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Comprehensive Review of Artificial Intelligence and Edge Computing for Precision Weed Control

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Abstract: Targeted weed management is an important element of precision agriculture, and accurate weed identification is a foundation for precision weed control. Over the past decade, convolutional neural networks have demonstrated high accuracy and generalization in recognizing weeds in agricultural environments. Edge computing, via edge devices, is one secure method to effectively deploy artificial intelligence algorithms (AI) for weed control on agricultural platforms. This study presents a bibliometric and systematic review of AI algorithms and edge-based systems for precision weed control from 2015 to 2025. Using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines, a systematic search was conducted in Scopus and Web of Science, resulting in the inclusion of 43 documents. Results show a significant surge in publications on AI-based weed control systems deployed on edge computing resources since 2019. The analysis reveals that RGB cameras are the preferred data acquisition method, while object detection models, specifically the YOLO family, are widely adopted for AI deployment. Pretraining or training optimizations are preferred over post-training model optimization to maximize inference and improve detection accuracy, while NVIDIA Jetson series edge devices are commonly used for deploying AI algorithms. Precision chemical control approaches dominate, but laser weeding technology is emerging as an alternative. Despite technological advances, challenges hinder commercial deployment, including reliance on manual data annotation and model vulnerability to environmental variability. Future research should focus on semi-supervised learning, synthetic data generation, and multimodal vision systems to improve robustness and reduce annotation dependence. Unified evaluation protocols are also needed to benchmark system performance.

Keywords: artificial intelligence, weed detection, weed control, edge device, precision agriculture

1. Introduction

Precision agriculture integrates sensors to observe or identify spatial and temporal variability in agricultural fields and actuators to respond with management actions to achieve sustainable and efficient farming [1, 2]. This is particularly important in targeted weed control—precision weed management—because weeds are a major challenge to agricultural productivity. Weeds compete with crops for essential resources and create favorable environments for harmful pathogens and insects, resulting in potential yield losses of over 45% and accounting for about a third of the total production cost of field crops [3]. In the US agricultural industry, weed control using herbicides accounts for 60% of the overall volume and 65% of the total pesticide expenditures used by farmers. While herbicides are effective, there are growing concerns about environmental impacts and the development of herbicide resistance in weeds from conventional herbicide applications [4]. An alternative mechanical weed control approach presents a more environmentally friendly option but can damage crops near weeds and disrupt soil structure. These challenges, coupled with the growing advancement and potential of new weed control approaches such as laser weed control, necessitate precision weed control.

Among other elements of precision weed control, accurate weed identification is a cornerstone. Over the past decade, convolutional neural networks (CNNs) have shown promising results in weed recognition. CNNs process digital images through multiple hierarchical layers, where each layer extracts more detailed information than the previous one. By applying nonlinear activations after each layer, CNNs capture complex patterns and relationships within the image [5]. This enables CNN-based algorithms, such as deep learning (DL) algorithms, to generalize better than image processing techniques and traditional machine learning (ML) algorithms. They have been integrated into different weed management practices, such as weed mapping, decision support, weed control, and navigation of robotic platforms, among others [1, 6, 7].

For artificial intelligence (AI) algorithms to be useful for weed management in the field, edge computing represent a secure method for deployment on edge devices. Edge devices are portable computing resources that process data close to where it is generated. Compared with cloud or remote computing, they offer advantages such as secure, real-time data processing, which is

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important for deploying AI algorithms on remote farms where internet connectivity is limited [6]. These devices range from CPU-based platforms like Raspberry Pi and Arduino to graphics processing unit (GPU)-enabled systems such as NVIDIA edge devices, which support parallel computation and faster data processing. However, deploying AI models on edge devices is challenging because these models are typically trained on large computing systems with millions of parameters, making model optimization essential for real-time field applications.

1.1. Motivation

Different studies have reviewed precision weed control technologies in agriculture. These reviews have examined topics such as unmanned ground vehicles for automated weed management, site-specific weed management systems and their components, precision spraying technologies, and machine vision challenges in robotic weeding [7]. Additionally, a systematic review has evaluated DL-based weed detection approaches for both static image analysis and real-time applications in robotic and aerial weed control systems [5].

While most of these reviews are systematic, they primarily focus on robotic platforms or DL and chemical weed control methods. However, they do not evaluate DL and edge device-based precision weed control systems (DEPWCS), detail their components, or examine operational factors that influence overall system performance. Moreover, studies rarely discuss how AI-based detection systems integrate with various weed control mechanisms, leaving a significant gap in understanding the design and deployment of AI and edge device-based precision weed management systems. This gap underscores the need for a comprehensive analysis of DEPWCS, focusing on their detection, control, and evaluation pipelines across different platforms for weed management.

1.2. Scope and objectives

This study systematically analyzes DEPWCS over the past decade. This systematic review adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [8]. The review not only examines different weed control methods but also considers guided platforms, such as robots and Cartesian systems, used in precision weed management. In addition, it explores trends in the software and hardware components of the detection–control–evaluation pipeline and the factors that influence the effectiveness of precision weed control. The focus on the past decade is motivated by rapid advances in vision AI since 2012, when AlexNet achieved unprecedented accuracy in large-scale image classification during the ImageNet Large Scale Visual Recognition Challenge [9]. This breakthrough marked a turning point, sparking widespread research and industry adoption of DL in computer vision. Specifically, the objective of this review is to answer the following four research questions (RQs):

1) What is the bibliography trend of DEPWCS?
2) What platforms are DEPWCS deployed on, and what weed control methods utilize DEPWCS?
3) What are the components of the DEPWCS pipeline, and how do they influence effectiveness?
4) How are DEPWCS evaluated?

The rest of the paper is organized as follows: Section 2 outlines the methodological framework for conducting the literature search, including the PRISMA framework; Section 3 presents the results, addressing the four RQs; Section 4 examines the challenges and future directions of DEPWCS; and finally, Section 5 concludes the paper.

2. Research Methodology

2.1. Literature search strategy

A systematic literature search was conducted in September 2025 on Scopus and Web of Science databases, targeting peer-reviewed journal articles and book chapters published between 2015 and 2025. Carefully selected keywords and Boolean operators were applied across titles, abstracts, and author keywords to comprehensively capture relevant studies. The full search string was as follows:

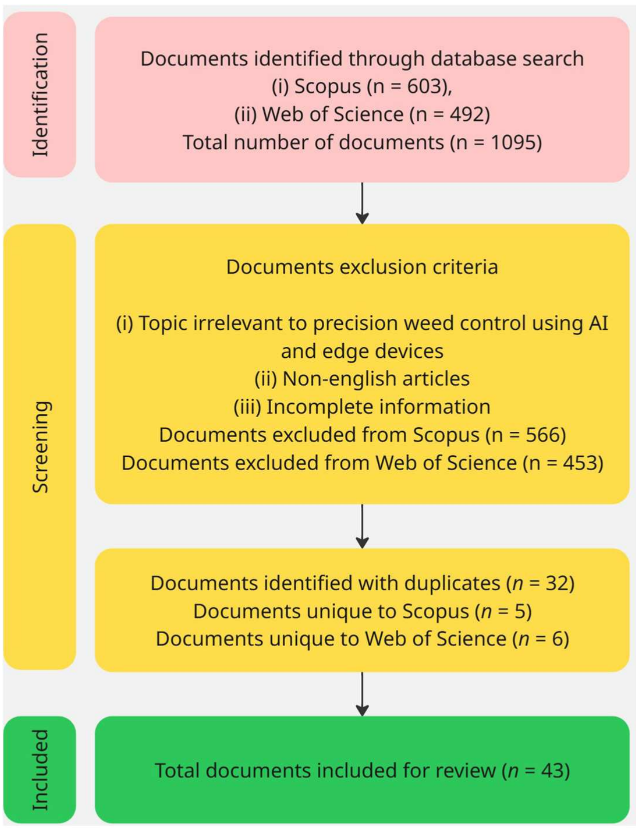
(“weed detection” OR “weed control” OR “precision weed*” OR “autonomous weed*” OR “weed management” OR “site-specific weed management”) AND (“artificial intelligence” OR CNN OR “deep learning” OR “edge comput*” OR “edge AI” OR “edge device*”)

The wildcard symbol (*) was used where appropriate to capture variations of keywords. For example, “precision weed*” ensures retrieval of terms such as precision weeding or precision weeder. Similarly, “edge comput*” retrieves terms such as edge computing and edge computer. Only studies published in English were included.

2.2. PRISMA screening and selection

The database query from Scopus and Web of Science yielded 603 and 492 retrieved documents, respectively (Figure 1). After

Figure 1
Overview of PRISMA screening and selection procedure for this study



reading the titles and abstracts of all retrieved documents to confirm coherence with the subject matter, 37 and 39 documents from Scopus and Web of Science were relevant to the application of AI and edge computing for precision weed control. Web of Science does not have a book chapter option, so only peer-reviewed research articles were extracted. During the screening stage, it was noted that although many researchers have studied the application of AI for weed detection, few have integrated their results for precision weed control. Of the relevant documents, 32 were duplicates across these two databases, resulting in a total of 43 unique selected articles used in this study.

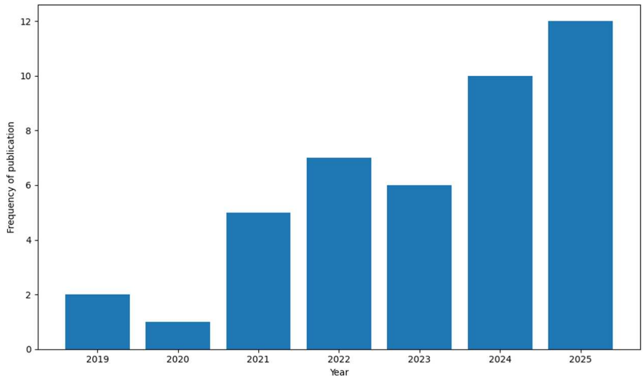
3. Results

3.1. What are the bibliography trends in DEPWCS?

3.1.1. Analysis of trend in the number of publications

The number of DEPWCS publications has increased significantly in recent years, peaking in 2025 (Figure 2). Although AI-based detection systems gained widespread recognition in 2012, the earliest publication reporting their deployment on edge devices for precision weed control did not appear until 2019. That year, only two articles were published, whereas by 2025, the number had risen to twelve.

Figure 2
Annual scientific publication on AI-based precision weed control using edge devices

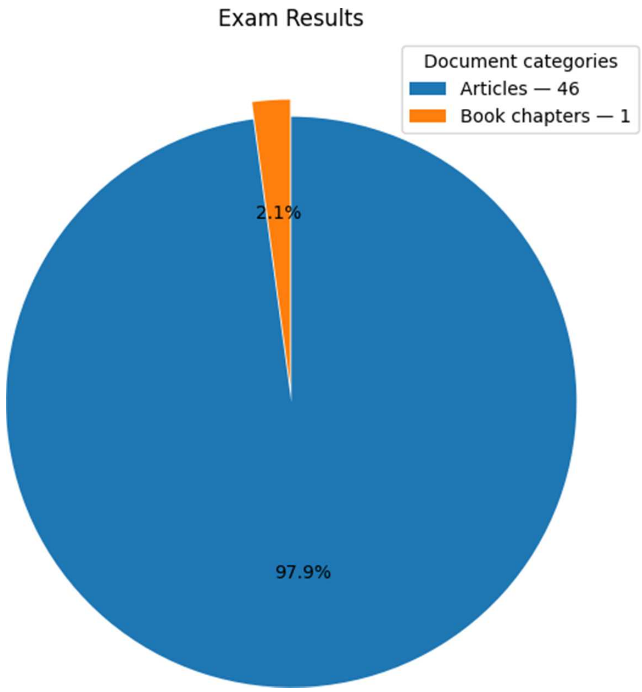


The apparent gap between 2015 and 2019 can be attributed to the limited research focus during that period on deploying AI models specifically for weed control. Earlier studies focused on foundational research, including exploring DL techniques for weed detection and mapping, improving detection accuracy, and enhancing model generalization, rather than on-field deployment within integrated precision weed control systems. Because edge computing hardware and real-time control technologies were still maturing, deployment-oriented research remained sparse.

The publication trend did not follow a continuous upward trajectory, particularly in 2022 and 2023. The decline observed around 2020 can be attributed to the disruptive impact of the COVID-19 pandemic, which constrained field experiments in this domain [10]. The reasons for the reduced number of publications in 2023 are less apparent and may require further investigation, potentially reflecting delays in research translation, publication cycles, or shifts in research focus.

Research activity in this domain has since accelerated and is expected to continue growing. This projected increase is driven

Figure 3
Publication distribution on AI-based precision weed control using edge devices



by rapid technological advances, including the availability of improved open-source DL models and lower hardware costs.

3.1.2. Analysis of publication sources and document distribution

The document type distribution (Figure 3) shows that journal articles account for most publications (97.9%), with only one book chapter (2.1%). This distribution suggests that the topic is primarily explored through journal research, reflecting an active, empirically driven field with limited representation in book-length or synthesized works.

Regarding publication sources, this study shows that researchers disseminated their work across a range of publication platforms (Table 1). *Computers and Electronics in Agriculture,* a leading journal in agricultural technology, accounted for one-quarter of the publications and had the highest number of articles related to this study, followed by the *Smart Agricultural Technology* journal.

The top publication outlets are primarily in engineering, agronomy, and applied sciences. These outlets are highly relevant to precision agriculture, ML and AI in agriculture, robotics and automation, smart farming systems, sensor networks, and real-time monitoring, which are core components of AI-driven precision weed control. Additionally, the book chapter was published in the *Springer Proceedings in Materials*.

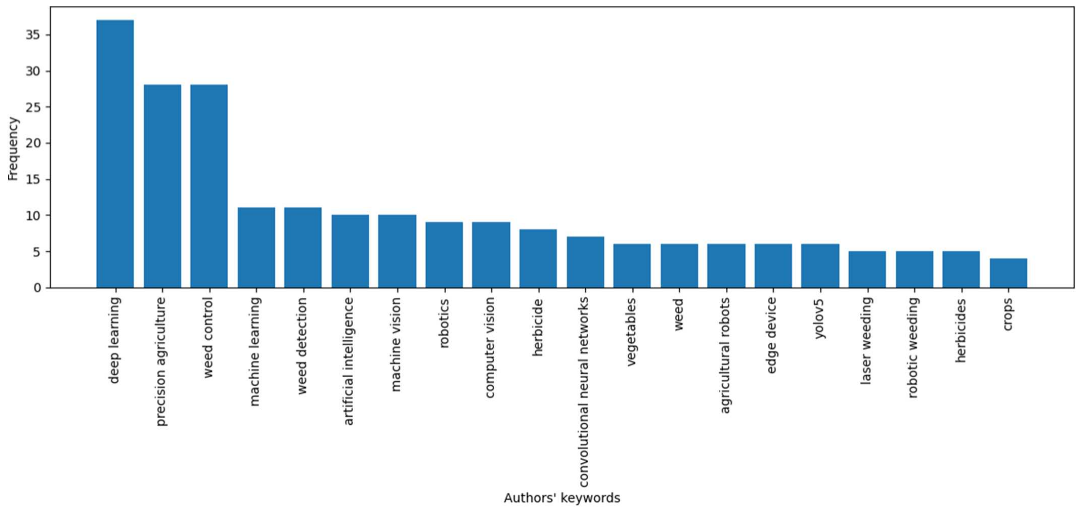
3.1.3. Keyword analysis and co-occurrence network

An analysis of the authors' keywords was conducted to explore the thematic structure, research focus, and evolving scope of this study. In total, 358 unique keywords were identified from 654 author-provided entries. Keyword frequency distribution and a word cloud (Figures 4 and 5) were used to illustrate the analysis. The term "deep learning" appeared most

Table 1
Publication source of documents

Sources	No. of articles
Computers and Electronics in Agriculture	6
Smart Agricultural Technology	4
Applied Sciences (Switzerland)	3
Agronomy	3
Sensors	3
Agriculture (Switzerland)	3
Biosystems Engineering	2
Frontiers in Agronomy	2
Pest Management Science	2
Crop Protection	2
Engenharia Agricola	1
Micromachines	1
Knowledge-Based Systems	1
Remote Sensing	1
Journal of Agriculture and Food Research	1
Weed Technology	1
IEEE Access	1
Journal of Agricultural Engineering	1
Frontiers in Robotics and AI	1
Frontiers in Plant Science	1
PLOS ONE	1
Journal of Crop Health	1
Springer Proceedings in Materials	1

Figure 4
Frequency of occurrence for top 20 author-provided keywords



frequently and dominated the word cloud, followed by other high-occurrence keywords such as "precision agriculture," "weed control," "machine learning," "weed detection," and "artificial intelligence." Notably, several top keywords, including "precision agriculture," "machine learning," "machine vision," "computer vision," "herbicide," and "robotics," were not part of the original search string, highlighting their importance in the scope of this study. The word cloud also reveals less frequent but more specific terms related to detection and control systems, including "remote sensing," "semantic segmentation," "targeted," "automation," and "pesticides."

The keyword co-occurrence network derived from the author-provided keywords is shown in Figure 6. In this network, nodes represent individual keywords, with node size proportional to keyword frequency. Links indicate the strength of co-occurrence between keywords, with thicker lines denoting

Figure 5
Word cloud of author-provided keywords

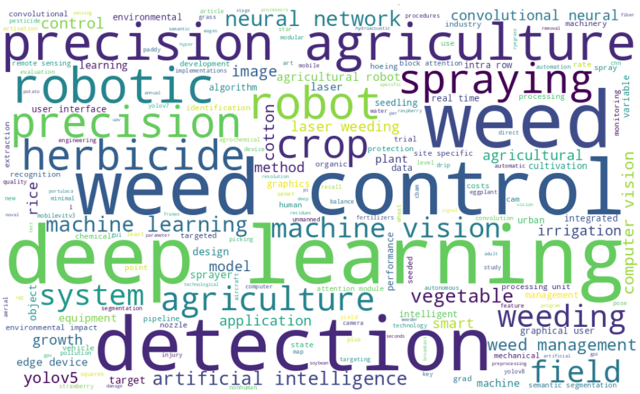
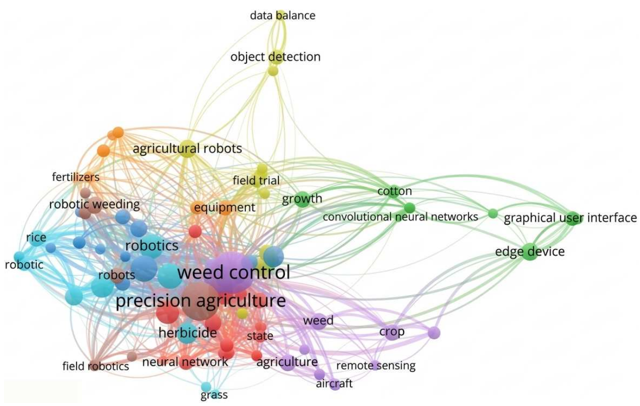


Figure 6
Keyword co-occurrence network based on author-provided keywords



stronger relationships. Colors represent distinct thematic clusters, and the layout reflects spatial relationships based on co-occurrence, with shorter distances between nodes indicating stronger relatedness.

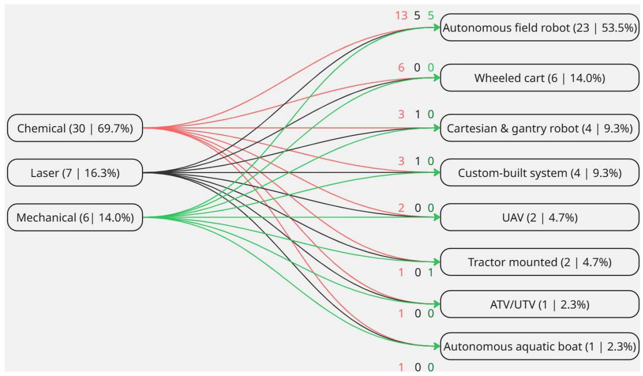
The keywords "weed control" and "precision agriculture" are the most prominent, representing the central themes of the network. The purple cluster includes terms such as "weed," "crop," "remote sensing," and "aircraft," indicating studies focused on remote sensing and aerial-based weed management. The blue cluster contains terms like "robotics," "fertilizers," and "robotic weeding," highlighting the integration of robotic technologies and automation in weed and crop management. Meanwhile, the green cluster features terms such as "convolutional neural networks," "edge device," and "graphical user interface," emphasizing computational, AI, and technology deployment aspects in precision weed control research.

3.2. What platforms are DEPWCS deployed on, and what weed control methods utilize DEPWCS?

3.2.1. Weed control platforms for deploying DEPWCS

The physical platforms used to deploy DEPWCS span a range of ground, aerial, and aquatic platforms (Figure 7). These include autonomous field robots, wheeled carts, Cartesian and gantry robots, unmanned aerial vehicles (UAVs), tractor-mounted systems, all-terrain vehicles/utility task vehicles, custom-built platforms, and autonomous aquatic boats.

Figure 7
Weed control methods that utilize DEPWCS and platforms for deployment



Autonomous field mobile robots dominate, accounting for over half of all deployments. Their prevalence reflects significant investment in purpose-built robotic platforms that integrate sensing, navigation, and actuation for autonomous weed control. Motorized and manually pushed wheeled carts are the second most common platform (14%). These systems offer a lower-cost, more accessible alternative for prototyping and early-stage field deployment compared with fully autonomous robots. Cartesian and gantry robots, typically constructed with aluminum frames, are mainly deployed in controlled or semi-controlled environments such as greenhouses and raised beds. These platforms either enable lateral movement of a single nozzle across the frame or provide three-dimensional actuation for precise targeting.

Custom-built systems—including laboratory testbeds, wheeled Cartesian configurations, and self-propelled upland gap sprayers—account for a similar proportion of deployments as Cartesian and gantry robots. Beyond ground-based platforms, a smaller number of studies explored aerial and aquatic applications. UAV-based weed control systems accounted for approximately 4.7% of deployments, while autonomous aquatic boats represented about 2.3%, demonstrating the feasibility of extending DEPWCS beyond ground platforms.

The strong emphasis on autonomous robotic platforms suggests that deployment has moved from laboratory-scale experimentation to real-world field applications. This trend also explains why many existing reviews in this domain focus predominantly on robotic weed control systems. The relatively low adoption of tractor-mounted platforms indicates a shift away from retrofitting legacy agricultural machinery toward designing integrated robotic solutions. Additionally, the limited number of UAV-based deployments highlights a research opportunity, particularly in addressing challenges related to payload constraints, actuation precision, and real-time onboard inference.

3.2.2. Weed control methods

The weed control methods that utilize DEPWCS fall into three main categories: chemical and mechanical methods and lasers. Chemical weed control that uses DEPWCS shifts from conventional blanket application methods, which commonly result in substantial pesticide waste and environmental pollution. This control method involves acquiring images or video and recognizing weeds using AI models. After weed recognition, targeted herbicide delivery is achieved through an electronically controlled spraying module, in which a microcontroller activates high-speed solenoid valves via relay switches to dispense precise herbicide doses at individual nozzles within the treatment zone. In most designs, a microcontroller or embedded processor communicates a spraying decision via a low-voltage signal, typically 5 V DC or 3.3 V from GPIO pins [11], and, in response, closes a separate circuit to supply the necessary higher voltage, commonly 12 V or 24 V, directly to the solenoid valves.

Solenoid valves have response times typically less than 60 ms and, in some cases, less than 50 ms, allowing the sprayer system to initiate and cease spraying precisely over the intended target areas [12]. To facilitate variable spray application based on weed density or vehicle speed, the spraying system can modulate the delivery volume by sending different pulse width modulation (PWM) signals to the solenoid valves, governing their duty cycle [13, 14]. Precision chemical control culminates at the nozzles, which are selected for their ability to deliver a consistent pattern over a defined area. Common models include BBG-30 [15], Agro-Top SpotFan 40–03 [16], Solo 4900654-P [11, 17, 18], and model 3004 fan nozzle [19]. Nozzles are often positioned at an adjustable height above the ground, ranging from 18 cm for turf applications to 1.2 m for broader coverage, and may feature a specific spray angle, such as 30° [13, 19].

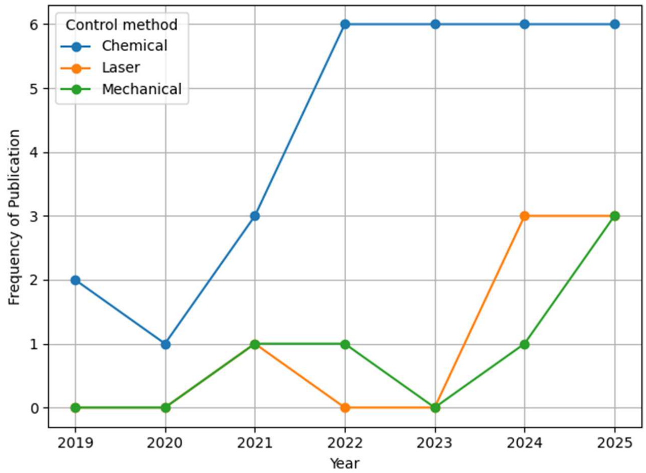
Precision mechanical weeding control is favored in organic agriculture as a chemical-free method [20]. This approach aims to remove weeds precisely while avoiding crop injury and minimizing soil disturbance. The overarching system architecture combines DL weed detection on edge devices with control elements, such as actuators and the weeding tool. Actuators provide the necessary torque and motion by translating command signals from the weed detection hardware into physical motion of the weeding tool. For example, a double-gear chain transmission mechanism employed a sprocket-and-chain drive to convert continuous motor rotation into a reciprocating swinging motion of the weeding tool [20]. Another example is a servo motor (Yaskawa SGMJV-02ADE6S) coupled with a harmonic reducer (50:1 ratio), which was used to drive a vertical disc weeding knife [21].

Emerging precision weed control approaches aim to further reduce reliance on chemical weed control while avoiding the complexity of mechanical weed control. Laser weeding was the only emerging weed control approach that utilized DEPWCS. Laser-based systems deliver thermal energy with extreme precision. This system eliminates weeds by destroying plant cells, often targeting the apical meristematic tissues or stems [22]. Laser control systems demand sub-millimeter precision (e.g., within 1 mm). This precision is necessary because the laser must target a specific, vulnerable apical meristem or stem base to deliver a lethal dose of thermal energy without harming nearby crops.

The actuation module of laser weed control features a high-energy laser source, such as a 25 W, 975 nm fiber-coupled diode laser, a 450 nm blue semiconductor laser, a 5W 450 nm diode laser, or a CO_2 laser, to precisely deliver thermal energy to the weed meristem or stem [22–25]. The effectiveness of laser technology depends strongly on weed size and growth stage, with smaller, early-stage weeds (cotyledon to two-leaf stage) being optimal targets [22]. Larger weeds require substantially higher energy inputs or multiple passes, which slows operation [24]. For example, research trials in vegetable crops (beet, spinach, and pea) demonstrated that multiple laser passes can achieve weed control as effective as, or superior to, conventional herbicides applied at label rates [22].

In summary, chemical weed control dominates DEPWCS research, representing roughly 70% of studies and the most widely adopted method across all deployment platforms, especially autonomous field robots (Figure 7). Laser-based weed control is the second most common approach (16.3%), slightly ahead of mechanical methods (14%), and has gained attention since 2021 for its chemical-free operation and high-precision targeting, primarily on autonomous robots, with limited use on Cartesian and custom-built platforms (Figure 8).

Figure 8
Weed control methods that utilize DEPWCS and platforms for deployment



The dominance of chemical weed control is largely due to the maturity, availability, and ease of integration of its key components, such as solenoid valves, spray nozzles, controllers, and commercial spray modules. This reduces the technical and economic barriers to deployment. Similarly, laser-based systems are gaining attention because their components are increasingly accessible and they offer the potential for sustainable weed management with minimal environmental impact. In contrast, mechanical weed control often requires custom-designed tools, higher engineering precision, and involves a greater risk of crop damage, contributing to its comparatively lower adoption in research and deployment.

3.3. What are the components of the DEPWCS pipeline, and how do they influence effectiveness?

The core technologies enabling AI-based precision weed control span the pipeline from data acquisition to weed removal (Figure 9). This section examines the key elements of this system and discusses the factors that govern its overall effectiveness.

3.3.1. Data acquisition—camera

Data acquisition with digital cameras is fundamental to AI-based weed control systems, as captured images serve as the primary input for both model training and real-time weed detection during deployment. The selection of an appropriate camera depends on factors such as camera modality, hardware compatibility, field of view (FOV), longitudinal placement, cost, frame processing speed, environmental conditions, and resolution [26].

1) Camera modality

The selection of a camera for weed control depends on the spectral differentiation capabilities of the sensor and the required processing speed. The camera modalities used in the reviewed studies include RGB, RGB-D, hydroacoustic, near-infrared (NIR), and multispectral sensors. Among these, RGB

Figure 9
Deployment pipeline for DEPWCS

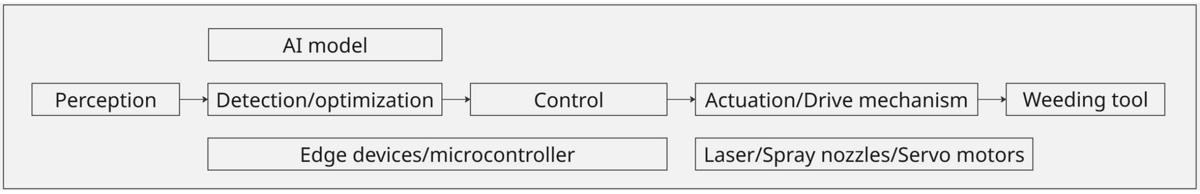
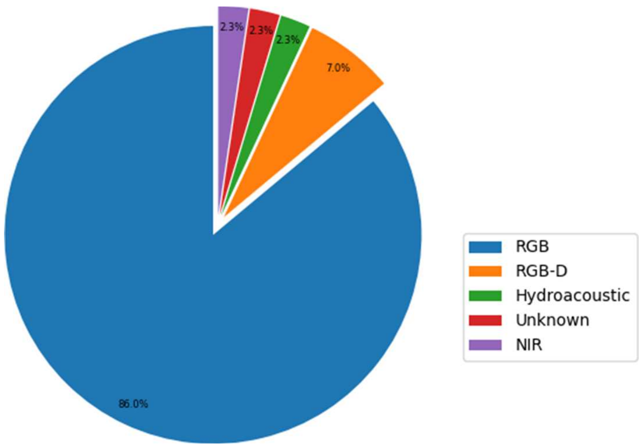


Figure 10
Camera modality used in DEPWCS



cameras dominate, appearing in over 84% of the reviewed studies (Figure 10). RGB-D cameras were used in only two studies, while hydroacoustic, NIR, and multispectral sensors each appeared once in the reviewed studies. The "unknown" category corresponds to the proprietary Carbon Robotics Autonomous LaserWeeder system, for which details of the onboard camera modality were not disclosed. The hydroacoustic camera was deployed for weed removal in water, where traditional optical cameras are limited by water turbidity and light availability.

RGB camera modality is preferred for its low computational demands, affordability, and ease of integration, despite known limitations in distinguishing visually similar plant species [12, 27]. Most vision-based AI models are trained on RGB images, which provide sufficient information for modern DL models to recognize objects while meeting the high frames per second (FPS) and low inference time required for moving platforms [28, 29]. Conventional RGB cameras are significantly cheaper than multispectral alternatives and offer better compatibility with standard onboard computing platforms and development environments [30]. In specialized control applications, sensors such as RGB-D (depth) cameras are integrated into systems requiring precise 3D localization for control tasks, such as laser weeding robots [31].

2) Camera field of view

The camera's FOV determines the area of the field captured during data acquisition and must align with the operational width of the weed control equipment. In some systems, a single camera FOV covers the spray coverage of multiple nozzles, requiring the cropped regions of interest in the image to correspond directly to the coverage area of each nozzle [30]. When wider operational widths are required, multiple cameras are installed with minimal overlap between their views to ensure complete coverage [16, 32].

Camera mounting height is closely related to FOV and target scale [12]. Lower mounting heights produce smaller FOVs but larger ground-target representations, which improves the detection of fine details but may require multiple cameras to cover large areas (Table 2). Additionally, FOV influences computational load: larger FOVs increase processing requirements and may reduce inference speed. To address this, some studies crop image dimensions (e.g., reducing image height) to decrease computational demand and increase frame rates during detection, although this may also influence the operating speed of the weed control platform [28].

Table 2
Camera mounting height and FOV in DEPWCS

Platforms	Camera mounting height (m)	FOV width dimensions (m)
UAV	>4	Wide aerial mapping
Autonomous field robots	1.0–1.4	0.8–1.6
Laser robots, wheeled carts	0.02–0.071	0.036–0.095

Other factors that influence camera selection include its longitudinal position and resolution. The prevailing design trend places the camera ahead of the control mechanism, allowing time for target detection and processing before engaging the actuator. This longitudinal offset must account for several timing factors: the vision processing time required for image acquisition, model inference, and decision generation; the communication delay in transmitting inference results from the detection system to the controller; and the actuator response time needed to execute control actions, such as activating spray valves or mechanical weeding knives.

Higher camera resolution produces larger file sizes, finer details, and a greater computational load, thereby increasing the processing time required by DL models [33, 34]. To accommodate the limited computational capacity of edge devices, DL models are often deployed with reduced input image sizes—commonly 513 × 513 or 640 × 640—even when the camera hardware supports higher resolutions [35, 36]. The data acquisition cameras used for AI-based precision weed control on edge devices are summarized in Table 3.

3.3.2. AI algorithms used in DEPWCS

This section examines AI algorithms deployed in DEPWCS. Specifically, it explores AI architecture, tasks, learning paradigms during model training, and optimization techniques.

Table 3
Data acquisition cameras used for precision weed control

S/N	Camera name	Camera specifications	Camera modality	Same camera for data collection and deployment	Note	Refs.
1	Daheng GetCamera (MER2-160-227U3C)	1.6-MP resolution; USB 3.0 data interface; 5 MP (F2.0, 6 mm) non-distortion lens; up to 227 FPS	RGB	Yes (multiple cameras used for data collection)	The camera was mounted on a robotic smart sprayer and selected due to its real-time capability. The camera has an IP67-rated camera housing to protect against harsh environmental conditions. Low cost <$1000	[26]
2	Daheng GetCamera (MER-503-36U3M/C)	1920 × 1080 pixels resolution; 36 FPS frame rate; USB 3.0 data interface	RGB	Yes	Image divided into eight identical-sized grid cells (240 × 216 pixels sub-images), corresponding to eight nozzles on the boom. Configured to automatic mode and deployed 1.2 m above the ground.	[37]
3	Zed 2i stereo camera	2688 × 1520 resolution; 1200 wide angle FOV; 20cm to 2m depth range; USB Type-C interface	RGB-D	No	The camera publishes a 3D point cloud that contains the (x, y, z) values needed to represent the center of the detected weed. Camera housed in an IP66-rated enclosure	[25]
4	HIKVISION MV-CA050-11UC (Hikvision, Hangzhou, China)	5MP resolution; 35 FPS frame rate; USB 3.0 data interface	RGB	No	The camera was used to capture HD-quality video for the semantic segmentation system for a variable-sprayer	[13]
5	Logitech (C920 network camera)	1920 × 1080 pixels maximum resolution; 30 FPS frame rate; USB 2.0 data interface; 78^0 diagonal FOV	RGB	No [29], Yes (others)	Three cameras with a resolution of 640 × 480 were merged into a single 1920 × 480 image and then resized to 1024 × 256. Each camera covers 0.36 m. Cameras were selected due to cost [32] Four cameras were used. The cameras were positioned 0.5 m from the ground and spaced 0.1 m from the spray bar. Camera selected for real-time capability and auto focus feature [29] The camera was used to capture real-time images for intra-row weeding control. It was mounted 1 m above the ground, with a 1 m distance between the camera and the weeding knife. During processing, the image resolution utilized by the model on the NVIDIA Orin NX development board was 480 × 288 pixels [38].	[29, 32, 38]

(*Continued*)

Table 3
(*Continued*)

S/N	Camera name	Camera specifications	Camera modality	Same camera for data collection and deployment	Note	Refs.
6	Intel RealSense D435i	1920 × 1080 maximum RGB resolution; 1280 × 720 Stereo depth resolution; 30 FPS frame rate; 69.4^0 (horizontal) × 42.5^0 (vertical) RBG FOV; USB 3.1 Gen 1 data interface	RBG-D	Yes (multiple cameras used for data collection)	Equipped on the laser weeding robot and positioned 600 mm above ground during testing.	[31]
7	Teledyne FLIR visible range vision camera	2448 × 2048 resolution	RGB	Yes	Positioned at a fixed height of 46.5 inches above the ground and connected to the NVIDIA Jetson AGX Orin edge device	[34]
8	Aluratek AWC01F webcam	2MP resolution; 90^0 wide angle FOV; USB 2.0 data interface	RGB	No	Three cameras were used to cover a row of strawberries (1.4 m). A 224 × 224 resolution for testing. The cameras were mounted at the positions of spray nozzles and selected due to their low cost	[18]
9	MV-UBD130C-T industrial camera	1280 × 960 resolution; upto 60 FPS frame rate; USB 2.0 data interface	RGB	No	Selected for real-time capability	[14]
10	Logitech StreamCam	1280 × 720 resolution; 78^0 diagonal FOV; USB-C data interface	RGB	Yes	Connected to NVIDIA Jetson Nano and used to stream the top view of the soybean plot. 19 FPS average inference speed	[11]
11	6-DZM-12 industrial camera (PHZL Co., Ltd.)	1360 × 1024 pixels resolution; 60 FPS frame rate; USB data interface	RGB	Yes	Two cameras were used, 200 mm horizontal distance between each camera and the actuator (weeding knife). Mounting height of 70 cm from the ground for better detection accuracy and to prevent injury to crops	[21]
12	Mindvision MV-UB130GM	1.2 MP resolution; 39 FPS frame rate; USB 2.0 data interface	RGB	Unsure	Camera selected to meet real-time requirements. The real-time detection speed reached 21.27 FPS for the overall system	[23]

(*Continued*)

Table 3
(*Continued*)

S/N	Camera name	Camera specifications	Camera modality	Same camera for data collection and deployment	Note	Refs.
13	K.U.L.T. iVision PV and multispectral camera (JAI, Japan)		RGB and multi-spectral, respectively	No (RGB), Yes (multispectral)	RGB camera was used to guide the hoeing blades between the crop rows using hydraulic side-shift control The multispectral camera was used to guide inter-row and intra-row weeding. Images were processed using the Excessive Green Red Index (ExGR) to enhance contrast between green vegetation and soil. Crops were removed from the ExGR image based on the size of plants to isolate weed coverage data	[39]
14	Parallel optical axis binocular camera (Model: PXYZ-S-AR135-130T400)	640 × 480-pixel resolution; 30 FPR frame rate; 3.4 mm focal length	RBG	No	Selected to obtain 3D information, which is essential for accurate laser targeting. It has good stereo matching and a low average error of 0.11 pixels. The stereo matching algorithm SGBM (Semi-Global Block Matching) was chosen over the BM algorithm to further improve localization accuracy. Camera height set to camera height should be set between 20 cm and 60 cm	[40]

1) AI algorithm tasks and architectures used in DEPWCS

Different computer vision tasks, including classification, object detection, segmentation, and keypoint detection, have been used for weed recognition in DEPWCS (Figure 11). Among these, object detection dominates, accounting for approximately 65% of the vision tasks used. Object detection algorithms simultaneously identify and localize weeds in digital images or video frames, making them well-suited for site-specific weed control. Within this category, the YOLO family and its variants are the most frequently adopted because of their favorable balance of accuracy and inference speed. Other detection models, such as Faster R-CNN and MobileNetV1, are used to a lesser extent (Table 4).

Classification-based approaches account for about 20% of the reviewed studies. These methods distinguish crops from weeds at the image or region level without explicit localization. Commonly used classification models include DenseNet, GoogleNet, VGG-16, and ResNet, with ResNet being the most frequently applied. However, since 2023, none of the reviewed studies have deployed classification-only models for DEPWCS, reflecting a shift toward localization-aware vision tasks better aligned with precision actuation.

Instance and semantic segmentation algorithms have also been investigated for DEPWCS, particularly when pixel-level delineation is required. Segmentation methods assign labels to a subset or all pixels in an image frame, providing fine-grained spatial information. For example, YOLOv8n-seg was used to first detect bounding boxes for weeds and lettuce, after which instance segmentation was applied only within these regions to generate masks for the detected crops and weeds [14]. In other studies, DeepLabV3-based models generated full-scene semantic masks distinguishing soil, crops, and weeds [19, 39].

More recently, keypoint-based detection has emerged as a promising approach for precision weed control. In a study, an autonomous laser weeding robot used a YOLOv8-pose model for object detection and pose estimation. The model classified regional targets, such as strawberry seedlings, weeds, and irrigation pipes, and also identified the precise coordinates of weed growth points (apical meristems) within detected bounding boxes, enabling highly targeted laser actuation [31].

A delay of approximately 1–2 years often exists between the release of state-of-the-art (SOTA) detection models and their adoption in DEPWCS. For instance, YOLOv5 and its variants—currently the most widely used models in DEPWCS

Figure 11
Computer vision task and architecture used in DEPWCS. CL = classification, KPD = keypoint detection, OD = object detection, S = segmentation

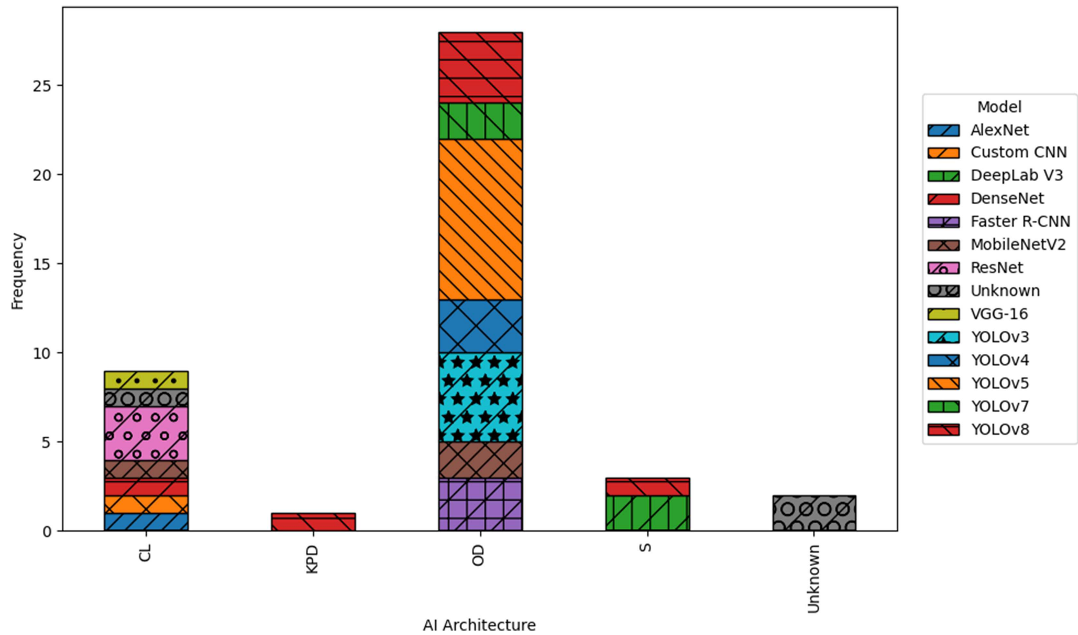


Table 4
Summary of AI models deployed on edge devices for weed control

Vision task	Model architecture	Detection categories	Optimization techniques	Performance	Refs.
Classification	EfficientNet-v2	Grass weeds/ broadleaf weed/no weed infestation	None	F1-score: 99.4% (grass weeds), 99.8% (no weed), 99.6% (broadleaf weeds)	[15]
	ResNet	Grass weeds/ broadleaf weed/no weed	None	F1-scores: 99.2–99.7%	[15]
	VGG-16	Strawberry/weeds; spotted spurge and Shepherd's purse	None	Recall of 88.0, and an F1-score of 88.0%. Rate of completely sprayed weeds (CS%): 86.0%	[18]
Object detection	MobileNet-SSD	Soybean/weed	TensorRT (PT)	mAP0.5: 76.0%. Inference speed: 19 FPS. Spraying recall during field testing: 100%	[11]
	Faster R-CNN	Cotton seedlings/weeds	Incorporated CBAM, BiFPN, and Bidirectional Feature Pyramid Network (BiFPN) structure, and the Bilinear interpolation algorithm to enhance feature extraction and reduce positioning error. (PTT)	mAP: 98.43%. F1: 98.5%. Frame rate: >43 FPS. Effective spraying rate (ESR): 98.9%	[35]

(*Continued*)

Table 4
(*Continued*)

Vision task	Model architecture	Detection categories	Optimization techniques	Performance	Refs.
	YOLOv3	Corn/broadleaf weeds/gramineous weeds	None	Average target detection success rate of 93.43%. In field trials, average weed control rate of 85.91% and a low average crop injury rate of 1.17%, operating at a speed of 1.8 km/h	[21]
	YOLOv3	Target: portulaca/non-target: pepper plants/sedge weed	None	Spraying precision of 71% and spraying recall of 78%. 2.4FPS on NVIDIA Jetson TX2	[32]
	YOLOv3-tiny	Potatoes/weeds; lamb quarters, corn spurry	None	mAP: 76.4%. Precision: 0.87 and recall: 0.75. Frame rate: 31.5 FPS	[41]
	YOLOv3-tiny	Target: portulaca/non-target: pepper plants/sedge weed	None	Spraying precision of 59% and spraying recall of 44% on Jetson TX2. Frame rate: 22 FPS	[32]
	YOLOv5-MobileNet-SE	Weed; *Cirsium setosum*	Replaced CSP darknet backbone with MobileNetv3. Added attention mechanism module (SE) for small target features. (PTT)	Model size reduced by 53.57% and FPS increased by 18.16%, compared to the YOLOv5s model. Field spray accuracy rate of 90.80% at a speed of 2 km/h	[12]
	MW-YOLOv5s	Rice seedling	Amalgamated YOLOv5s Backbone structure with MobileViTv3. Incorporated the WIoU_loss loss function to improve the precision and speed of rice seedling recognition. (PTT)	Precision: 90.05%. mAP: 92.32%. Frame rate: 19.51 FPS. Weed control rate of 82.4% and a seedling injury rate of 2.8%	[36]
	YOLOv5s_FasterNet_CBAM_WIoU	Corn/weed	Included the C3GC and GSConv modules. NVIDIA Jetson TX2. (PTT)	mAP: 95.2%. Frame rate 76.9%. Effective weed identification rate: 90%. ESR: 96.3%. Model optimization increased detection speed by 8.46% compared to the original YOLO v5s	[27]
	YOLOv7	Weed; *Veronica didyma*	Semi-Global Block Matching (SGBM) algorithm. (PTT)	Recall: 95.65%. mAP@0.5: 97.2%	[40]

(*Continued*)

Table 4
(*Continued*)

Vision task	Model architecture	Detection categories	Optimization techniques	Performance	Refs.
	YOLOv8n-CBAM-C3Ghost	Cotton weeds	Integration of CBAM (Convolutional Block Attention Module) and C3Ghost block into the YOLOv8 nano backbone, resulting in a lightweight model. (PTT)	mAP@50: 97.60%. F1-score: 94.40%. Frame rate: 13.84 FPS on the NVIDIA Jetson Nano	[28]
	DIN-LW-YOLO (improved YOLOv8)	Strawberry seedlings/weeds/drip irrigation pipes	Integrates the EMA attention mechanism. Replaces the C2f module with the C2f-DCNv3 module. (PTT)	Regional target detection mAP: 89.3%. Weed growth point mAP of 85.0%. Frame rate: 31.0 FPS, Weed control rate: 92.6% and a 1.2% seedling injury rate.	
	YOLOv8s-CBAM	Lettuce/purslane weed	Integrated CBAM into the YOLOv8s network to improve recognition accuracy. A class knowledge distillation method based on transfer learning was used to compress the model. (PTT)	mAP@0.5: 98.9%. Model size 6.2 MB. Frame rate: 21.27 FPS. Field simulation: 100% detection and weeding success rate in low-density scenes, overall weeding success rate of 76.9%	[23]
	Improved Swin-T-YOLOv8 + Slim-neck	Corn/weed	Used dual-mode image fusion (RGB + NIR). Architectural improvements included the Swin-transformer backbone for small target features and Slim-neck module to reduce computational cost. (PTT)	mAP@0.5: 96.0%. Precision: 94.0%. Frame rate 120 FPS. Field conditions: weed detection accuracy of 82.1%, and the effective simulation rate for laser removal was 72.3%	[42]
Segmentation	DeepLab V3 + MobileNetV2 (semantic segmentation)	Wheat/weed/background	The original Xception backbone network was replaced with the lightweight MobileNet V2 network to reduce the overall parameter count and computational load, and the CA attention mechanism (Coordinate Attention module) was integrated to enhance segmentation accuracy. (PTT)	MioU: 73.34%. Mean pixel accuracy: 80.76%. Single-image segmentation time: 0.09 s.	[13]

(*Continued*)

Table 4
(*Continued*)

Vision task	Model architecture	Detection categories	Optimization techniques	Performance	Refs.
	Improved YOLOv8n-seg (instance segmentation)	Lettuce/weed; purslane, chickweed, depressed plantain, green bristlegrass, and taraxacum	Optimization utilized C2f_Star, DSConv (Depthwise Separable Convolution), and SimAM attention mechanism. (PTT)	Box mAP: 90.5%, Mask mAP: 89.8%. Reduced parameters by 30%. Inference speed of 15.7 ms. Average recognition accuracy of 95.2% and a target spraying success rate of 97.2%	[14]

Note: PT – post-training optimization; PTT – pretraining/training optimization.

(Figure 11)—were released in 2020, yet the earliest edge-based deployments for precision weed control appeared around 2022 [18, 43]. Similarly, YOLOv8, released in early 2023 with capabilities for object detection, instance segmentation, and key-point detection, was first reported in DEPWCS applications in 2024 [28, 42]. This delay may reflect the time required for model validation, adaptation, optimization, and system-level integration.

The multi-task capability of recent YOLO versions partly explains their dominance in DEPWCS. In particular, the emergence of keypoint detection for identifying weed apical meristems reflects a shift from detecting whole plants to targeting specific anatomical structures, which is especially important for high-precision methods such as laser weeding. To accelerate technological advancement, future research should aim to reduce the gap between the release of SOTA models and their deployment in DEPWCS by exploring newer model variants, such as YOLOv9, YOLOv10, and YOLOv11, for precision weed control applications.

2) Learning paradigm of AI algorithms used in DEPWCS

AI algorithms for vision-based weed detection rely on various learning paradigms, including supervised, semi-supervised, unsupervised, and self-supervised learning, as well as few-shot, zero-shot, active, and reinforcement learning. Among these, supervised learning dominates the reviewed studies due to its superior feature extraction, robust performance, and generalization in complex field conditions. However, it requires large, manually annotated datasets, which are time-consuming and costly to produce. To mitigate this, many studies use transfer learning, open-source datasets [44–46], and data augmentation techniques [26, 27–29, 37]. Despite these strategies, reliance on supervised learning persists, and there remains a shortage of annotated datasets beyond RGB imagery, with limited coverage for multispectral or RGB-D data.

Moreover, issues such as class imbalance, insufficient diversity in field conditions, and regional bias continue to hinder the generalizability and scalability of these datasets [44]. Furthermore, augmentation using Generative Adversarial Networks (GANs) might fail to fully capture natural variability caused by lighting changes, occlusion, soil background variation, and plant overlap, leading to synthetic images that are not fully representative of field conditions [43]. Given these challenges, it is recommended that alternative approaches to supervised learning, such as self-supervised adaptive target recognition algorithms or unsupervised learning, be explored.

3) Optimization of AI algorithms used in DEPWCS

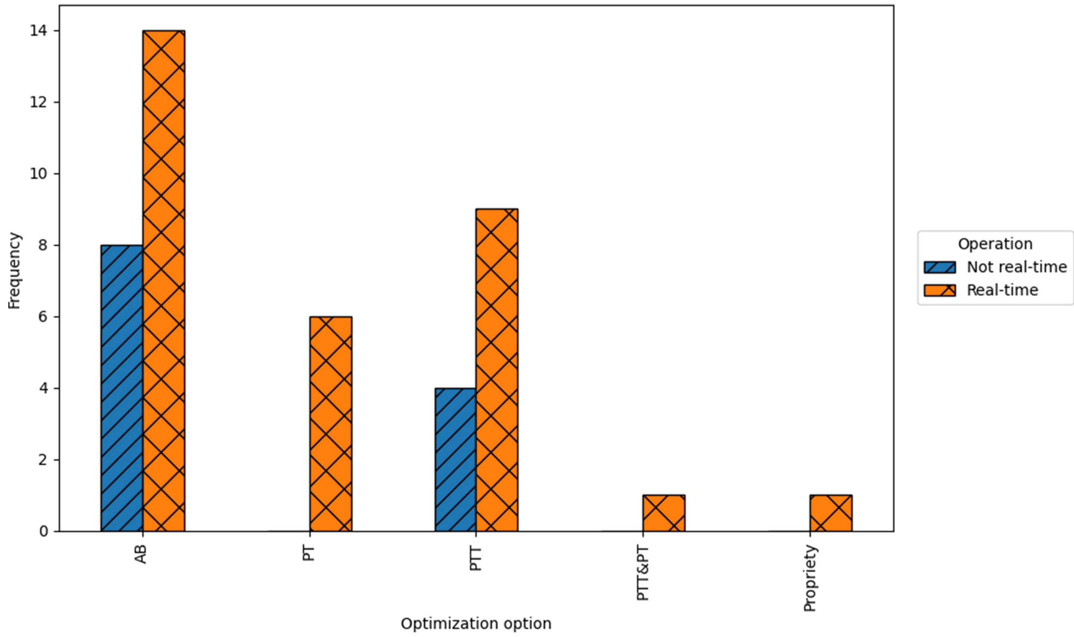
AI algorithms are typically trained on powerful computing resources but are deployed on edge devices with limited computing power and memory. In addition, image processing is sometimes required for real-time applications, such as simultaneous weed detection and control while the platform is in motion, requiring optimization. Based on the reviewed studies, more than 50% did not employ explicit model optimization techniques, relying instead on fine-tuning and/or data augmentation strategies (Figure 12). Of these studies, approximately 64% operated under real-time conditions.

Model optimization can be applied both during training and after training (post-training) through techniques that improve network architecture, enhance feature extraction, or adapt models for lightweight, real-time deployment. Training-stage optimization approaches included replacing Complete Intersection over Union with Weighted Intersection over Union (WIoU) to better account for positional, scale, and aspect ratio differences between predicted and ground-truth bounding boxes [27], the use of lightweight models and custom-designed modules to ensure efficient yet rich feature extraction [26, 28], class knowledge distillation [23], and the use of Convolutional Block Attention Module (CBAM) to improve model focus on salient image regions [23, 27, 28, 35]. About 30% of the reviewed studies applied optimization during pretraining or training, with the majority of these achieving real-time detection and control performance (Figure 12).

About 14% of the reviewed studies employed post-training optimization, and all were conducted under real-time operating conditions (Figure 12). Post-training optimization focuses on maximizing inference speed and efficiency on the target hardware through model compression, quantization, and deployment-specific software accelerators. Quantization is a common post-training optimization technique. It reduces the numerical precision of model parameters from 32-bit floating-point to 8-bit integers. This substantially reduces memory footprint and latency, enabling deployment on edge devices. Frameworks like TensorRT apply quantization and have been widely used to accelerate inference on NVIDIA devices [13].

Although more than half of the reviewed studies did not employ explicit model optimization techniques, the use of optimization is clearly increasing. For example, nine studies applied optimization between 2021 and 2023, whereas 11 studies employed optimization in just the last two years of this review period (2024–2025). This shift may be attributed to the importance

Figure 12
Optimization status of DEPWCS. AB = absent/no optimization



Note: PT = post-training optimization; PTT = pretraining/training optimization.

of AI model optimization in enabling higher platform speeds and improving system efficiency. For instance, Platform speeds typically ranged from 0.01 m/s to 0.5 m/s without optimization, compared with 0.45 m/s to 1 m/s for systems using post-optimized models. Therefore, greater adoption of optimization strategies is encouraged, particularly through the exploration of alternative post-training deployment frameworks, such as OpenVINO, to further enhance edge inference performance.

3.3.3. Edge devices and controllers used in DEPWCS

DEPWCS integrates AI model deployment hardware, high-level controllers, low-level controllers, and actuators, forming a hardware stack that supports weed recognition and the precise execution of control actions. This section outlines edge computing resources and controllers used for weed recognition and control.

The reviewed studies show that NVIDIA hardware dominates DEPWCS edge devices for weed detection (Figure 13). In particular, the Jetson family is the most frequently adopted NVIDIA device. The NVIDIA Jetson series is relatively inexpensive and provides dedicated GPUs or specialized cores to handle the computationally intensive nature of AI algorithms [33]. Examples include NVIDIA Jetson AGX Orin, NVIDIA Jetson Nano, NVIDIA Jetson TX2, and Xavier NX (Table 5). In addition, some DEPWCS use high-performance GPUs integrated directly onto mobile platforms when maximum accuracy or speed is required, often pushing the boundary of a typical "edge" constraint due to

Figure 13
Edge devices used in DEPWCS

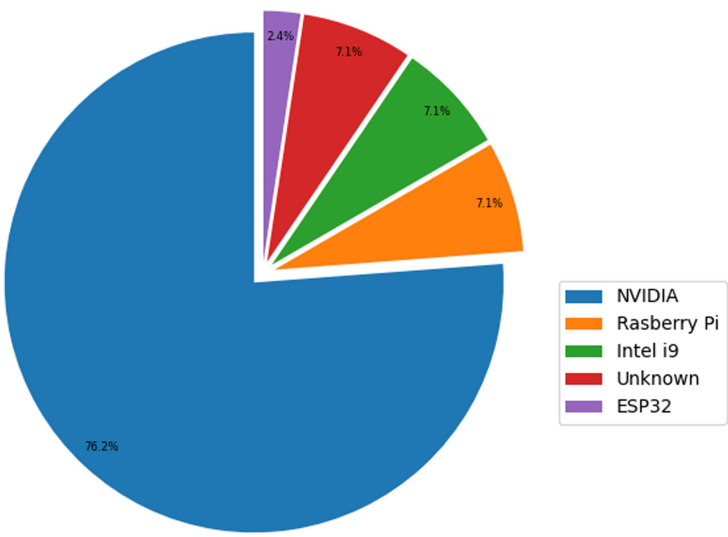


Table 5
Edge devices used for the deployment of AI models in DEPWCS

Device	RAM size (GB)	Architecture/cores	Refs.
Jetson AGX Orin (32 GB)	32	Ampere; 1792 CUDA cores, 56 Tensor Cores	[35, 40]
Jetson AGX Xavier	32	Volta; 512 CUDA cores GPU	[28]
Jetson Xavier NX	8/16	Volta; 384 CUDA core, 48 Tensor cores	[35]
Jetson TX2	8	Pascal; 256 CUDA cores	[26, 32]
Jetson Nano	4	Maxwell; 128 CUDA cores	[11, 17, 28, 33,47]
NVIDIA GTX 1070 Ti	8	Pascal; 2432 CUDA cores	[32]
NVIDIA GeForce RTX 1080	11	Pascal; 2560 CUDA cores	[18]

higher power draw and cost. Some of these devices are NVIDIA GTX 1070 Ti and GTX 1080 [18, 32].

Aside from edge devices involved in weed detection, there are dedicated low-level microcontrollers that typically receive target coordinates or binary activation commands from the high-level AI unit and convert them into electrical signals to drive mechanical actuators, such as motors, pumps, and valves. These low-level microcontrollers are broadly categorized as Arduino-based, STM32-based, and other specialized controllers.

The Arduino controllers used in DEPWCS include models such as Arduino UNO R3 [48], Arduino Mega 2560 [15], Arduino Nano [11], and Arduino ATmega328 [18]. Their core task is to read and decode serial data, typically containing spraying decision flags (0 or 1), target coordinates, or target distances, to accurately trigger actuators. Arduino controllers also handle complex mechanical movements: the Arduino UNO was used as a laser controller to release a laser beam [25], and the Arduino Mega has been deployed as a rover controller for driving and steering, communicating via Robot Operating System (ROS), and as an arm controller for positioning mechanical manipulators and nozzles using stepper motors [3].

STM32-based controllers are used as robust controllers for complex actuation tasks, motion control, and sensor data acquisition in modern weeding robots. Models such as the STM32F407 and STM32F429 and the Nucleo F411RE have been used for weed control [12, 14, 21, 42]. These controllers manage essential functions, including sensor data acquisition, analog-to-digital conversion, and motor and actuator drive control.

Other specialized controllers have also been used to support real-time actuation in precision weed control systems. For example, the C37 controller regulated weeding-knife actuation signals via CAN communication [38]. Programmable logic controllers have been integrated into variable-rate spraying systems for wheat, where they compute and adjust the PWM duty cycle of solenoid valves based on machine speed and detected weed density [13]. Similarly, the MC5 intelligent controller communicates with the onboard computer via a CAN-to-USB interface to transmit vehicle speed information and regulate the sprayer's operating speed [19].

3.3.4. Actuators and weeding tools used in DEPWCS

Actuators and weeding tools form the physical execution layer of DEPWCS. In chemical weed control, downstream actuation is achieved through relays, solenoid valves, and nozzles. Relays serve as electrical interfaces that allow low-voltage control signals from microcontrollers or embedded processors to switch higher-voltage circuits that supply solenoid valves, enabling fast, selective nozzle activation. Solenoid valves are the main actuators, offering response times typically below 50–60 ms, enabling accurate synchronization between weed detection, vehicle motion, and spray timing [17, 41]. Nozzles, commonly flat-fan or fan-shaped, define the spatial distribution and coverage of herbicide application, and their type, spacing, height, and spray angle are tailored to crop structure and operating speed [11, 15, 16].

In mechanical systems, actuators such as 24 V DC motors with chain or gear transmissions are commonly used in modular weeding systems to generate reciprocating or swinging tool motions, with relays and proximity switches ensuring reliable start–stop control and positional feedback [20]. For high-speed intra-row applications, servo motors combined with harmonic reducers enable precise control of rotating disc knives, allowing dynamic avoidance of crops based on platform speed and tool geometry [21]. The weeding tools themselves vary widely, including cultivator wheels for paddy fields [36], rotating disc-mounted knives for row crops [35], and inverted pyramid-shaped tools designed to extract deep-rooted weeds in hard soils [20].

Lastly, laser methods rely on high-energy laser sources, such as fiber-coupled diode lasers, blue semiconductor lasers, or CO_2 lasers, combined with precision beam-steering mechanisms, including Cartesian manipulators, pan–tilt servo units, or galvanometric scanners [23, 25]. Laser exposure time and energy dosage are carefully controlled, and techniques such as beam dithering are used to increase the effective treatment area on weed stems [25]. Experimental studies in vegetable crops have shown that laser weeding can achieve weed control efficacy (WCE) comparable to or exceeding that of conventional herbicides while minimizing crop injury and eliminating chemical inputs [23, 25]. However, performance remains sensitive to weed size, growth stage, and morphology, with larger or grass-type weeds requiring higher energy inputs or multiple passes.

3.4. How are DEPWCS evaluated?

Evaluation of DEPWCS is conducted at both the model and system levels. Model-level evaluation assesses the algorithm's detection accuracy and inference speed. Detection performance for weed recognition is typically quantified using standard metrics such as precision, recall, F1-score, and mean average precision (mAP). These metrics are computed from true positives (TP), false positives (FP), true negatives, and false negatives (FN), as summarized in Table 6.

System-level evaluation of DEPWCS focuses on how effectively AI-driven detection decisions translate into physical weed control under operating conditions. Although evaluation protocols vary slightly across chemical, mechanical, and emerging control methods, the reviewed studies reveal common core metrics used to assess system performance. These metrics collectively

Table 6
Accuracy metrics for AI detection models

Metric	Calculation	Significance and application
Precision (P)	$\frac{TP}{TP+FP}$	Minimize false positives and prevent unintended crop damage Values ranged widely across studies, from above 95% in ResNet-based classifiers to lower field precision (≈60%) for some custom YOLO-based weed detectors
Recall (R)	$\frac{TP}{TP+FN}$	Measures the completeness of weed detections. Weed recognition models achieved recall values above 90%
F1-score	$\frac{2 \times P \times R}{P+R}$	The harmonic mean of precision and recall. Provides a balanced measure of overall accuracy. Strong F1 performance (typically >90%) in both laboratory and field conditions, while even moderate F1-scores (>50%) were considered operationally acceptable in complex field environments
Intersection over Union (IoU)	$\frac{TP}{TP+FP+FN}$	Measures the overlap between the predicted bounding box and the ground-truth box. IoU threshold of 0.5 was mostly used
Mean average precision (mAP)	$\frac{1}{\lvert classes \rvert} \sum_{c \in classes} \frac{\lvert TP_c \rvert}{\lvert FP_c \rvert + \lvert TP_c \rvert}$	The average of average precision across all detected categories. It is the primary evaluation metric for object detection models (e.g., YOLO, Faster R-CNN). mAP metric > 95% were often reported at IoU of 0.5

evaluate detection-to-actuation accuracy, agronomic effectiveness, crop safety, and economic and environmental impact.

Across all control methods, WCE—also known as the weed control rate or weed removal rate—is the most widely reported agronomic metric. WCE is typically calculated by comparing weed counts or biomass before and after treatment and expressed as a percentage [36]. Closely related is the crop injury rate, which quantifies unintended crop damage and serves as a critical indicator of system safety, particularly for intra-row operations in both chemical and mechanical systems [21, 27]. Together, WCE and the crop injury rate capture the fundamental trade-off between effective weed suppression and crop protection, regardless of the actuation mechanism employed.

Beyond agronomic evaluation, many studies emphasize application—or execution-level evaluation, which accounts for interactions among AI inference, platform motion, and actuator timing. Common execution metrics include the effective spraying rate (ESR), which measures the proportion of correctly detected weeds that are successfully treated; the mistaken spraying rate (MSR) or crop injury rate, which quantifies non-target treatments; and the leakage spraying rate (LSR), which captures missed or inadequately treated weeds relative to the total weed population [27]. These metrics are conceptually analogous to precision, FP, and FN but are measured at the actuation level rather than at the image or bounding-box level. Similar hit-rate concepts are used in mechanical systems (e.g., effective intra-row weeding coverage exceeding a defined threshold) [21] and in laser-based systems through the laser beam hit rate [25].

Laboratory and controlled-environment evaluations are commonly used as precursors to field trials. Conveyor-belt test benches are frequently used to simulate real-time operation and evaluate timing, targeting accuracy, and actuation reliability in DEPWCS [14]. In chemical weed control, water-sensitive paper is widely used to quantify droplet deposition, percent area coverage, and relative recognition hit rates on both target weeds and non-target crops [12, 41]. Comparable physical evaluation criteria are applied in mechanical systems, such as soil disturbance metrics and blade intrusion into crop shelter zones [21], and in laser systems, where success may be defined by the absence of weed resprouting after a period (e.g., 15 days) or by biomass reduction relative to untreated controls [24, 32]

Economic and environmental performance are typically assessed using Herbicide Usage Reduction or Spray Volume Reduction (SVR), which measures chemical savings relative to uniform broadcast application [11, 15]. Precision weed control systems have reported SVR values exceeding 80% under favorable weed densities and field conditions [14, 41]. Environmental safety is further evaluated by measuring herbicide residues in runoff water following spot spraying compared with blanket spraying or by demonstrating nonsignificant differences in area coverage while achieving high SVR [47]. For nonchemical approaches, longer-term indicators such as crop yield, biomass, stunting, and regrowth suppression are used to confirm sustained agronomic benefits and minimal crop competition [21, 36].

4. Challenges and Future Direction

4.1. Challenges

The challenges associated with DEPWCS in agricultural environments can be categorized into limitations related to the environment, the data and models, and system integration and operational speed. Agricultural fields are highly dynamic and unstructured, introducing uncertainties that significantly affect the robustness and reliability of automated weed control systems.

Environmental factors such as illumination, terrain, motion, and weather strongly influence system performance. Variations in lighting conditions—including sudden changes in illumination, direct sunlight, reflections, and strong shadows—negatively affect DL-based detection accuracy [25]. Low-light conditions, particularly near dusk, further degrade model performance, while shadows cast by the platform itself can cause incorrect camera exposure and misclassification [35]. Uneven terrain causes weeding platforms to deviate from predefined paths, leading to unstable velocities and inaccurate positioning, which in turn result in targeting errors during rapid actuation [27]. Ground unevenness causes structural vibration, resulting in motion blur and actuator position shifts, which decrease recognition and weed control accuracy. Uneven terrain causes weeding platforms to deviate from predefined paths, leading to unstable velocities and inaccurate positioning, which in turn result in targeting errors during rapid actuation [30].

Limitations in data and model robustness pose another major challenge. Most reviewed systems rely on supervised learning, which requires large volumes of manually annotated data that are costly and time-consuming to produce. Limited variability in training datasets restricts model generalization across diverse field environments, including different lighting conditions, weed densities, and growth stages [31, 33]. All reviewed systems rely on supervised learning, which depends on manually annotated data—an expensive and time-consuming requirement. While open-source annotated datasets are expanding, there remains a shortage of high-quality object detection and segmentation datasets, and the accuracy of available annotations is not always verified. These limitations hinder model robustness under varying field conditions, such as lighting changes, weed density fluctuations, and growth-stage variations.

Although open-source annotated weed datasets are increasingly available, there remains a shortage of high-quality object detection and segmentation datasets, and the reliability of annotations is not always guaranteed. Weed detection is further complicated by visual similarity between crops and weeds, as they often share comparable colors and morphological features [15, 37]. This challenge is exacerbated by substantial intra-class variation among weeds, where models may learn only dominant visual patterns and fail to recognize less common or visually subtle weed forms, leading to reduced detection performance in complex field scenarios [26]. Small weeds, low-contrast targets, and clustered weed growth also pose difficulties, as systems optimized for individual plant targeting often underperform in dense patches, resulting in partial coverage or missed weeds [42].

System integration and operational speed constraints further hinder effective deployment. Real-time operation is limited by the computational capabilities of edge devices, particularly when running tasks such as weed detection, navigation, and tracking simultaneously [25]. This challenge is exacerbated by the limited training and post-training optimization of weed detection algorithms, which constrains the operational speed of weed control platforms. While detection model and system-level efficiency are often reported, the contributions of other components of DEPWCS—aside from the detection models—are frequently overlooked. These evaluations could include time lag, operational errors, and the influence of sensor data fusion and microcontroller output handling. Platform mobility introduces additional synchronization challenges, as many smart sprayer systems require the platform to stop before actuation to maintain accuracy [15, 30]. Continuous motion can cause timing mismatches between perception, decision-making, and actuator triggering, leading to misaligned spray application, reduced targeting precision, and lower levels of automation in real-world field operations.

4.2. Future directions and research opportunities

Future work should prioritize reducing reliance on manual annotation. Research should investigate semi- and unsupervised learning, weak labeling, and domain adaptation and should also explore synthetic image generation using GANs, Large Language Models (LLMs), or Vision Language Models (VLMs)-based augmentation frameworks to balance class distribution and expand rare-weed representation. Research may further explore variable-rate chemical delivery, in which nozzle dosage automatically adjusts based on weed size, density, and vehicle speed to optimize herbicide use.

Advancing multimodal vision systems presents an important research opportunity. Integrating visible, infrared, depth, or multispectral imaging could improve robustness under varying illumination, occlusion, and soil–crop background conditions. Equally important is expanding data diversity through cross-season data collection across different geographic regions, weed growth stages, soil types, and weather conditions to strengthen generalizability.

Refining detection and target localization, with an emphasis on methods such as YOLO-pose anchor regression and skeleton-based feature extraction, can be explored. This helps precisely locate critical weed structures, such as apical meristems or emergence points, for laser-based ablation. In addition, developing algorithms for adaptive laser power control, capable of adjusting energy output based on weed species and growth stage, will greatly enhance thermal weeding efficiency. Although laser technology currently dominates emerging precision weeding trends, exploring additional nonchemical precision approaches, such as electro-thermal approaches, remains open.

Additionally, efforts should be directed toward reducing the gap between the release of SOTA DL models and their deployment in DEPWCS. The current 1–2-year gap between model release and adoption for DEPWCS should be shortened to accelerate AI integration in agriculture. Furthermore, model acceleration through post-training optimization should be encouraged. Exploring efficient post-training deployment frameworks can enhance edge inference performance and support faster implementation of detection models.

Finally, there is a strong need for standardized evaluation protocols. While emerging metrics better capture real-world spraying performance, inconsistencies limit comparisons across studies. Establishing unified benchmarks—for perception accuracy, actuation precision, edge computing integration, and field-level agronomic impact—would significantly accelerate scientific progress and facilitate technology adoption.

5. Conclusion

A comprehensive review of vision AI and edge device-based systems for precision weed control over the past decade was conducted. This review reveals that deploying AI models on edge devices for precision weed control gained traction in 2019, with *Computer and Electronics in Agriculture* ranking as the journal with the most publications in this space. The systematic review confirms the pivotal role of DL in transforming site-specific weed management. Supervised CNN algorithms and their variants, particularly the YOLO family trained on RGB images, have become the dominant approaches, demonstrating superior inference speed, performance, and generalization compared to other models.

These models primarily use pretraining and training optimization rather than post-training optimization to maximize inference speed, accuracy, and efficiency. Although the core technological components have advanced significantly, the overall deployment pipeline remains centered on precision chemical control, using high-speed solenoid valves and relays to deliver targeted herbicide spraying. Nonetheless, nonchemical approaches, including mechanical weeding and the rapidly maturing laser weeding technology, offer promising alternatives for sustainable and environmentally friendly weed control.

Despite demonstrable success in laboratory settings and initial field trials, persistent challenges limit the widespread adoption of AI-based precision weed control systems in field conditions. Robustness against real-world environmental variability remains a hurdle, as changes in illumination, shadows, and platform motion caused by uneven terrain negatively affect detection accuracy and control precision. Furthermore, the heavy reliance on supervised learning creates a fundamental bottleneck, demanding vast, expensive, and time-consuming manual annotation, which limits model generalization across diverse geographic regions, weed species, and growth stages. A significant operational challenge is the computational complexity of running multiple algorithms (detection, tracking, navigation) simultaneously on edge devices, resulting in system lag and synchronization errors between detection and actuation. Moreover, evaluation methods often fall short, as conventional image-level metrics are only crude indicators of actual field performance and fail to fully account for the complete operational pipeline and the consequential risk of crop injury or unnecessary spraying.

To facilitate the transition of these systems from research prototypes to effective commercial tools, future efforts must prioritize model robustness, resource efficiency, and standardized evaluation. Research should pursue alternative learning paradigms, such as semi-supervised or unsupervised learning, and consider synthetic data generation techniques, including GANs and LLMs, to reduce reliance on manual annotation and improve data diversity. Advancing multimodal vision systems, which integrate RGB, depth, and spectral data, are key to enhancing resilience against environmental factors such as occlusion and shadows. Finally, establishing unified, application-level evaluation protocols that accurately measure the integrated performance of the edge device, AI model, and actuators in real-time field conditions is necessary to accelerate scientific benchmarking and ensure successful commercial deployment.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Adeayo Adewumi: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Dharmendra Saraswat:** Conceptualization, Methodology, Validation, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition.

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