of 85%.

Using hyperspectral cameras can capture subtle spectral differences between crops and weeds. However, pixel-based recognition is inefficient. Machine learning algorithms, such as SVM and Random Forests, 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 multi-feature 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 remains a critical issue that needs to be addressed.

Analysis of these references and comparison of various feature-based recognition methods indicate 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 MX et al. (2019) proposed a two-stage algorithm based on Faster Region-based Convolutional Neural Networks (Faster R-CNN) integrated with Feature Pyramid Networks (FPN), which achieved good detection performance in complex backgrounds in cotton fields. Fawakherji et al. (2019) developed a model that accurately classified crops and weeds by generating patches from binary images for robotic use. Dos 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 central processing unit (CPU) systems, reducing computational costs. Some researchers have optimized deep learning algorithms for better recognition performance (Bah MD et al. 2019; Krizhevsky A et al. 2017; Sun Jun et al. 2018). Other studies have utilized One-Stage object detection algorithms from the YOLO series for weed detection (Sun H., et al. 2024; Ying BY et al. 2021; Zhang WK et al. 2023). In deep network research, Li et al. (2023) proposed E2CropDet, a deep learning-based crop row detection network that achieved end-to-end detection at 166 frames sec^{-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 multi-stage algorithm design (Adhikari SP et al. 2019; Huang S 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 artificial intelligence 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 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 100mm under various conditions, with a lateral deviation range of 25-69mm during straight-line driving. Corpe

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et al. (2013) developed a GPS-based agricultural robot equipped with multiple sensors for environmental information detection, considering complex field conditions.

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 intra-row 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 0.15m at a travel speed of 0.8m/s, with an average tracking error of less than 0.03m 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, centimeter-level localization accuracy RTK-DGPS 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 1.9cm and a standard deviation of less than 4.1cm. 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 UK and the US 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, 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 weed recognition. Kise et al. (2005) applied stereo vision 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 et al. (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 corn fields 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 J 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.

Firstly, 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

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to correct GPS errors. Bakker et al. (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 inter-row mechanical weeding.

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

Thirdly, the GPS/DR integrated navigation system has been applied to weeding robots. Ding et al. (2005) 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/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-degree downward angle and collecting concurrent timestamped data. Data fusion generated a three-dimensional (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 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.

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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. This paper will present the sources and descriptions of the public datasets obtained, detailed in Table 3.

Progress in research on intelligent weeding robots

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

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 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.

Subsequent designs focused on Site-Specific Weed Management (SSWM) for smart sprayers. Hussain et al. (2020) designed a variable-rate smart sprayer that achieved the highest accuracy using the YOLOv3-tiny model, saving up to 42% of spray liquid. Partel et al. (2018) 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. designed and developed a YOLOv4-based smart spraying system, achieving an average effective spray rate of 93.33%, with 100% precision and a recall

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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 & Spray robot (2021) developed by John Deere combines a vision system with a precision spraying system, achieving an identification accuracy of over 98%. It classifies weeds and crops using vision technology. Powered by tractors, it can operate continuously for long periods, working up to 12 hours in large-scale crop fields such as cotton (*Gossypium hirsutum* L.) 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 Greeneye Technology weeding robot(2021), whose core technology is its artificial intelligence-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 to traditional weeding methods, SSP reduces herbicide usage by over 87% on average.

The SprayBox robot (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 hr^{-1} and identify and process over 500,000 plants, reducing chemical herbicide usage by approximately 95% compared to traditional spraying techniques. It has been scaled for use in carrot (*Daucus carota* L.) 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 5.3μg of glyphosate per droplet, reducing herbicide usage by tenfold. Spaeth et al. (2024) reported savings of 10-55% 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 bermuda [Cynodon dactylon (L.) Pers.] grass lawns.

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These systems improve weed and crop identification accuracy, allowing for targeted herbicide application. EcoRobotix, a Swiss company, developed a solar-powered weeding robot (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 to gather weed information and applied multi-feature 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(2022), equipped with 0.5mm resolution cameras capable of distinguishing weeds in a short time and accurately spraying herbicides on them.

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 residual drugs 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 regenerate in the targeted spraying area later. 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 servo motor 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 difficult to grasp. 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 general environment 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 inter-row mechanical weeding technology was limited due to the continued dominance of cost-effective chemical weeding methods, leading to low market demand for expensive intelligent inter-row mechanical weeding equipment. However, recent advancements in domestic electronic information, automatic control, and artificial intelligence technologies have spurred extensive research into inter-row mechanical weeding by researchers, driving the emergence of intelligent inter-row mechanical weeding equipment. Table 4 details the mechanical weeding robot actuators and their characteristics.

Mechanical weeding robots face challenges in removing inter-row 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 completing 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

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penetration of specific wavelength laser radiation into tissues, the thermal effects within irradiated tissues, and the associated damage mechanisms are critical for the successful control of laser weeds. Hoki et al. (2000) irradiated young rice plants with lasers of different wavelengths (532 nm and 1064 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-degree-of-freedom five-rotation parallel mechanical arm for dynamic laser weeding. Fatim 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(2022) in the United States, 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 8-10 hours per charge, with a range of 1.5-3 km hr^{-1}, depending on the density of weeds. The CO_2 laser module array emits once every 50ms, with an accuracy of 3mm, and can perform laser weeding on 8 targets at the same time. It can handle 6-8 ha d^{-1}, and the laser system can handle up to 100 weeds sec^{-1} without the need for chemical agents, making it particularly suitable for organic farmland that needs to avoid chemical residues (Figure 13b). The Tom weeding robot (2018), developed by the Small Robot in the UK, uses laser technology for precise weeding and is designed for organic farming, reducing chemical herbicide usage and being environmentally friendly. Its AI-based recognition system has an accuracy rate of over 95%, consuming 15-25 kWh d^{-1}, working for 12 hours on a single charge, and covering 1.5-2 km hr^{-1}. It can process 20 ha of farmland daily. The LaserWeeder robot from EcoRobotix(2020), based in Switzerland, combines laser technology with AI for precision weeding in refined farmland operations. Its vision and AI systems achieve a recognition accuracy of 99%. Powered by a battery, it consumes around 20 kWh d^{-1}, working continuously for 8-10 hours and covering 5-10 ha d^{-1}. The WeedBot

Laser Weeder (2022), developed by the Europe-based company WeedBot, 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 over 98%. Battery-powered, it consumes around 25 kWh per day and can work continuously for 8 hours, covering 1.5-2 km hr^{-1} and processing approximately 10 ha day^{-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. 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 current weeding robots are still in the prototype development stage, companies like FarmWise (2020) and Carbon Robotics (2022) are gradually moving towards commercialization. This paper reviews two major technical issues of weeding robots: (1) weed detection; (2) 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 inter-row 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, multi-modal 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 multi-

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sensor fusion technology, machine vision, field navigation technology, and multi-disciplinary 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 multi-functional 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. Considerations for optimal inter-row 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. By integrating 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 learning deep learning algorithms. 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 towards 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 lifecycle 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 no damage to crops. Monitoring through the digital twin model allows real-time simulation and analysis of the robot's components' operational status. 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. This data enables 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.

5G technology, with its ultra-low latency, 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. 5G 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, i.e., 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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Table 1 Color-based recognition results

Feature	Recognition methods	Crops	Recognition accuracy	Reference
Color	RGB space + Otsu automatic threshold segmentation	-	crop row：86.35%-92.8%	García-Santillán et al. (2017)
	RGB space + color depth fusion algorithm	Broccoli、Lettuce	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	crops：82.1%	Chen et al. (2009)
	RGB space + setting brightness threshold + discriminant analysis method	Beet	crops：88.5% weeds：88.1%	Jafari et al. (2006)
	HSV space + shape erosion and dilation algorithm	Broccoli	crops：99.04%	Hamuda et al. (2017)
	HSI space + constructing Mahalanobis distance classifier	Broccoli	crops：93.6%	Li et al. (2016)

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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	Wild millet	-	Adhikari et al. (2019)
Caffe Net architecture for training neural networks	-	weeds：97%	Dos et al. (2017)

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Table 3 Public datasets

Classifications	Description of the data set	Source	Reference
Applied to deep learning models	Annotated Carrot and Weed Image Dataset	https://github.com/cwfid/dataset	Haug et al. (2015)
	6 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 7853 annotations, including 6 food crops and 8 weeds, totaling 1118 images.	https://www.ncbi.nlm.nih.gov/pmc/articles/ PMC7305380/	Sudars et al. (2020)
	The with weed image dataset containing 47 different species of plants, 315038 plant objects representing 64,292 individuals, totaling 7590 RGB images.	https://gitlab.au.dk/AUENG-Vision/OPPD	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)
	Multi-spectral camera	carrots：https://lcas.lincoln.ac.uk/nextcloud/index.php/s/RYni5x ngnEZEFkR	Bosilj et al. (2020)

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		onions : https://lcas.lincoln.ac.uk/nextcloud/index.php/s/e8uiyr ogObAPtcN	
Includes a large number of images	CNU Weed Dataset contains 21 weed species from five families, totaling 208,477 weed images	https://www.sciencedirect.com/science/article/pii/S0168169919319799#s0025	Trong et al. (2020)
	The GrassClover image dataset contains 31,600 unlabeled and 8,000 synthetic data sets for red clover, white clover, 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	Deepweed dataset evaluates encoder-decoder architecture to distinguish crops from weeds	Deepweed: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 data sets	https://github.com/zhangchuanyin/weed-datasets	Jiang et al. (2020)
	The "Plant Seedling" dataset contains 12 different plant species.	https://www.kaggle.com/vbookshelf/v2-plant-seedlings-dataset	Giselsson et al. (2017)

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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 et al. (1997) Fogelberg et al. (1999)
Claw tooth	High assembly accuracy is required, rotation is required to avoid seedlings, and the damage rate to seedlings is less than 8%.	Hu et al. (2012)
Weed whacker	Using laser sensors and motor control to avoid seedlings along the sine wave, the seedling damage rate is 23.7%	Cordill et al. (2011)
Oscillating hoe shovel	The cam swing rod swings to avoid seedlings, and GPS localization technology can be used	Wang et al. (2021)
Rotating hoe shovel	Good mechanical properties, seedling damage rate 4.54%	Quan et al. (2021)
Eight-claw style	Taking the distance between the weeding blade teeth and the crop as the threshold, the seedling damage rate is less than 10%	Chen et al. (2010)
In-line weeding knife	Use machine vision technology to detect seedling position information and control the movement trajectory of the hoe	Pérez-Ruiz et al. (2014)
Rotary press type	Based on real-time detection by ultrasonic sensors, avoid seedlings through hydraulic	Saber et al. (2015)

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	means	
Notched disc knife type	The machine vision system is used to collect crop and seedling information, and the traverse mechanism is controlled to perform knife setting and rotational weeding.	Garford (2023)、Tillett et al. (2008)
Spring tooth type	The structure is simple and will cause damage to crops in the seedling stage.	Midtiby et al. (2012)
Finger weeding knife	Used to remove weeds in small areas and under soft soil conditions	Riemens et al. (2007)
Comb type	During the cultivation period, corn avoids seedlings and performs one-way intermittent rotation.	Jia et al. (2019)
Oscillating hoe	Use cameras to determine crop position and achieve inter-plant weeding	Frank Poulsen Engineering (2016)

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Table 5 Circuit design and characteristics of laser weeding device

Main circuit design or components	Specificities	Reference
Conveyor + 2-axis deflector	Using stereo cameras to identify plants and simulate moving vehicles to target weeds	Nadimi et al. (2009)
Laser generator + robotic arm	Robotic arm points laser beam at weeds with little error	Ge et al. (2013)
4-degree-of-freedom parallel mechanism	The 3UPS-RPU 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	2-DoF for Laboratory Simulation of Static Laser Weeding with Laser Beam, Proposed New Path Planning Algorithm for Weeding	Xiong et al. (2017)
2-axis deflector for mirrors + lenses	Unable to realize the need for stabilization, affected by complex field conditions	Rakhmatulin et al. (2020)
Two-freedom five-rotation parallel robotic arm	For dynamic laser weeding, the average error in accuracy was 0.62 mm, and the dynamic weeding efficiency was about 0.72 s/weed with a dwell time of 0.64 s	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)

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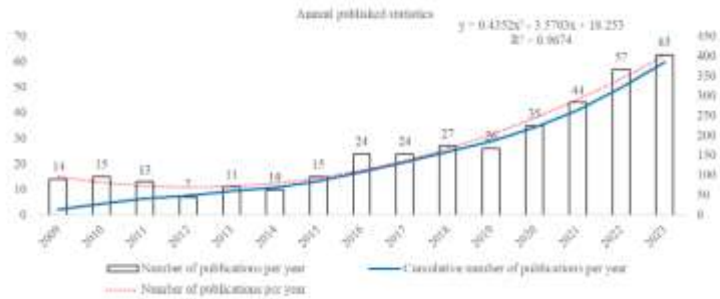

Figure 1. Annual publication volume of research literature

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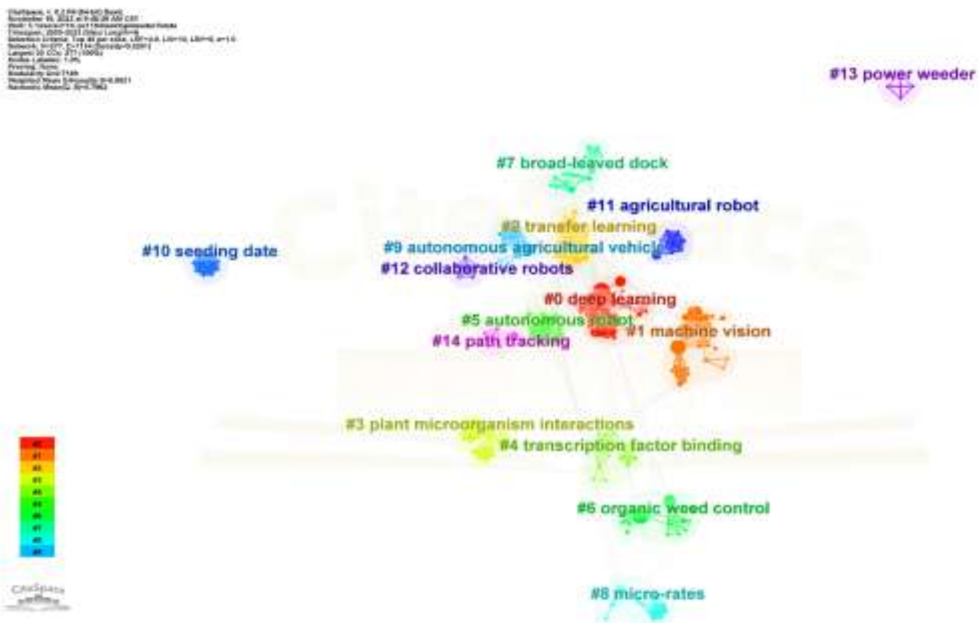

Figure 2. Co-occurrence graph of key terms

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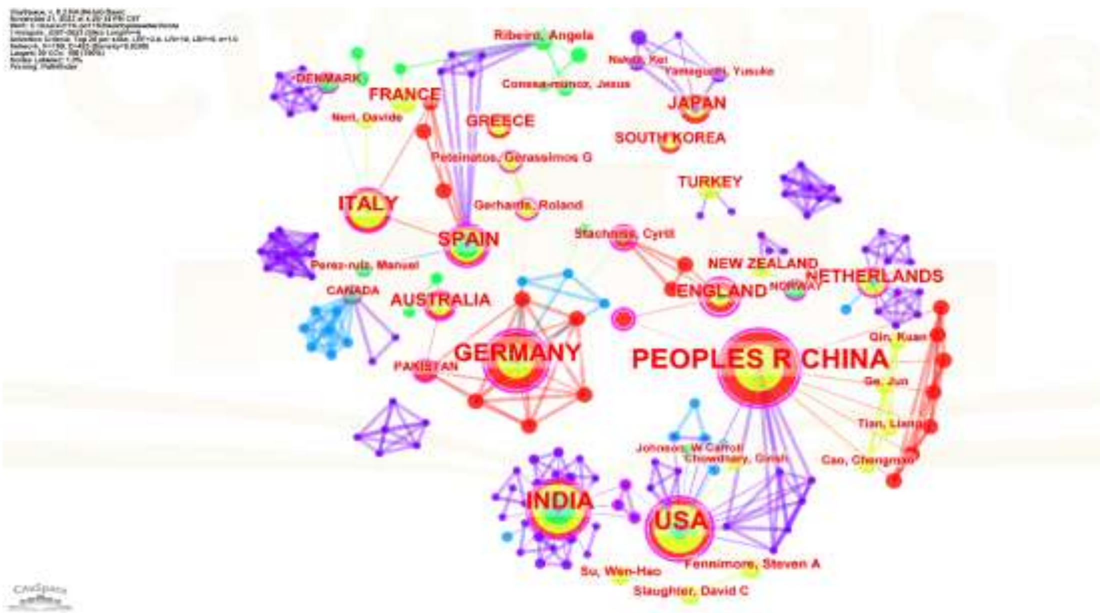
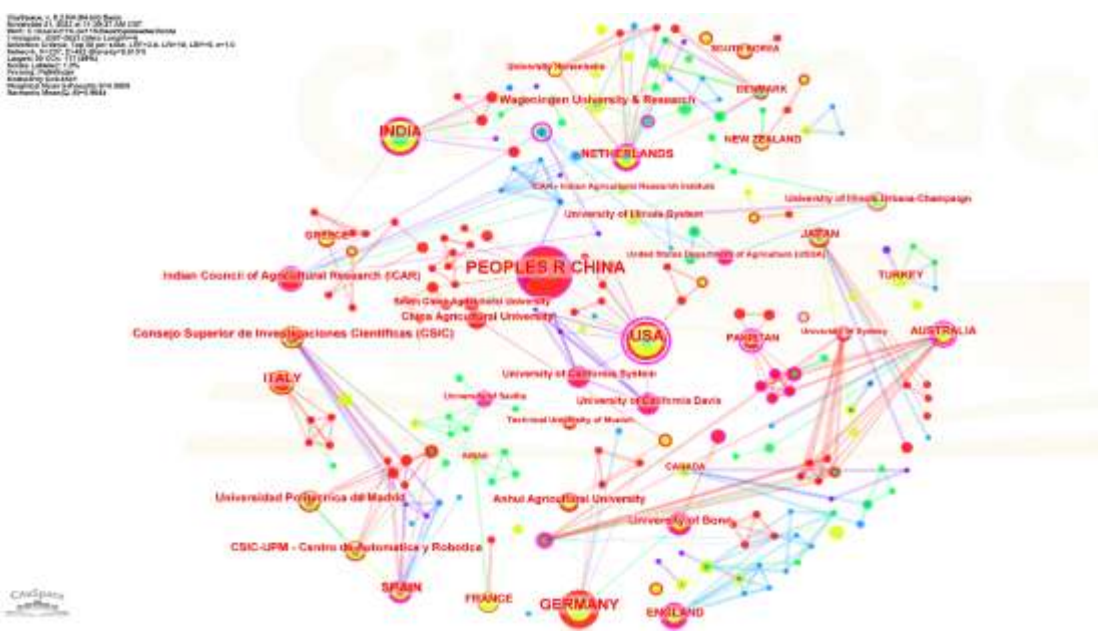


a)



b)

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

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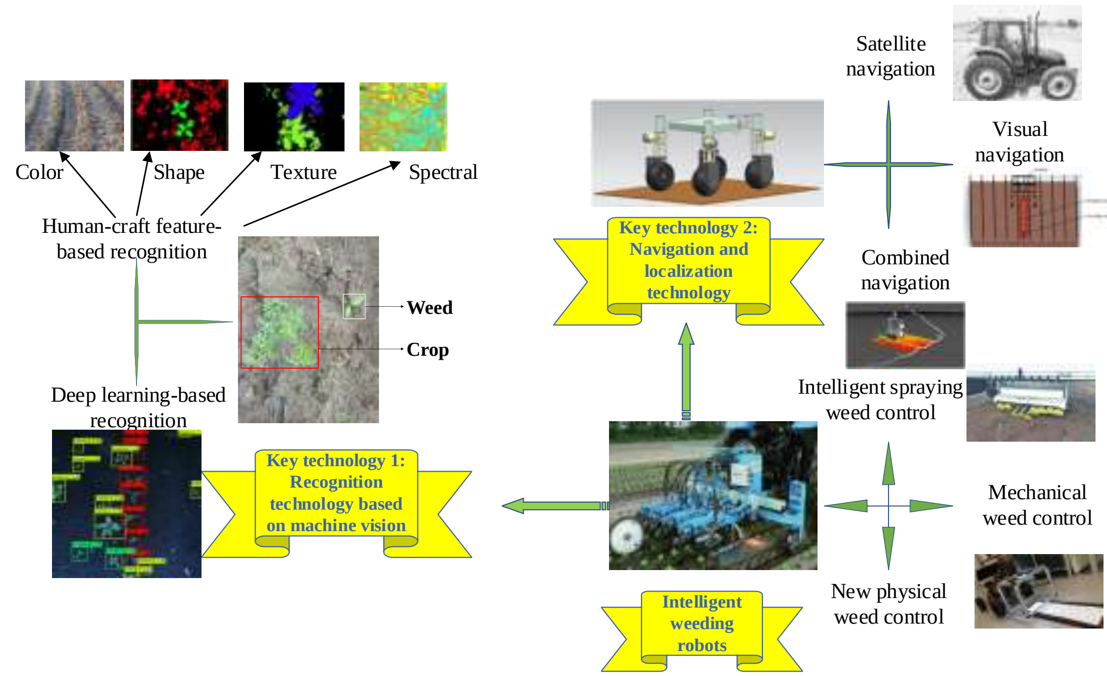

Figure 4. Key technologies of intelligent weed control

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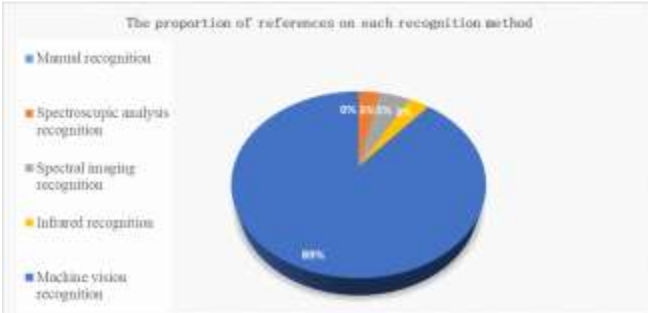

Figure 5. The proportion of each recognition method in the references

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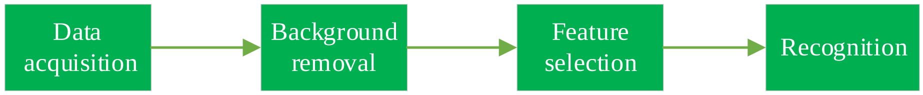

Figure 6. Recognition of traditional machine learning

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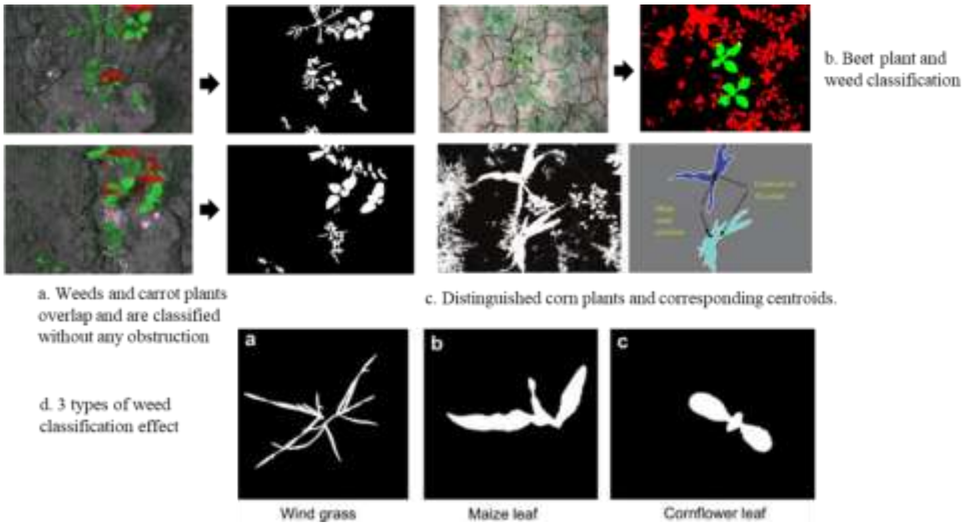

Figure 7. Classification performance based on shape features

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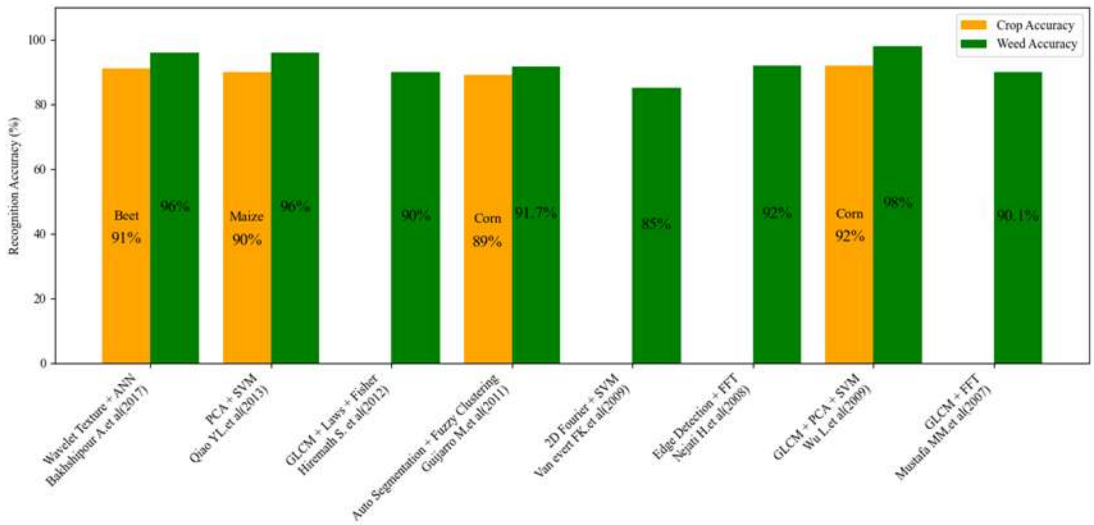

Figure 8. Texture-based crop/weed recognition accuracy

Notes: ANN and SVM represent Artificial Neural Networks; Support Vector Machines. PCA refers to Principal Component Analysis; GLCM refers to Gray-Level Co-occurrence Matrix; FFT refers to Fast Fourier Transform.

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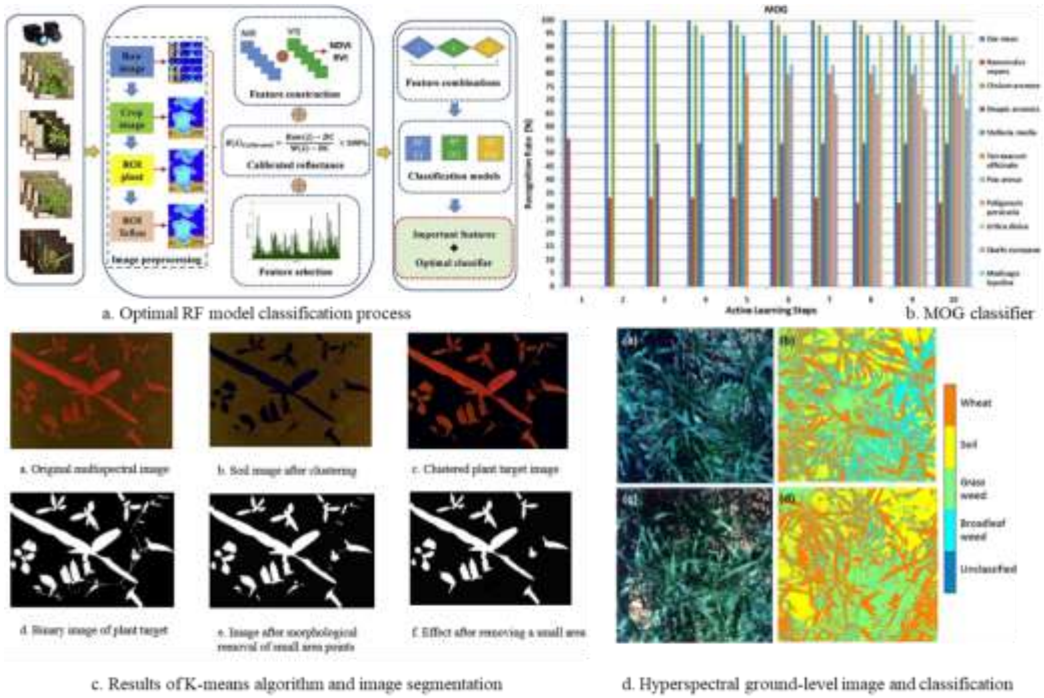

Figure 9. Classification performance based on spectral features

Notes: RF stands for Random Forest; MOG stands for Mixture of Gaussians.

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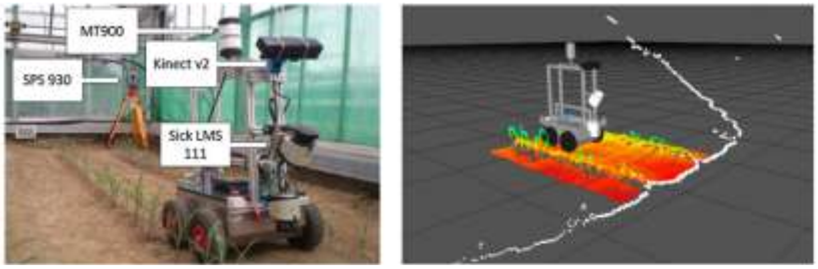

Figure 10. Robot platform and data visualization

Notes: SPS930 refers to Universal Total Station (Trimble, Sunnyvale, USA); Kinect v2 refers to a sensor(Microsoft, Washington, DC, USA); LMS111 refers to 2D-LiDAR laser scanner (SICK, Waldkirch, Germany); Trimble MT900 refers to Machine Target Prism (Trimble, Sunnyvale, USA). .

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a) b)

Figure 11. Precision spraying robots

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a) b)

Figure 12. Drone weeding and weeding robots

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a）　　　　　　　　　　　　　　　　b)

Figure 13. Laser weeding robots

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