Crop Protection 176 (2024) 106522

Contents lists available at ScienceDirect

Crop Protection

journal homepage: www.elsevier.com/locate/cropro

# Transforming weed management in sustainable agriculture with artificial intelligence: A systematic literature review towards weed identification and deep learning

Marios Vasileiou [a,*], Leonidas Sotirios Kyrgiakos [a], Christina Kleisiari [a], Georgios Kleftodimos [b,c], George Vlontzos [a], Hatem Belhouchette [d,e], Panos M. Pardalos [f]

[a] Department of Agriculture, Crop Production and Rural Environment, University of Thessaly, Fytoko, 38446, Volos, Greece
[b] CIHEAM-IAMM (Institut Agronomique Méditerranéen de Montpellier), 34090 Montpellier, France
[c] MoISA, Univ Montpellier, CIHEAM-IAMM, CIRAD, INRAE, Institut Agro, IRD, Montpellier, France
[d] CIHEAM-IAMM, UMR ABSys, F-34093, Montpellier, France
[e] ABSys, Univ Montpellier, CIHEAM-IAMM, CIRAD, INRAE, Institut Agro, Montpellier, France
[f] Department of Industrial and Systems Engineering, University of Florida, 401 Weil Hall, Gainesville, FL, 32611-6595, USA

A R T I C L E I N F O

*Keywords:*
Weed management
Artificial intelligence
Deep learning
Precision agriculture
Agroecology
Sustainability

A B S T R A C T

In the face of increasing agricultural demands and environmental concerns, the effective management of weeds presents a pressing challenge in modern agriculture. Weeds not only compete with crops for resources but also pose threats to food safety and agricultural sustainability through the indiscriminate use of herbicides, which can lead to environmental contamination and herbicide-resistant weed populations. Artificial Intelligence (AI) has ushered in a paradigm shift in agriculture, particularly in the domain of weed management. AI's utilization in this domain extends beyond mere innovation, offering precise and eco-friendly solutions for the identification and control of weeds, thereby addressing critical agricultural challenges. This article aims to examine the application of AI in weed management in the context of weed detection and the increasing impact of deep learning techniques in the agricultural sector. Through an assessment of research articles, this study identifies critical factors influencing the adoption and implementation of AI in weed management. These criteria encompass factors of AI adoption (food safety, increased effectiveness, and eco-friendliness through herbicides reduction), AI implementation factors (capture technology, training datasets, AI models, and outcomes and accuracy), ancillary technologies (IoT, UAV, field robots, and herbicides), and the related impact of AI methods adoption (economic, social, technological, and environmental). Of the 5821 documents found, 99 full-text articles were assessed, and 68 were included in this study. The review highlights AI's role in enhancing food safety by reducing herbicide residues, increasing effectiveness in weed control strategies, and promoting eco-friendliness through judicious herbicide use. It underscores the importance of capture technology, training datasets, AI models, and accuracy metrics in AI implementation, emphasizing their synergy in revolutionizing weed management practices. Ancillary technologies, such as IoT, UAVs, field robots, and AI-enhanced herbicides, complement AI's capabilities, offering holistic and data-driven approaches to weed control. Additionally, the adoption of AI methods influences economic, social, technological, and environmental dimensions of agriculture. Last but not least, digital literacy emerges as a crucial enabler, empowering stakeholders to navigate AI technologies effectively and contribute to the sustainable transformation of weed management practices in agriculture.

* Corresponding author.
*E-mail addresses:* mariosvasileiou@uth.gr (M. Vasileiou), lkyrgiakos@uth.gr (L.S. Kyrgiakos), chkleisiari@uth.gr (C. Kleisiari), kleftodimos@iamm.fr (G. Kleftodimos), gvlontzos@uth.gr (G. Vlontzos), belhouchette@iamm.fr (H. Belhouchette), pardalos@ise.ufl.edu (P.M. Pardalos).

https://doi.org/10.1016/j.cropro.2023.106522
Received 30 September 2023; Received in revised form 31 October 2023; Accepted 8 November 2023
Available online 14 November 2023

## 1. Introduction

Agriculture, the cornerstone of global food production, grapples incessantly with the persistent menace of weed infestations. The presence of weeds presents a substantial risk to agricultural productivity, since they engage in resource competition with crops for essential elements such as water, nutrients, light, and space (Tshewang et al., 2016). Consequently, this interference hampers the growth and development of cultivated plants. Weeds also disrupt the uniform growth of crops, leading to uneven crop maturity and complicating harvesting processes (Yu et al., 2019b). Beyond the realm of resource competition, some weed species harbor pests and diseases, serving as reservoirs for agricultural pathogens that can devastate crops (Ahmad Loti et al., 2021). Moreover, the existence of weeds can impede the efficacy of mechanical and manual farming practices, necessitating increased labor and resources for weed control (Molinari et al., 2020). Subsequently, the economic impact of weeds is substantial, encompassing crop yield losses, increased production costs, and the potential for lower-quality harvests. According to the findings of Adeux et al. (2019), a research study conducted over a period of three years, highlight that majority of the weed communities resulted in substantial yield losses in unweeded zones, ranging from 19% to 56%. In essence, the uncontrolled spread of weeds exerts a profound and adverse influence on agricultural sustainability, productivity, and overall economic viability.

Traditionally, the practice of weed management has predominantly relied on the use of herbicides, which has raised significant apprehensions regarding the long-term viability of the environment and the safety of food production. Herbicides are chemical compounds designed to control and eradicate weeds and have significantly contributed to the enhancement of crop yields and the amelioration of the deleterious consequences of weed competition by specifically targeting and eradicating weed species, minimizing labor demands, and enhancing crop development (Modi et al., 2023). Nevertheless, the utilization of herbicides has elicited noteworthy apprehensions, encompassing both environmental and food safety considerations. The indiscriminate application of herbicides may result in herbicide-resistant weed populations, necessitating more potent and environmentally harmful herbicides (Chu et al., 2022). Moreover, herbicide residues can persist in soil and water systems, potentially affecting non-target plants, aquatic life, raw food products, and human health. In light of these challenges, there is a growing imperative to embrace more precise and eco-friendly approaches to weed management, which is precisely where Artificial Intelligence (AI) techniques step in.

Effective weed management strategies, bolstered by AI and innovative technologies, are indispensable in mitigating these deleterious effects and ensuring the prosperity of agriculture. The utilization of AI technology in weed management endeavors to address the ecological consequences associated with herbicides by enhancing their efficacy, diminishing the quantity of chemicals employed, and limiting the presence of residues (Hakme et al., 2020). This strategy ultimately fosters a more sustainable and conscientious method for controlling weeds in agricultural practices. AI methods comprise a diverse range of technologies, including computer vision, machine learning, and deep learning, each possessing distinct capabilities in tackling the intricate challenges posed by weed proliferation (P. Wang et al., 2022). Deep Learning (DL), a subfield of machine learning (ML) distinguished by the use of Artificial Neural Networks (ANN), is currently positioned at the forefront of advancements in weed identification (Nasiri et al., 2022). Its capacity to extract nuanced features from data and identify complicated patterns has significantly enhanced the precision and effectiveness of weed detection (Ghatrehsamani et al., 2023). Deep learning models, which have been trained on extensive datasets, demonstrate an unparalleled capacity to accurately differentiate between crops and weeds, even in complex and dynamic agricultural environments (Rai et al., 2023). Furthermore, DL has made substantial contributions to various aspects of precision agriculture, encompassing identification and counting of crop plants (Rai and Flores, 2021), detection of diseases in crops (Liu and Wang, 2021), identification of crop stress (Butte et al., 2021), detection of crop rows (Bah et al., 2020), fruit harvesting (Onishi et al., 2019), detection and grading of fruits for freshness (Ismail and Malik, 2022), and site-specific weed management (Liu et al., 2021).

The economic ramifications of AI adoption in weed management are profound. By precisely identifying and targeting weeds, AI contributes to resource optimization, most notably in herbicide application and, specifically, land and labor (Kirtan Jha et al., 2019). More precisely, it is essential to consider land as a finite resource due to population augmentation (Ramankutty et al., 2018) and soil degradation (Kopittke et al., 2019), underscoring the need to enhance productivity on current agricultural land as a matter of utmost importance. Moreover, the concept of labor is undergoing transformation as the ability to engage in continuous work under progressively harsher circumstances expands. (Gallardo and Sauer, 2018). This attribute plays a significant role in bolstering the resilience of agricultural systems. Along with that, Acemoglu and Restrepo (2019) indicate that the change to Agriculture 5.0 will have an impact on in-field human labor, resulting in the creation of new employment to support AI activities.

The adoption of AI technology in agriculture is still in its nascent stages and poses a complex challenge, for which the existing literature has not yet provided a comprehensive overview. Therefore, it is crucial to build a clearly defined research framework, and researchers are actively contributing to the existing body of knowledge by conducting surveys to improve understanding of this topic. This study uses SLR as a methodological framework to investigate and consolidate previous research completed on AI in agriculture with respect to weed identification and deep learning. Table 1 displays comparable contributions in the domain of AI in weed management.

In essence, the confluence of AI and weed management represents a huge shift in agricultural paradigms. This Systematic Literature Review (SLR) embarks on an exploratory journey that delves into the intricacies of AI in weed management, unveiling the transformative potential it holds for agriculture and the broader ecosystem. As we navigate through these intricacies, we encounter not only innovations but also multifaceted challenges that underscore the intricate interplay between technology, economics, society, and the environment. In this symphony of change, AI, tightly intertwined with weed management, emerges not only as a harbinger of transformation but as a dedicated steward of progress, nurturing the seeds of a greener, more sustainable future for agriculture and the world.

Subsequent sections encompass a description of the materials and methods utilized, an analysis of the findings of the SLR, a comprehensive discussion of AI in weed management and final conclusions drawn from the study.

## 2. Materials and methods

When researching a certain research issue, subject, or phenomenon, it is common practice to perform a systematic literature review in order to identify, assess, and analyze all pertinent studies (Snyder, 2019). This method is seeing an increase in popularity due to its adherence to a comprehensive and rigorous protocol, which facilitates the assessment of relevant research that is accessible and pertaining to a specific topic matter (Xiao and Watson, 2019). Furthermore, this approach facilitates the identification of research gaps within current studies, hence providing opportunities for future research (Kitchenham and Charters, 2007).

The present study employs the SLR, following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Kyrgiakos et al., 2023; Page et al., 2021b), as a methodological framework to investigate and consolidate prior research undertaken on the application of artificial intelligence in weed management, with a specific focus on weed identification and deep learning in agriculture. This framework includes four phases: *(1)* identification, *(2)*

**Table 1**
List of recent literature reviews.

| Source | Methodology | Contributions | No. of Articles analyzed |
|---|---|---|---|
| Rai et al. (2023) | Systematic Literature Review | • Present an overview of advanced technology used for precise weed removal.<br>• Provide an overview of DL models and the existing methodologies utilized for the detection of weeds.<br>• Present limitations of DL pertaining to each sensing categories | 60 |
| Ghatrehsamani et al. (2023) | Qualitative Literature Review | • Explore the application of AI methods for accurate and sustainable weed control strategies.<br>• Provides an overview of the management of herbicide-resistant weeds, including the problems and opportunities.<br>• Discussion of innovative technologies for the management of herbicide-resistant weeds. | N/A |
| Sachithra and Subhashini (2023) | Systematic Literature Review | • Develop a comprehensive comprehension of the AI technologies now utilized in the agriculture sector.<br>• Examine diverse AI initiatives to accomplish sustainability goals for growth.<br>• Analyze how existing and developing technologies help farms grow sustainably. | 115 |
| Hassan et al. (2021) | Systematic Literature Review | • Explores various control mechanisms employed for automating agricultural processes.<br>• Offers a comprehensive overview of the operational process and revenue of a smart agriculture system. | 65 |

screening, *(3)* eligibility, and *(4)* inclusion. The search was conducted utilizing the Scopus and Web of Science (WoS) databases, combining the terms "weed management", and "artificial intelligence". This yielded a total of 5821 outcomes, with 5713 from Scopus and 108 from WoS. To ascertain the final survey terms, the aforementioned data were exported and thereafter inputted into the VOSViewer software (Waltman and Ecken, 2010). The results of the software are depicted in Fig. 1, which showcases three delineated clusters of keywords, with a minimum threshold of 260. The keyword that exhibits the highest occurrences is "deep learning", with a number of 815. Additionally, as depicted in Fig. 1, the keyword "deep learning" is highly related to the agricultural keywords. Thus, in order to improve the results of the present study, this term was added to the survey as an alternative term for "artificial intelligence", as it is in a different cluster.

Given the updated terms, the total number of outcomes is 7,641, with 7434 from Scopus and 207 from WoS. Considering this search focuses on full articles, a considerable number of articles were irrelevant to the scope of this study. Consequently, the search was limited to examining the article's title, abstract, and keywords, resulting in a total of 319 articles for further evaluation (Scopus = 209 + WoS = 110). In addition, all the search parameters were defined to include publications from 2016 onwards, revealing a notable exponential growth trend up until 2022, as depicted in Fig. 2.

Subsequently, by narrowing the search to only journal articles and conference papers and discarding duplicates (62) and articles written in languages other than English (4), 99 articles remained for full-text assessment. This study incorporated a total of 68 articles identified through full-text assessment, including 5 articles using snowballing (Wohlin, 2014). Fig. 3 provides an overview of the SLR method, as outlined in accordance with the PRISMA guidelines (Page et al., 2021a).

The search was performed on August 24, 2023, encompassing articles published within the year 2023 up until that date. The final query code is given in Appendix A.

## 3. Results

The objective of this report is to augment the comprehension of AI applications in weed management with a focus on weed identification and deep learning implementation. During the assessment process of the selected articles, six thematic foci were identified, which focus on different aspects of AI implementation in weed management. These areas include the general information of the articles, field information, factors of AI system adoption, AI implementation, ancillary technologies utilized, and the of AI methods adoption, as shown in Fig. 4.

These Thematic Foci are broken down into criteria that were used to classify the articles. Table 2 presents these criteria along with their corresponding descriptions.

### 3.1. General information

The General Information category entails four main criteria, encompassing *(i)* the publication year, *(ii)* the publishing company, *(iii)* the source type, and *(iv)* the document type. The majority of the documents assessed are journal articles (62), with a smaller number of high-quality conference papers (6) that present a comprehensive work. The analysis mostly incorporated publications from the year 2022 (27), followed by those published in 2023 (20), as depicted in Fig. 5.

Considering the information pertaining to the publishing company, Fig. 6 presents a visual representation of the quantity of documents attributed to each publisher in the present study, categorized according to their source type. The publishers that had fewer than three articles in this study were grouped into the category labeled as "Other". Elsevier emerges as the publisher with the highest number of journal articles in this study (22), while most of the conference papers (4) are published from IEEE.

Furthermore, the classification of the articles was conducted according to their respective content types, encompassing frameworks (31), case studies (20), and algorithm (17) (Fig. 7).

### 3.2. Field information

In the context of AI-enabled weed management, field information serves as the foundational bedrock upon which precise, effective, and sustainable weed control strategies are constructed. Field information encompasses critical criteria such as the country of operation, the weed species at hand, and the crop type under cultivation. Each of these criteria carries profound significance in shaping AI-driven weed management practices.

The geographical context of weed management is of paramount importance, as different regions and countries are characterized by unique agroclimatic conditions, weed species prevalence, and agricultural practices. AI models, specifically those developed for the purpose of identifying and managing weeds, necessitate meticulous calibration to effectively address the specific challenges and conditions within a

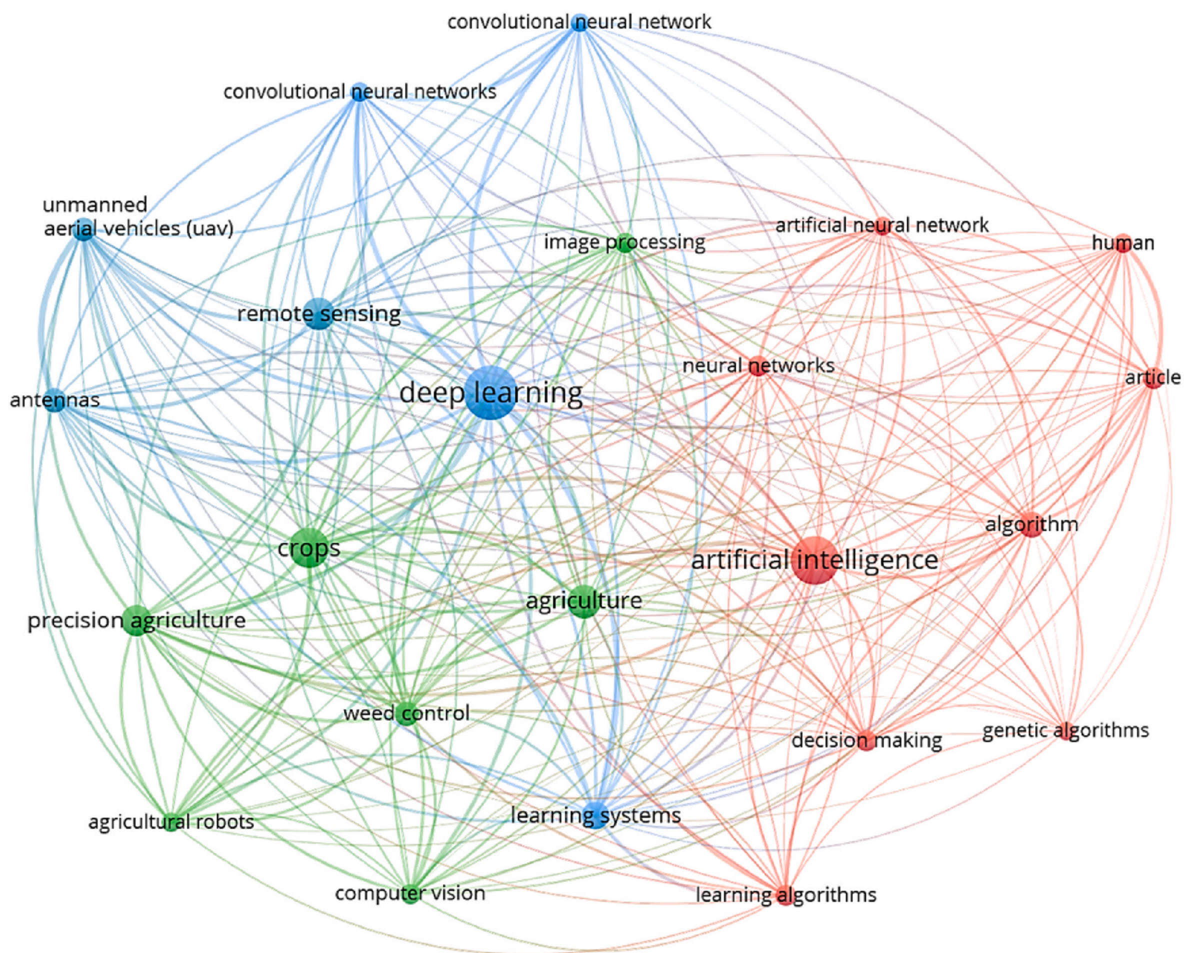


**Fig. 1.** Relationship of the keywords regarding “weed management”, and “artificial intelligence”.

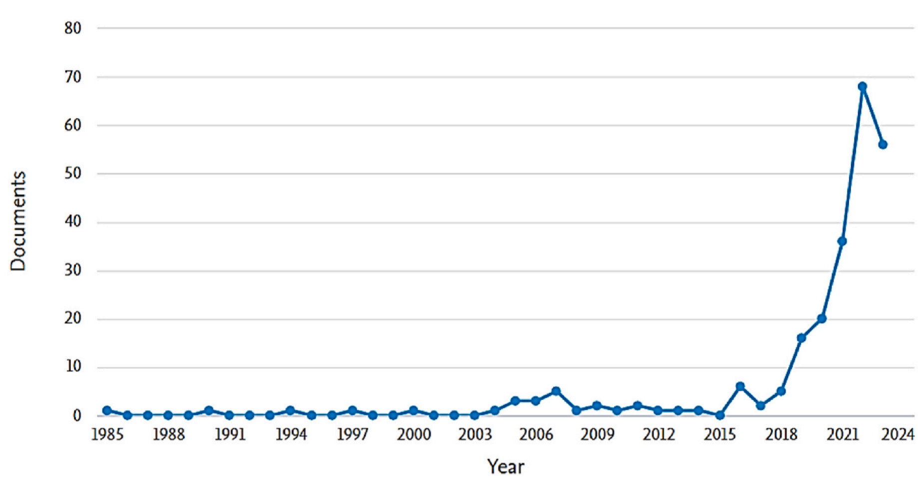


**Fig. 2.** Number of publications per year pertaining to the three terms in the final search query.

given country (Roslim et al., 2021). The selection of appropriate AI algorithms, the design of training datasets, and the calibration of weed detection models are influenced by the country factor. Moreover, it facilitates the incorporation of AI models into specific agricultural settings, ensuring that weed management approaches are in accordance with local limitations and preferences. Considering the importance of the country of origin within the context of AI-enabled weed management, it is essential to take into consideration the countries that are documented in the publications indicated (Fig. 8). Within the scope of this analysis, China (17) emerges as the nation to which most articles are referring to perform experiments, followed by the USA (12).

In addition, the precise identification of weed species plays a crucial role in weed management as weed species can vary widely in their growth habits, resistance to herbicides, morphological characteristics, and competitive abilities. In order to provide targeted control measures, it is important for AI models to possess the capability to discern between different kinds of weeds. The precise identification of weed species plays a crucial role in determining the most suitable herbicides and

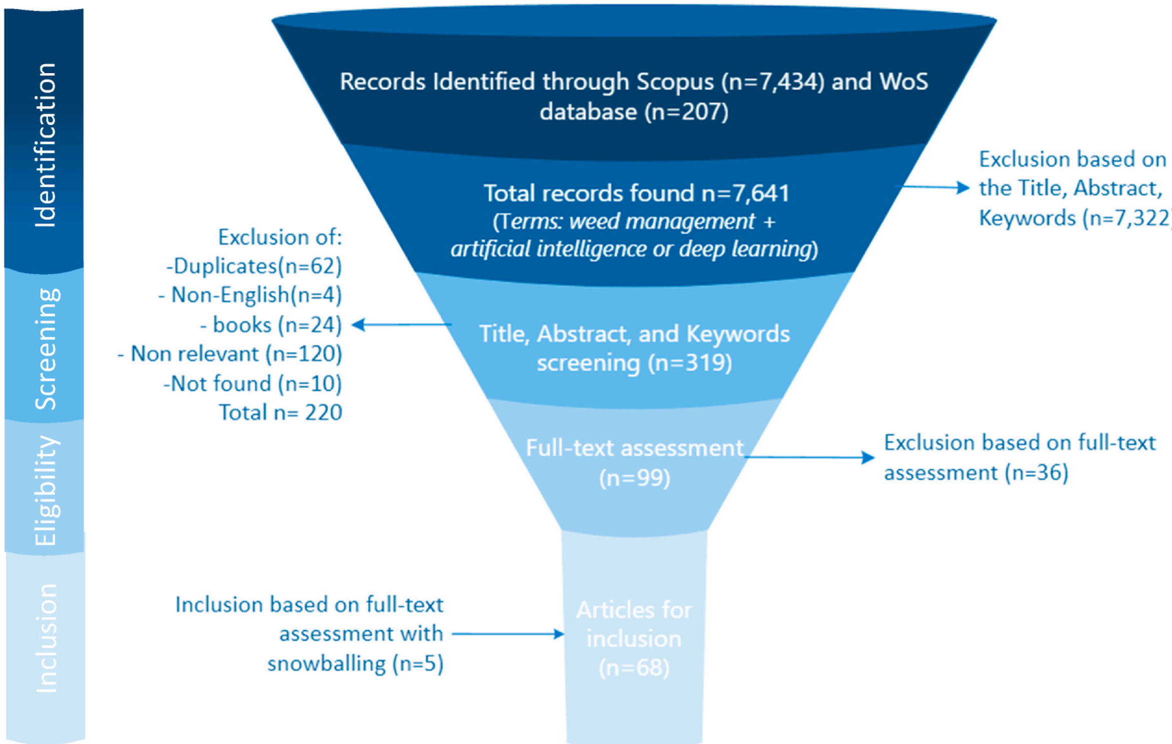


**Fig. 3.** Funnel diagram of SLR methodology using PRISMA guidelines.

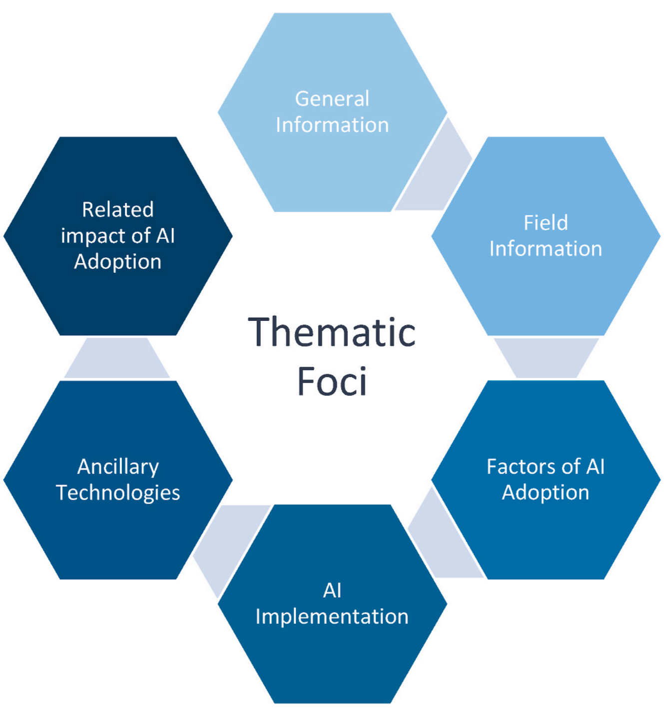


**Fig. 4.** SLR Thematic Foci of criteria.

management techniques, hence enhancing the efficient allocation of resources and minimizing excessive herbicide use (Thompson et al., 2010). Moreover, through the process of mapping and assessing the prevalence of weed species, AI can contribute to long-term weed management strategies, hence facilitating the advancement of cropping systems that are both more robust and environmentally sustainable (Valente et al., 2022). Table B1 in Appendix B quotes the various weed species identified in each article.

Furthermore, the crop type under cultivation directly impacts weed management decisions, as different crops exhibit varying tolerances to weed competition and herbicide applications. In order to ensure the preservation of crop health and productivity, it is important for AI systems to possess a comprehensive understanding of the particular crop under consideration. This knowledge is crucial for the accurate identification of the weeds (Saqib et al., 2023). Moreover, the implementation of AI-based weed management techniques allows for the customization of methods according to the specific growth stages and vulnerability of the cultivated crop, hence augmenting the synergy between AI and crop cultivation (Roslim et al., 2021). The application of AI across various crops exemplifies the adaptable nature of this technology in the realm of weed management. The crops included in this study found in the articles reviewed are: wheat (*Triticum aestivum*), cotton (*Gossypium*), sugar beet (*Beta vulgaris*), rice (*Oryza sativa*), corn (*Zea mays*), lettuce (*Lactuca sativa*), soybean (*Glycine max*), potato (*Solanum tuberosum*), sugarcane (*Saccharum officinarum* L.), bell pepper (*Capsicum annuum*), bok choy (*Brassica rapa*), barley (*Hordeum vulgare*), wild blueberry (*Vaccinium angustifolium*), carrot (*Daucus carota*), chinee apple (*Ziziphus mauritiana*), pineapple (*Ananas comosus*), sesame (*Sesamum indicum* L.), and peanut (*Arachis hypogaea*); as can be seen in Fig. 9. In addition, some articles referred to identification of multiple crops, such as in Peteinatos et al. (2020) in which they identify Maize, sunflower, and potatoes. Similarly, there are articles that they do not specify the crop type because they only identify weeds. The crop that has been referred to the most is wheat.

In summary, field information, encompassing country-specific conditions, weed species diversity, and crop type considerations, stands as a cornerstone in the edifice of AI-enabled weed management. These criteria serve as guidelines for the development of AI models tailored to regional contexts, empower precise weed species identification, and facilitate the selection of crop-specific weed control strategies.

### 3.3. *Factors of AI system adoption*

The integration of AI into the domain of weed management signifies

**Table 2**
Summary of the criteria assessed throughout the SLR implementation.

| Category | Criteria | Description |
|---|---|---|
| 1. General information | Year | The publication year of the article. |
| | Publisher | The name of the Publisher (counted only those that appeared at least in 3 articles). |
| | Source type | Journal or Conference paper. |
| | Document type | Framework, Case study, or Algorithm. |
| 2. Field information | Country | Country of origin of the experiments conducted or images acquired. |
| | Weed species | Weed species detected in each study. |
| | Crop Type | Crop type of the application. |
| 3. Factors of AI system adoption | Food safety | Herbicide practices for weed control sometimes lead to water and soil pollution and pesticide residues that can affect food safety. |
| | Increase in efficacy | Conventional methods for weed control often result in high production costs or herbicide resistance. There are articles trying to increase the effectiveness of weed management by utilizing AI techniques. |
| | Herbicide reduction – eco-friendliness | Efforts are undertaken to minimize or eradicate the utilization of herbicides. |
| 4. AI implementation | Functionality | Purpose of using artificial intelligence in weed management. |
| | Capture technology | The selection of the imaging equipment holds significance due to the distinct characteristics exhibited by each device. Some articles utilize open-source datasets to train and test their algorithms. |
| | Training dataset | The number of images used for training the AI model is recorded. |
| | AI model | The AI model used in each study is recorded as it offers distinct characteristics. |
| | Outcomes and Accuracy | Each study presents different results depending on the AI model used and the dataset. These outcomes are recorded. |
| 5. Ancillary Technologies used | IoT | The incorporation of IoT devices and cameras facilitates the monitoring of the weeds. |
| | UAVs | UAVs and drones are utilized in order to capture images of the field. A multitude of articles are incorporating aerial robotics for image acquisition and pesticide spraying. |
| | Field robots | Terrestrial vehicles are employed to enhance and automate the process of weed removal, either through mechanical means or via pesticide spraying. |
| | Herbicides | Herbicides are chemical substances employed for the purpose of managing or regulating weed growth. |
| 6. Related impact of AI methods adoption | Economic | The article takes into consideration the economic impact of the AI adoption. |
| | Social | The article discusses the effects that it presents with regards to customers or society in general. |
| | Technological | The article contributes to the technological progress of AI in weed management. |
| | Environmental | The article takes into consideration the environmental aspect of AI utilization in weed management. |

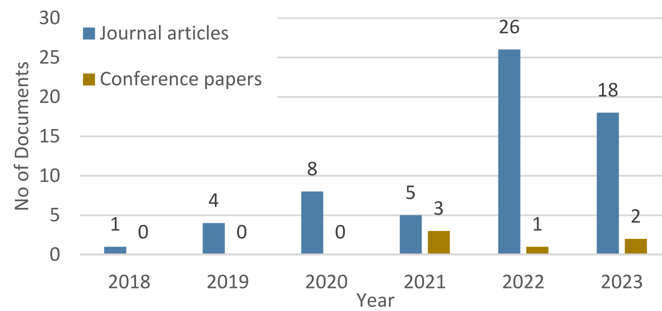


**Fig. 5.** Year-wise and source-type publications included in this analysis.

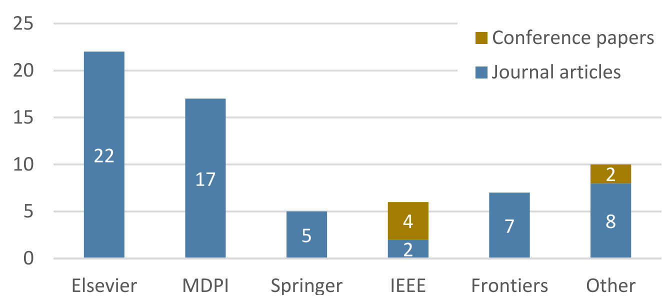


**Fig. 6.** Number of articles per publisher, categorized according to their respective source types.

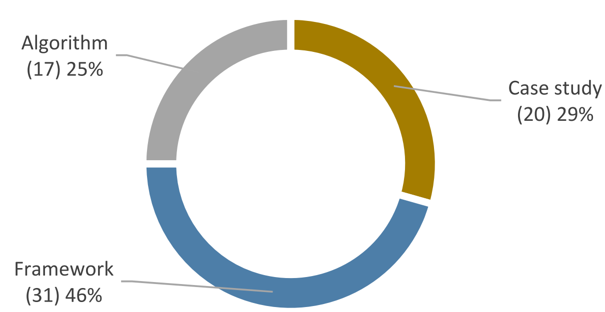


**Fig. 7.** Articles classified by their respective content type.

a transformative juncture in agricultural practices, entailed by factors shaping the adoption of AI systems. This thematic Foci delves into three pivotal criteria: Food safety, Enhanced Effectiveness, and Herbicides Reduction - Eco-friendliness in which distinctive facets of AI-driven weed management emerge, from its implications for human health and environmental sustainability to its capacity for resource optimization and crop yield augmentation. Table B1 in Appendix B quotes the articles reviewed in this study and classifies them based on these three factors, while Fig. 10 quantifies these articles referring the three factors.

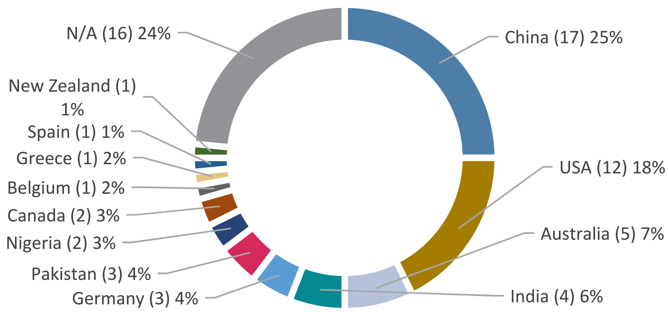


**Fig. 8.** Countries in which experimentations take place in this SLR.

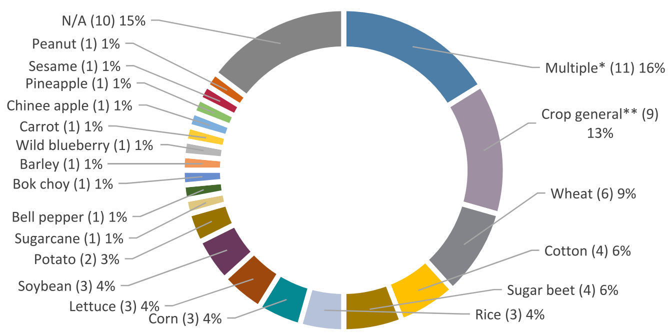


**Fig. 9.** Crops applied AI-enabled weed management. (* The article investigates more than one crops, ** The article refers crop in general).

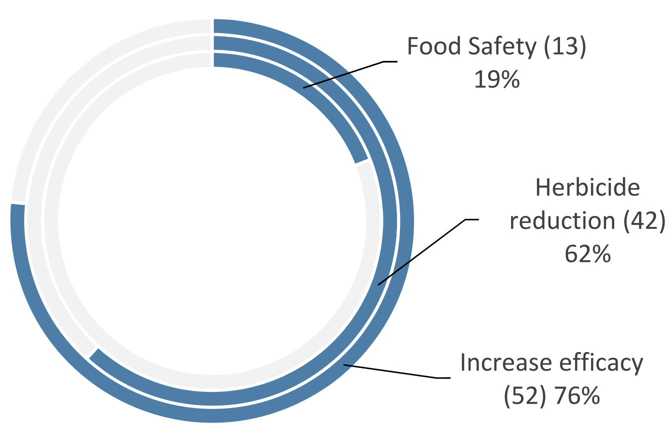


**Fig. 10.** Quantity of articles referring the three factors.

### 3.3.1. *Food safety*

Ensuring food safety is an indisputable imperative in the agricultural sector, considering its direct and significant impact on human health. Traditional weed control practices have conventionally placed significant reliance on the use of chemical herbicides to address weed infestations, inadvertently giving rise to a range of concerns related to food safety (Dang et al., 2023). The application of herbicides, while effective in weed suppression, is not without repercussions. Residues from herbicides can accumulate on crops and in the surrounding soil, potentially leading to the contamination of food products and, therefore, presenting a tangible risk to consumers and the environment (Subeesh et al., 2022). In 2023, a study by the Environmental Working Group found that nearly 75% of conventionally grown fresh food available in the USA is found to contain traces of potentially hazardous pesticides, aligning with similar studies which have shown that herbicide residues are present in a variety of food products (Environmental Working Group, 2023). In addition, in the European Food Safety Authority found that glyphosate residues were present in a variety of food products, including cereals, bread, and pasta, underling that glyphosate is a probable human carcinogen (European Food Safety Authority (EFSA), 2015). Similarly, a study by the Canadian Food Inspection Agency found that herbicide residues were detected in over 10% of fruit and vegetable samples tested, highlighting that Minimum Residue Levels (MRLs) of herbicides exceeded safety limits in some samples (Canadian Food Inspection Agency, 2020). These findings raise concerns about the potential health risks associated with exposure to herbicide residues in food. While the World Health Organization (WHO) has stated that the levels of herbicide residues typically found in food are not a significant health risk (World Health Organization, 2022), some scientists and public health experts have expressed concern about the potential long-term effects of exposure to herbicide residues, such as cancer and reproductive problems (Asghar and Malik, 2016).

The advent of AI technologies has reformed the landscape of weed management, as AI systems exhibit a high degree of accuracy in weed identification and classification. The high level of precision exhibited by AI-driven weed management solutions allows for accurate differentiation between crops and weeds and can empower farmers to administer herbicides with unprecedented precision, targeting only the weeds (Jin et al., 2022a). The implementation of AI technologies not only reduces the likelihood of herbicide residue accumulation, but also substantially decreases the potential for unintentional contamination of food products. In this SLR, 19% (13) of the studies highlight this factor for adoption (Fig. 10).

### 3.3.2. *Increase in efficacy*

The pursuit of agricultural productivity hinges upon the continuous improvement of weed management practices. As weeds persistently challenge crop yields and agricultural efficiency, there arises an imperative to enhance the effectiveness of weed control measures (Gerhards et al., 2022). The optimization of weed management practices plays a crucial role in enhancing agricultural productivity and minimizing economic losses. Conventional weed control measures often confront challenges such as imprecise application, labor-intensive manual labor, and delayed reactions to weed outbreaks (Jiang et al., 2023). These shortcomings underscore the compelling need for innovative approaches that amplify the effectiveness of weed management strategies. AI and its inherent capabilities to rapidly and precisely detect weeds within agricultural fields play a crucial role in improving the effectiveness of weed management strategies.

Two fundamental aspects highlight the enhanced effectiveness brought about by AI in weed management: precision and timeliness (Mishra and Gautam, 2021). AI-driven systems exhibit an unparalleled level of precision in distinguishing between crops and weeds, enabling the specific targeting of herbicides, reducing unintended harm to crops, and promoting resource conservation (Movedi et al., 2022). Furthermore, AI can operate in real-time or near-real-time, perpetually monitoring fields for weed presence. Timely identification of weeds allows for immediate intervention, thereby minimizing the timeframe in which weeds can proliferate and compete with agricultural crops, aligning with the dynamic nature of agriculture and contributing significantly to the overall effectiveness of weed management (Thanh Le et al., 2021). In this SLR, 76% (52) of the studies highlight this factor for adoption (Fig. 10).

### 3.3.3. *Herbicide reduction – eco-friendliness*

In light of the simultaneous imperatives of maintaining crop productivity and promoting environmental sustainability, the pursuit of ecologically sound methods for weed control has gained significant prominence within agriculture. The conventional use of herbicides in agriculture has historically played a central role in weed management, and although herbicides have demonstrated efficacy in the reduction of weeds, their extensive utilization has resulted in unexpected environmental repercussions (Duke and Dayan, 2022). The leaching of herbicides into soil and water has the potential to impact non-target organisms, contaminate water bodies, and facilitate the emergence of herbicide-resistant weed strains (Xia et al., 2022). The ecological footprint of herbicides necessitates a paradigm shift towards more environmentally sustainable practices.

AI emerges as a catalyst for herbicide reduction and eco-friendliness in weed management. AI-based solutions demonstrate exceptional performance in accurately and promptly identifying weeds at an early stage and empower producers to specifically target and address the presence of weeds, consequently reducing or eliminating the reliance on herbicides (Johansson et al., 2007). There are studies highlighting the importance of reducing the herbicide utilization that can be found in Table B1 in Appendix B. In this SLR, 62% (42) of the studies highlight this factor for adoption (Fig. 10).

### 3.4. AI implementation

The integration of AI into weed management practices signifies a transformative stride in contemporary agriculture. This technology not only offers the potential for improved efficiency and effectiveness in weed control but also aligns with the emerging priorities of sustainability and precision agriculture. This thematic group of criteria pertains to the system that is employed in weed management. These criteria encompass *(i)* the functionality of AI, *(ii)* the capture technology, the vital bridge connecting the physical agricultural environment to the digital realm of AI, *(iii)* the training dataset, the foundation upon which AI models learn and adapt, *(iv)* the AI model, the intricate algorithmic brains that drive decision-making, and *(v)* outcomes and accuracy, the ultimate litmus test of AI's practical value in weed management. Table B2 in Appendix B quotes the articles reviewed in this study and provides information on AI implementation regarding the criteria.

#### 3.4.1. Functionality

AI systems are specifically developed to address certain challenges. In this study, the criterion "Functionality" serves as a precursor to the AI application. These applications encompass weed detection, weed and crop identification, weed mapping, or weed removal. The functionality factor signifies the ability of AI systems to address real-world challenges, provide real-time insights, offer decision support, and integrate with precision agriculture practices.

#### 3.4.2. Capture technology

Capture technology is recognized as a fundamental element that serves as the basis for the effectiveness and precision of solutions driven by AI. Capture technology encompasses the suite of hardware and sensors employed to gather data from the agricultural environment. It constitutes an essential interface between the physical world of crops and weeds and the digital realm of AI. The quality, type, and precision of capture technology directly influence the richness and relevance of data available for AI systems.

The availability of high-quality data is crucial for the successful implementation of weed management strategies. It facilitates data acquisition by employing various sensors, cameras, and other data-gathering devices. These include mobile phone cameras, drone cameras, professional cameras, Lidars, and hyperspectral systems. The quality and reliability of this data are paramount, as AI models heavily rely on it for accurate decision-making. In this study, the capture technologies used for image acquisition for the training process in each study were classified in four categories: Phone camera, UAV camera, camera, and open-source dataset. Fig. 11 illustrates the distribution of articles across different categories, while cameras are the most used means of capture technology.

#### 3.4.3. Training dataset

In conjunction with capture technology, the availability of high-quality training datasets is essential for AI model development.

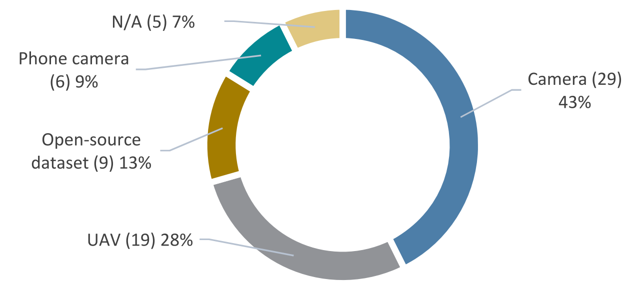


**Fig. 11.** Categorization of image acquisition technology for the training process.

Training datasets, comprising labeled images and data, enable AI models to learn and make accurate weed identification and management decisions (Bochtis et al., 2022b). Training datasets serve as the foundational building blocks upon which AI models learn and develop the capability to make informed decisions regarding weed identification and management (Sudars et al., 2020). The quality, diversity, and representativeness of these datasets profoundly influence the accuracy and reliability of AI-driven weed management systems (Olsen et al., 2019).

The size and volume of training datasets can significantly impact the performance of AI models. Larger datasets, generally, lead to more robust and accurate models. Nevertheless, the process of gathering and labeling vast datasets can be a demanding task. The utilization of labeled data, wherein each image or data point is annotated with explicit information indicating the presence or absence of a weed, is an essential requirement in the context of supervised machine learning (Shorewala et al., 2021). It enables AI models to establish correlations between distinct patterns and characteristics and needs to be as precise as possible, as it is of utmost importance in the training process.

#### 3.4.4. AI model

The core of AI integration in weed management is around a complex network of algorithms, neural networks, and computational intelligence. AI models play a crucial role in facilitating decision-making processes within the realm of weed management (Bochtis et al., 2022c). These models integrate extensive quantities of data, encompassing collected photos, sensor inputs, and environmental characteristics, and condense this knowledge into practical and useful insights (K Jha et al., 2019). The essence of AI models in this study lies in their ability to identify and classify weeds accurately, enabling informed and timely interventions.

AI models used in weed management predominantly fall into the domains of deep learning for computer vision. Deep learning is a subset of machine learning that focuses on the utilization of artificial neural networks, with a specific emphasis on convolutional neural networks (CNNs) for image-related tasks (Ofori and Omar, 2021). These CNNs demonstrate exceptional performance in the field of image recognition, rendering them very suitable for the task of weed identification. The AI models used in the reviewed articles vary and are quoted in Table B2 in Appendix B. These include, the You look only Once (YOLO) in many versions, Single-shot MultiBox Detector (SSD), EfficientDet, RetinaNet, CenterNet, Faster Region-based Convolutional Neural Network (RCNN), Region-based Fully Convolutional Network (RFCN), ResNet101, DarkNet53, MobileNet, VGG, DenseNet, ShuffleNet, MNASNet, EfficientNet, Alexnet, GoogLeNet, InceptionV3, Xception, VGGNet, DetectNet, CBAM, and U-net.

#### 3.4.5. Outcomes and accuracy

The accuracy of AI models is a key determinant of their practical utility in weed management. Performance metrics such as precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC) are commonly used to assess model accuracy. The accuracy of AI models in weed management is not merely a statistical measure but a practical imperative. The precision of weed management interventions relies heavily on the accurate identification and classification of weeds and high accuracy could ensure that herbicides are applied judiciously, targeting weeds while sparing crops, thus minimizing economic losses and reducing environmental impact (Hussain et al., 2020).

Accuracy, though fundamental, is not the sole performance metric for AI models in weed management. A more nuanced evaluation involves metrics such as precision, recall, and the F1-score (Ong et al., 2019). Precision is a metric that measures the ratio of accurately recognized weeds to the total number of identified instances, hence decreasing the risk of false positives. Recall, on the other hand, quantifies the ratio of accurately detected weeds out of the total number of existing weeds, thereby addressing the concern of false negatives. Furthermore, the F1-score serves as a means of achieving equilibrium between precision and recall, providing a comprehensive metric that encompasses the total performance of a model. In addition to precision, recall, and the F1-score, AI practitioners often employ Receiver Operating Characteristic (ROC) curves and the Area Under the ROC curve (AU-ROC) to assess model performance (Valente et al., 2022). ROC curves plot the true positive rate against the false positive rate, providing insights into a model's discriminatory ability across different decision thresholds, while AUC-ROC quantifies the overall discriminative power of the model, with higher values signifying better performance. Last but not least are mean Average Precision (mAP) value and Intersection over Union (IoU) metrics. mAP is a comprehensive metric used to evaluate the model's ability to accurately and effectively identify and categorize objects present in a picture or dataset, while IoU is a metric used to evaluate the accuracy of object localization in tasks like image segmentation and object detection (Saqib et al., 2023; Xu et al., 2023). Subsequently, Mean Intersection over Union (MioU) is also referred in the literature, which is the mean value across all classes or category of objects in an image or a dataset (Wang et al., 2020).

### 3.5. Ancillary technologies used

The integration of AI in the agricultural sector has brought forth a new era of accuracy and productivity in the realm of weed management (Bochtis et al., 2022a). Yet, the efficacy of AI-driven weed management extends beyond the capacity of AI alone. It is further supported by the seamless integration of ancillary technologies that work in concert with AI, elevating the precision and scope of weed control strategies. Collectively, these technologies synergistically enhance data acquisition, monitoring, decision-making, and intervention, shaping a holistic approach to weed management in modern agriculture. In the context of this SLR, four predominant technologies are identified to be utilized in conjunction with AI: IoT, UAVs, field robots, and herbicides. Table B2 in Appendix B quotes the articles reviewed in this study and classifies them based on these technologies, while Fig. 12 quantifies these articles referring to the technologies used.

#### 3.5.1. IoT

The convergence of IoT and AI has ushered in a new era of precision in weed management. IoT devices, including sensors, remote cameras, and data loggers, play a crucial role in the acquisition of real-time environmental data, facilitating the ability of AI systems to make well-informed decisions (Kulkarni et al., 2020; Tanveer et al., 2023). Possessing an accurate understanding of environmental characteristics plays a crucial role in enhancing the timing of herbicide application, allocation of resources, and modeling of weed development (U. Farooq et al., 2022). In addition, the incorporation of remote sensing technologies, including satellite imaging and sensors placed on drones, into IoT framework enhances the capacity for data acquisition (Quan et al., 2023). These technologies facilitate the utilization of artificial intelligence in accessing high-resolution imaging and multispectral data, thereby enabling the generation of comprehensive weed maps and the timely identification of weed presence. Furthermore, data fusion techniques combine IoT-generated data with remote sensing data, enhancing AI's ability to identify weed infestations accurately (Gutiérrez et al., 2008). In this SLR, 4% (3) of the studies utilize this technology for their solution (Fig. 12).

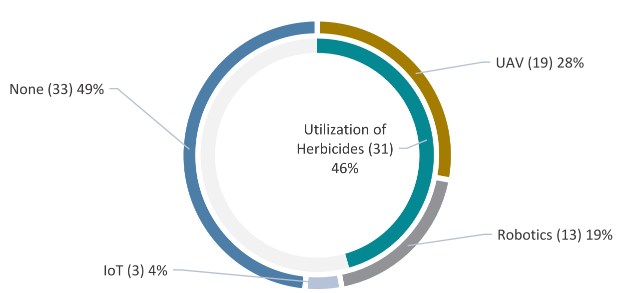


**Fig. 12.** Quantity of articles referring to the technologies used.

#### 3.5.2. UAVs

UAVs, often referred to as drones, have emerged as indispensable tools for AI-driven weed management. UAVs equipped with advanced camera and sensor technologies provide an aerial perspective of agricultural fields, facilitating the utilization of AI systems to effectively monitor and evaluate the presence of weed infestations with unparalleled accuracy. In the majority of research studies included, the UAVs are used to capture high-resolution images and aerial maps of agricultural fields, providing valuable data for weed detection and classification that are subsequently labeled and utilized for AI training (Olsen et al., 2019). In addition, Farooq et al. (2022) utilize AI models to analyze aerial images to identify weeds, assess their distribution, and generate detailed weed maps. The utilization of aerial perspective facilitates the identification of isolated weed patches that may be missed at ground level. Beyond aerial imaging, UAVs equipped with precision sprayers have significantly transformed weed management strategies. These advanced UAVs have the capability to not only acquire high-resolution imagery and generate weed maps, but also enable precise administration of herbicides to specific targets, by autonomously identifying weed-infested areas from their aerial vantage point and precisely administering herbicides, thereby guaranteeing the execution of weed control measures with unparalleled precision (Bah et al., 2018). This integration of UAV technology with herbicide delivery serves to reduce herbicide consumption and optimize resource allocation, hence fostering the adoption of sustainable and ecologically conscious weed management approaches in the agricultural sector. In this SLR, 28% (19) of the studies utilize this technology for their solution (Fig. 12).

#### 3.5.3. Field robots

Field robots represent the next frontier in AI-driven weed management, providing ground-level precision and automation. Equipped with advanced sensors and AI algorithms, these robots navigate agricultural fields, identify weeds, and apply targeted treatments. Field robots utilize computer vision and machine learning techniques to effectively discern and distinguish between various crops and weeds in real-time scenarios. AI algorithms are utilized to analyze and interpret data obtained from onboard cameras, enabling robots to make autonomous decisions regarding weed control, minimizing the need for human intervention. Weed control encompasses the utilization of either mechanical (Quan et al., 2022) or spraying devices (Jin et al., 2023) to apply precise treatments with pinpoint accuracy, targeting only the areas with weed infestations. This precision minimizes herbicide usage, reduces environmental impact, and conserves resources. In this SLR, 19% (13) of the studies utilize this technology for their solution (Fig. 12).

#### 3.5.4. Herbicides

Herbicides, though traditionally used in weed management, are currently experiencing advantages from AI-enhanced precision by optimizing herbicide application, ensuring that these chemicals are used judiciously and with minimal environmental impact (Chu et al., 2022). This reduces herbicide usage, minimizes crop exposure, and decreases the risk of environmental contamination. In addition, AI models can optimize herbicide dosages based on weed species, growth stages, and distribution. In this SLR, 46% (31) of the studies utilize herbicides for their solution (Fig. 12).

### 3.6. Related impact of AI methods adoption

The integration of AI methods into weed management has wide-ranging consequences across various dimensions, encompassing economic, social, technological, and environmental dimensions. This thematic foci explores the multifaceted impact of AI methods adoption in conjunction with AI in weed management. Table B2 in Appendix B quotes the articles reviewed in this study and classifies them regarding their impact. Table B3 in Appendix B quotes the articles reviewed in this study and classifies them based on the related impact, while Fig. 13 quantifies these articles referring to the related impact.

#### 3.6.1. Economic

The utilization of AI-driven weed management systems yields substantial economic advantages for farmers and the agricultural sector as a whole. By accurately identifying and targeting weeds, AI helps optimize the use of resources, most notably herbicides, so farmers can reduce herbicide expenditures, minimize overuse, and allocate resources more efficiently. This optimization not only lowers production costs but also leads to increased crop yields with extensions to crop competitiveness and productivity, resulting in higher revenues for farmers (Hussain et al., 2020). Furthermore, the reduction in manual labor for weed control tasks, thanks to AI and automation, contributes to labor cost savings, further bolstering the economic viability of agriculture (Modi et al., 2023).

In light of the previous literature review conducted by Du et al. (2023), which posits that agricultural studies pertaining to AI applications predominantly focus on the technical aspects while neglecting the economic component, it was deemed necessary to incorporate this dimension in the present research analysis to enhance its specificity. Partel et al. (2019a) endeavored to address this matter by developing an affordable system (~1500$) for weed management that has above 70% precision and recall rates. In addition, Khan et al. (2023) conducted a comparative analysis of the effects of Hand Weeding (HW) and AI on plant weight and spike count in wheat cultivation. Their results suggest that there was no statistically significant difference between the two methods (HW: 92 cm, 55, AI: 89 cm, 53), indicating that the AI applications are mature enough to replace human labor partially or completely. Simultaneously, the operational cost of AI was found to be less than HW, substantiating its superiority and indicating its potential for future applications. Although the advantages of adopting these practices based on both economic and environmental criteria are clearly apparent, their actual implementation remains limited. In this SLR, 19% (13) of the studies refer to the economic impact of their solution (Fig. 13).

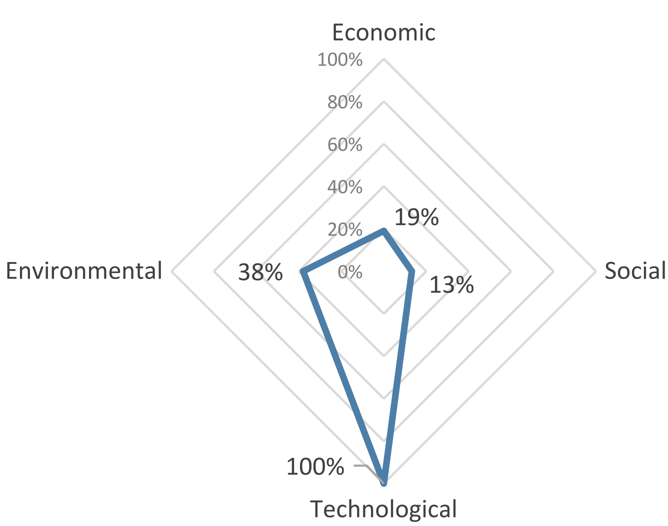


**Fig. 13.** Quantity of articles referring to the related impact.

#### 3.6.2. Social

The adoption of AI methods in weed management carries a profound social impact, particularly with regard to consumers and their confidence in the safety of food products. AI's role in reducing herbicide usage and promoting a more eco-friendly environment directly contributes to food safety, benefiting consumers in several ways. These benefits include the substantial mitigation of the potential for herbicide contamination on crops, thereby providing consumers with a guarantee of the integrity of their food products (Dang et al., 2023). Simultaneously, the utilization of AI-driven technology effectively reduces the level of chemical exposure experienced by agricultural workers and nearby communities, thereby aligning with the prevailing health and safety priorities (Jin et al., 2022a). Furthermore, the ecologically conscious consumers are attracted to the eco-friendly strategy of AI, which emphasizes the promotion of sustainable food sources (Gallo et al., 2023). Overall, AI's contributions foster customer confidence within the agriculture sector, so strengthening the notion that contemporary technologies are actively striving to prioritize the welfare of consumers and the ecological sustainability of the planet (Subeesh et al., 2022). In this SLR, 13% (9) of the studies refer to the social impact of their solution (Fig. 13).

#### 3.6.3. Technological

The adoption of AI methods in weed management represents a significant technological advancement in agriculture. It serves as a catalyst for innovation in the field, fostering the development of cutting-edge technologies such as precision agriculture, IoT integration, and robotics. These technological advancements not only enhance the management of weeds but also possess wider implications in the field of agriculture (Bochtis et al., 2021). AI-driven systems facilitate the integration of emerging technologies, hence augmenting the total technological landscape of the agriculture industry. Therefore, articles that contribute to the advancement of technology are recorded. In this SLR, all the studies have technological impact of their solution (Fig. 13).

#### 3.6.4. Environmental

One of the most crucial aspects of AI methods adoption in weed management is its positive environmental impact. By enabling precise weed identification and targeted herbicide application, plays a crucial role in reducing pesticide usage and mitigating the environmental footprint associated with weed control. This reduction in chemical input leads to a healthier agroecosystem, with fewer pollutants entering soil and water systems. Furthermore, the implementation of AI-driven weed management systems promotes the adoption of sustainable agricultural techniques, so harmonizing with ongoing conservation endeavors. Overall, the environmental impact of AI extends beyond its application in weed management, thereby making a significant contribution to the development of a more sustainable and environmentally friendly agricultural landscape. In this SLR, 38% (25) of the studies refer to the environmental impact of their solution (Fig. 13).

## 4. Discussion

The preceding sections have meticulously examined the multifaceted landscape of AI in weed management, focusing on weed identification in agriculture, in the context of six thematic foci. In light of the complexities inherent in this technological shift, it is crucial to partake in a discourse that synthesizes the key findings and elucidates the ramifications of weed control facilitated by artificial intelligence. In this discussion, impacts of AI on food safety, its role in enhancing weed management effectiveness, and its contribution to eco-friendliness through herbicides reduction are contemplated. Furthermore, the broader context of AI implementation, the significance of training datasets and AI models, and the importance of accuracy and performance metrics in the successful adoption of AI systems are considered. The discussion is concluded by a reflection on the implications of AI integration for ancillary technologies in weed management and its broader impact on economics, society, technology, and the environment.

AI-driven weed management stands as an embodiment of transformative change, notably within the context of food safety. The utilization of chemical herbicides in traditional agricultural practices has been consistently linked to apprehensions surrounding the potential contamination of food commodities, and multifold reports have been raised regarding herbicide residues in a variety of food products (Canadian Food Inspection Agency, 2020; Environmental Working Group, 2023; European Food Safety Authority (EFSA), 2015). These findings raise apprehensions among consumers about the possible health hazards linked to the pesticide residues present in food, while scientists argue whether the levels of herbicide residues commonly detected in food do pose a substantial health hazard (Asghar and Malik, 2016; World Health Organization, 2022). A recent survey conducted by (Consumer Reports, 2015), revealed that pesticides are a matter of apprehension for 85% of Americans, shifting to organic products. However, with AI's precision in weed identification and targeted herbicide application, the risk of herbicide residues on crops is significantly reduced (Jiang et al., 2023). This is not only an immediate concern but also contributes to the bolstering of consumer confidence in the safety and integrity of food products. In addition, the judicious application of herbicides, facilitated by AI, contributes to a reduction in the ecological footprint associated with weed control. The agricultural sector's progress towards eco-friendliness is underscored by AI's role in minimizing the ingress of pollutants into soil and water systems (Lou et al., 2022). Consequently, AI-driven weed management not only addresses weed proliferation but also ushers in an era characterized by environmentally responsible agriculture. Furthermore, the adoption of AI in weed management transcends conventional practices by the enhancement of the effectiveness of weed control strategies. By engaging in accurate weed identification, farmers get the ability to selectively target weeds, leading to enhanced resource allocation and reduced herbicide overuse (Dang et al., 2023; Tang et al., 2017). Consequently, agricultural resources are used more efficiently, crop yields experience a noteworthy increase, production costs are reduced, and revenues are augmented. Moreover, the reduced reliance on manual labor for weed control tasks is a testament to the potential for labor cost savings, further advancing the economic viability of agriculture (Acemoglu and Restrepo, 2019).

The successful implementation of AI in weed management is influenced by several critical factors. The choice of capture technology, encompassing sensors, drones, and other data acquisition tools, profoundly influences data quality and model accuracy; the construction of AI models relies on the foundational role of meticulously collected and comprehensive training datasets; and the selection of AI models, whether conventional machine learning or deep learning, dictates the level of precision in weed identification. Furthermore, the importance of accuracy and performance metrics cannot be understated; these metrics guide model refinement and validation, ensuring reliable results in real-world applications. The synergy between these factors underpins the comprehensive endeavor of AI implementation in weed management, offering a potent pathway towards agricultural innovation and weed and crop identification. The literature has employed leaf feature disparities in order to discriminate between crops and weeds (Dyrmann et al., 2016; Lottes et al., 2018; Wu et al., 2021). These include plant color (Lv et al., 2022), leaf texture (Bakhshipour et al., 2017), spectra (Shirzadifar et al., 2020), and shape (Bakhshipour and Jafari, 2018; Swain et al., 2011) of weeds. In addition, deep learning has the ability to conduct intricate feature extraction, effectively handle substantial volumes of data, and has exhibited its potential in diverse agricultural domains, including crop classification (Kamath et al., 2022a), pest and disease identification (Ahmad Loti et al., 2021), yield prediction (van Klompenburg et al., 2020), farmland management (Quan et al., 2023), and growth analysis (Yasrab et al., 2021).

What is more, the integration of AI with ancillary technologies is crucial in shaping the future of agriculture regarding weed management. The internet of things, UAVs, field robots, and AI-enhanced herbicides, complement AI's capabilities, fostering a holistic and data-driven approach to weed control. These technologies enhance data acquisition, monitoring, decision-making, and intervention, ultimately advancing the precision and scope of weed management strategies. These technologies enhance data acquisition, monitoring, decision-making, and intervention, ultimately advancing the precision and scope of weed management strategies. Notably, a research endeavor was to devise an innovative and advanced mechanical robotic weeding system that operates within crop rows. This system was designed to possess intelligent capabilities by leveraging deep learning techniques for the purpose of accurately detecting and distinguishing between crops and weeds. The findings of the study provide evidence supporting the viability of the suggested approach for controlling weeds within rows, with an 85.91% weed removal rate and a 1.17% crop injury rate. Similarly, UAVs are employed for image acquisition and facilitate weed mapping as indicated by several research endeavors in this study (Ajayi et al., 2023; Bah et al., 2018; 2020; de Camargo et al., 2021; Gallo et al., 2023; Genze et al., 2022; Huang et al., 2020; Xu et al., 2023). Moreover, the proliferation of diverse sensors has facilitated the potential for weed management to be accomplished through the analysis of a broad spectrum of images obtained from various remote sensing platforms. In brief, the amalgamation of AI with ancillary technologies represents a convergence of innovation and sustainability, promising to redefine the contours of weed management practices in agriculture.

Meanwhile, the adoption of AI methods in weed management radiates its influence across economic, social, technological, and environmental dimensions. From economic perspective, AI-driven weed management optimizes resources, enhances yields, and reduces production costs. Socially, it empowers farmers, ensures food safety, and fosters consumer confidence. Technologically, it advances agricultural innovation and synergizes with emerging technologies. Environmentally, it promotes sustainable practices and decreases the ecological footprint of weed control. Collectively, these dimensions underline the profound influence of AI methods adoption on agriculture and its broader societal and environmental impact. Despite these profound implications, the existing body of work predominantly emphasizes the technological dimension of AI applications in weed management while comparatively neglecting economic and social aspects. This phenomenon could be attributed to the prevalent practice of conducting studies in experimental fields rather than in actual agricultural settings, hence posing challenges in accurately quantifying the economic gains resulting from practical implementation. Similarly, the impact of the social aspect is challenging due to the involvement of numerous factors. However, it is widely recognized that organic products are considered in a favorable light by consumers (Consumer Report, 2022). Following current Common Agricultural Policy's (CAP) guidelines (European Commission, 2023), it seems that the technological levels in weed management have been highly ameliorated, thus more emphasis should be given on the economic, environmental aspects, to increase the applicability of the examined practices considering sustainability.

In summary, the implementation of AI-driven weed management has the potential to significantly impact the field of agriculture by revolutionizing existing techniques and paradigms. The preceding discourse elucidates the diverse facets of this process, encompassing the augmentation of food safety and efficacy, the mitigation of pesticide usage, and the promotion of environmental sustainability. It also underscores the pivotal role of AI in revolutionizing weed management practices and fostering a sustainable and efficient agricultural ecosystem. As AI continues to evolve and integrate with complementary technologies, its potential to address weed proliferation while advancing agricultural sustainability remains a promising beacon for the future.

The integration of AI into weed management promises transformative benefits, but it is not without its challenges. One of the most significant hurdles faced in this technological shift is resistance to change. As agriculture adapts to AI-driven weed management practices, stakeholders encounter various forms of resistance that can impede the transformation and limit its potential impact. One of the main factors hindering the widespread adoption of AI in weed management is the strong attachment to and dependence on conventional farming methods. Generations of farmers have honed their skills and knowledge in conventional weed control methods, such as manual weeding and blanket herbicide application, and the prospect of transitioning to AI-driven solutions can be met with skepticism, as it represents a departure from established and validated practices. Moreover, the complexity of AI technology can be daunting, especially for individuals lacking a strong background in digital technologies. Farmers and agricultural professionals may perceive AI systems as daunting, fearing that they lack the technical expertise required to operate and troubleshoot these systems effectively. Consequently, digital literacy emerges as a catalyst for enabling and accelerating the transformation of agricultural practices. Digital literacy encompasses the knowledge, skills, and competencies required to effectively navigate, understand, and utilize digital technologies, including AI, in the context of weed management and serves as an empowerment tool for farmers and agricultural professionals as they adapt to AI-driven weed management. Understanding AI algorithms, data collection processes, and model outputs allows them to make informed decisions and optimize weed control strategies.

## 5. Conclusions and future research

In this article, a systematic literature review was conducted regarding artificial intelligence in weed management, in order to identify criteria towards weed identification and deep learning in agriculture. Six thematic foci were identified with 23 criteria used to classify the articles. Of the 5821 documents found, 99 full-text articles were assessed, and 68 were included in this study. These articles were assessed based on the field information, factors of AI system adoption, AI implementation, Ancillary Technologies used, and related impact of AI methods adoption.

The exploration of AI in weed management reveals a transformative potential with profound implications for agriculture, food safety, and environmental sustainability. As this SLR concludes, several key takeaways emerge, underlining the significance of AI-driven weed management in the agricultural sector. AI integration in weed management signifies a paradigm shift from conventional practices, marked by precision in weed identification and optimized herbicide use, enabling agriculture to transition towards secure, more efficient, and eco-friendly weed management. Enhanced food safety is a direct outcome, as AI adoption reduces the risk of herbicide residues on crops, fostering consumer confidence and ensuring the purity and safety of the food supply chain. The utilization of AI in weed management methods has been found to greatly enhance their efficacy. This is mostly due to the ability of AI to accurately identify weeds and apply herbicides in a targeted manner. By doing so, AI optimizes the allocation of resources, reduces production costs, and increases crop yields. Consequently, the implementation of AI in weed management strategies has the potential to greatly improve agricultural productivity. AI plays a pivotal role in promoting eco-friendliness by reducing herbicide usage, contributing to sustainability goals, minimizing environmental impact, and fostering responsible agricultural practices. Last but not least, the integration of AI with ancillary technologies, such IoT, UAVs, field robots, and herbicides, promises to revolutionize weed management practices, offering opportunities for holistic, data-driven approaches to weed control.

The review identifies several avenues for future research. The investigation of multi-criteria decision-making frameworks that account for diverse factors, such as crop type, weed species, and regional variations, could optimize AI-driven weed management strategies for various agricultural contexts. The assessment of the long-term environmental and economic sustainability of AI-driven weed management practices is essential, including ecological impact, resource savings, and economic feasibility. Expanding the study of AI in weed management to diverse geographic regions and assessing its adaptability to different agricultural systems can provide valuable insights into global adoption patterns and challenges. Furthermore, in the context of the NATAE Horizon project (NATAE, 2023), the agroecology transition can be particularly appropriated in North Africa by identifying the most effective combinations of agroecological practices and establishing a standardized approach to designing locally-adapted strategies for transitioning to agroecology. Additionally, the project aims to foster collaboration and knowledge sharing by establishing a sustainable Mediterranean network and community, enhancing digital literacy.

## Funding

This project has received funding from the European Union's HE research and innovation programme under grant agreement No 101084647.

## Declaration of competing interest

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

## Data availability

All data are given in the text

## Acknowledgement

This project has received funding from the European Union's HE research and innovation programme under grant agreement No 101084647. Views and opinions expressed are, however, those of the authors only and do not necessarily reflect those of the European Union or the European Research Executive Agency (REA). Neither the European Union nor the granting authority can be held responsible for any use that may be made of the information the document contains. The publication of the article in OA mode was financially supported in part by HEAL-Link.

## Appendix A

The final query on Scopus is "TITLE-ABS-KEY ({weed} AND {management} AND (({Artificial} AND {intelligence}) OR ({deep} AND {learning}))) AND PUBYEAR >2015 AND PUBYEAR <2024 AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "cp")) AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (SRCTYPE, "j") OR LIMIT-TO (SRCTYPE, "p"))" while on WoS is "((TI=(weed management)) OR PUBL=(weed management) OR AB=(weed management)) AND ((TI=(Artificial Intelligence)) OR PUBL=(Artificial Intelligence) OR AB=(Artificial Intelligence) OR (TI=(deep learning)) OR PUBL=(deep learning) OR AB=(deep learning))".

## Appendix B

**Table B1**
Classification of the articles reviewed in this study pertaining to field information and factors of adoption

| Source | Country of case | Weed species | Crop type | Food safety | Increase in efficacy | **Herbicide reduction / eco-friendliness** |
|---|---|---|---|---|---|---|
| Saqib et al. (2023) | Pakistan | *Chloris cucullata* (grass), *Cirsium arvense* (creeping thistle), *Convolvulus arvensis* (bindweed) and *Eschscholzia californica* (california poppy) | Wheat | ● | ● | |
| Panati et al. (2023) | N/A | broadleaf, soil, grass | Soybean | | ● | |
| Quan et al. (2022) | China | broadleaf weeds, gramineous weeds | Crop general | | ● | |
| Jiang et al. (2023) | China | gramineous weeds, broadleaf weeds | Corn | | ● | ● |
| Albraikan et al. (2022) | N/A | N/A | Crop general | | ● | |
| (H. Zhang et al., 2022) | China | *Portulaca oleracea, Eleusine indica, Chenopodium album, Amaranth blitum, Abutilon theophrasti, Calystegia* | Peanut | | | ● |
| Hussain et al. (2020) | N/A | lambsquarters (*Chenopodium album*) | Potato | | ● | ● |
| (U. Farooq et al., 2022) | N/A | N/A | Sesame | ● | ● | ● |
| Fatima et al. (2023) | Pakistan | Horseweed, herb paris, grasses, and small weeds | Multiple | ● | | ● |
| Modi et al. (2023) | India | billygoat weed (*Ageratum conyzoides* L.), purple nutsedge (*Cyperus rotundus* L.), scarlet pimpernel (*Anagallis arvensis* L.), Lepidium didymum (*Coronopus didymus* L.), field bindweed (*Convolvulus arvensis* L.), ragweed parthenium (*Parthenium hysterophorus* L.), spiny sowthistle (*Sonchus asper* L.), corn spurry (*Spergula arvensis* L.) and asian scalystem (*Elytraria acaulis* L.) | Sugarcane | | ● | ● |
| Sapkota et al. (2022) | USA | morningglories (Ipomoea spp.), johnsongrass (Sorghum halepense (L.) Pers.), Palmer amaranth (Amaranthus palmeri S. Watson), prostrate spurge (Euphorbia humistrata Engelm.), browntop panicum (Panicum fasiculatum Sw.). | Cotton | | ● | |
| Xu et al. (2023) | USA | N/A | Soybean | | ● | ● |
| Kong et al. (2023) | China | setaria viridis, eleusine indica, wild pea, petunia | Multiple | | ● | |
| Barnhart et al. (2022) | USA | amaranth (*Amaranthus palmeri*) | Soybean | | ● | ● |
| Valente et al. (2022) | Germany | *Rumex obtusifolius* (Rumex or broad leaved dock) | Crop general | | ● | |
| Danilevicz et al. (2023) | Australia | Lupin | Crop general | | | ● |
| Gallo et al. (2023) | China | *Mercurialis annua* (French mercury) | Sugar beet | | | ● |
| Costello et al. (2022) | Australia | Parthenium (*Parthenium hysterophorus* L.) | N/A | | ● | ● |
| Sapkota et al. (2020) | USA | Italian Ryegrass | Wheat | | ● | |
| Moraitis et al. (2022) | Greece | N/A | Lettuce | ● | | ● |
| (G C et al., 2022) | USA | horseweed, kochia, ragweed, and waterhemp | Multiple | | ● | ● |
| Hu et al. (2020) | N/A | 8 species unidentified | N/A | | ● | |
| Jin et al. (2022b) | China | N/A | Bok choy | | ● | ● |
| Lou et al. (2022) | China | *Echinochloa crusgalli (L.) Beauv, Solanum nigrum L, Chenopodium album Linn, grass* | Corn | | ● | |
| Wang et al. (2020) | China | N/A | Sugar beet | | ● | |
| Dang et al. (2023) | USA | 12 weed species - unspecified | Cotton | ● | ● | ● |
| Hennessy et al. (2022) | Canada | Hair fescue, sheep sorrel | Wild blueberry | | | ● |
| (P. Wang et al., 2022) | China | 25 weed species | N/A | | ● | ● |
| Subeesh et al. (2022) | India | N/A | Bell pepper | ● | | ● |
| Thanh Le et al. (2021) | Australia | Wild radish, Capeweed | Barley | | ● | |
| (A. Wang et al., 2022) | N/A | N/A | Crop general | | | ● |
| (A. Farooq et al., 2022) | N/A | N/A | N/A | ● | ● | |
| Olsen et al. (2019) | Australia | Multiple | Multiple | | ● | ● |
| Yu et al. (2019a) | USA | dandelion (*Taraxacum officinale Web.*), ground ivy (*Glechoma hederacea* L.), and spotted spurge (*Euphorbia maculata* L.) | Crop general | | ● | ● |
| Liu et al. (2023) | China | cleavers (*Galium aparine* L.), chickweed (*Malachium aquaticum* L.), Persian speedwell (*Veronica persica Poir*), shepherd's purse [*Capsella bursa-pastoris (L.) Medik*], and sweet woodruff [*Galium odoratum (L.) Scop.*]. | Wheat | | ● | ● |

(continued on next page)

**Table B1** (*continued*)

| Source | Country of case | Weed species | Crop type | Food safety | Increase in efficacy | **Herbicide reduction / eco-friendliness** |
|---|---|---|---|---|---|---|
| Chen et al. (2022) | USA | Multiple | Cotton | | ● | ● |
| Amarasingam et al. (2023) | New Zealand | Mouse-Ear Hawkweed (*Pilosella officinarum*) | N/A | | ● | |
| Zou et al. (2022) | China | *Trigonotis peduncularis, Rorippa indica (L.) Hiern, Cirsium setosum, Chenopodium album* L. | Wheat | | ● | |
| Rahman et al. (2023) | USA | Carpetweed (*Mollugo verticillata*), Morningglory (*Ipomoea genus*), and Palmer Amaranth (*Amaranthus palmeri*) | Cotton | | ● | ● |
| Fathipoor et al. (2023) | N/A | N/A | Carrot | | ● | ● |
| (J.-L. Zhang et al., 2022) | China | Geminate Speedwell weeds, Wild Oats weeds, Malachium Aquaticum weeds, Asiatic Plantain weeds, Sonchus Brachyotus | Lettuce | ● | | ● |
| Nasiri et al. (2022) | N/A | N/A | Sugar beet | | ● | |
| Ajayi and Ashi (2023) | Nigeria | N/A | Multiple | ● | ● | ● |
| Farooque et al. (2023) | Canada | lamb's quarters (*Chenopodium album* L.), and corn spurry (*Spergula arvensis* L.) | Potato | | ● | ● |
| Cai et al. (2023) | China | N/A | Pineapple | | | ● |
| Saleem et al. (2022) | Australia | 8 types | Chinee apple | | ● | ● |
| Jin et al. (2022a) | USA | dallisgrass, goosegrass, Virginia buttonweed | N/A | | ● | ● |
| Gao et al. (2020) | Belgium | Hedge bindweed (*Convolvulus sepium*) | Sugar beet | | ● | |
| Xu et al. (2021) | N/A | Black-grass, Charlock, and Cleavers | Multiple | | ● | |
| Ma et al. (2019) | China | N/A | Rice | | ● | |
| Huang et al. (2020) | China | *L. chinensis, Cyperus iric, Digitaria sanguinalis (L), Barnyard Grass* | Rice | ● | | |
| Li et al. (2021) | N/A | N/A | N/A | ● | | |
| Kamath et al. (2022b) | India | sedges, grasses, and broadleaved | Crop general | | ● | ● |
| Peteinatos et al. (2020) | N/A | N/A | Multiple | ● | | ● |
| Xia et al. (2022) | China | barnyardgrass, velvetleaf | N/A | | | ● |
| Ajayi et al. (2023) | Nigeria | N/A | Multiple | | ● | |
| de Camargo et al. (2021) | Germany | N/A | Wheat | | ● | ● |
| Ofori and Omar (2021) | N/A | Multiple | N/A | | ● | |
| Pérez-Porras et al. (2023) | Spain | poppy (*Papaver rhoeas*) | Wheat | | ● | ● |
| Bah et al. (2018) | N/A | N/A | Crop general | | ● | ● |
| Osorio et al. (2020) | N/A | N/A | Lettuce | | ● | |
| Partel et al. (2019b) | N/A | N/A | N/A | ● | ● | ● |
| Etienne et al. (2021) | USA | N/A | Multiple | | ● | ● |
| Halstead et al. (2021) | USA | N/A | Multiple | | ● | |
| Khan et al. (2021) | Pakistan | N/A | Multiple | | ● | ● |
| Quan et al. (2023) | China | N/A | Corn | | ● | |
| Kamath et al. (2022a) | India | N/A | Rice | | | ● |
| Genze et al. (2022) | Germany | Goosefoot (*Chenopodium album* L.), Field pennycress (*Thlaspi arvense*), Wild chamomile (*Matricaria chamomilla*), Common gypsyweed (Veronica officinalis) and Cotton thistle (Onopordum acanthium) | Crop general | | | ● |

**Table B2**
Classification of the articles reviewed in this study pertaining to AI implementation and ancillary technologies used

| Source | Functionality | Training Dataset | Capture Technology for dataset and testing | AI model | Outcomes and Accuracy | Auxiliary technologies | Herbicide |
|---|---|---|---|---|---|---|---|
| Saqib et al. (2023) | Weed identification | 1065 | Logitech HD 920c webcam pro camera with a resolution of 1 MP and dimensions of 1280 × 720 | YOLOv3, YOLOv4, YOLOv3-tiny, YOLOv4-tiny | mAP = 73.1% | None | No |
| Panati et al. (2023) | Weeds and crops identification | 15336 | Open-source dataset | 4- layer customized CNN | N/A | None | No |

(*continued on next page*)

**Table B2** (*continued*)

| Source | Functionality | Training Dataset | Capture Technology for dataset and testing | AI model | Outcomes and Accuracy | Auxiliary technologies | Herbicide |
|---|---|---|---|---|---|---|---|
| Quan et al. (2022) | Weed detection | 20000 | Pictures with resolutions of 630 × 512 pixels | YOLOv3 | crop detection = 98.50%, weed detection = 90.9%, weed removal = 85.91%, crop injury = 1.17% | Robotics | No |
| Jiang et al. (2023) | Weed detection and removal | 8000 | RER-USBFHD01M-LS36 camera 1980 × 1080 | YOLOv5 | removal rate of 90.0%–94.5%, crop damage rate of 1.95%–0.82%, detection accuracy: 93.33%, 15.28% of the standard herbicide dosage was used | Robotics | Yes |
| Albraikan et al. (2022) | Weed detection | 3000 | N/A | MBMODL-WD | accuracy 98.99%, precision 96.13 | None | No |
| (H. Zhang et al., 2022) | Weed identification | 3355 | Fuji Finepixs4500 camera - 2017 × 2155 pixels | EM-YOLOv4-Tiny | mAP = 94.54% | None | No |
| Hussain et al. (2020) | Weed detection and removal | 12000 | Canon PowerShot SX540 HS camera, Logitech C920 Webcam HD Pro | tiny-YOLOv3 | 42% reduced sprayd liquid | Robotics | Yes |
| (U. Farooq et al., 2022) | Weed detection | 1300 | Open-source dataset | YOLOv4-tiny | mAP = 85.55%, average loss = 0.25 | IoT | No |
| Fatima et al. (2023) | Weed detection and removal | 9000 | 1280 × 1024 pixel camera | YOLOv5 | mAP = 88% | Robotics | No |
| Modi et al. (2023) | Weed identification | 5094 | 48 MP Sony IMX586 | DarkNet53 | Accuracy 99.1%, precision 99.3% | None | Yes |
| Sapkota et al. (2022) | Weed identification | 1230 | 100-MP FUJIFILM GFX100 | Mask R–CNN | mAP = 80% | UAV | No |
| Xu et al. (2023) | Weeds and crops detection | 1181 | Camera resolution 4864 * 3648 pixels | ResNet101_v and DSASPP | accuracy of 0.905 IoU score of 0.959 | UAV | No |
| Kong et al. (2023) | Weeds and crops identification | 2140 | Oneplus8P - 48 MP camera | YOLOv5 | mAP = 84.3% | None | No |
| Barnhart et al. (2022) | Weeds and crops identification | 4492 | Zenmuse X5R RAW camera | YOLOv5 | mAP = 77%, highest F1 score = 72% | None | Yes |
| Valente et al. (2022) | Weed detection | N/A | Phantom 3 Professional UAV's camera | MobileNet, VGG, Resnet, DenseNet, ShuffleNet, EfficientNet, MNASNet | F1-Score = 78.36% and AUROC = 93.74% | UAV | No |
| Danilevicz et al. (2023) | Weed detection | 9171 | Open-source dataset, and DJI Phantom 4 unoccupied aerial vehicle (UAV) RGB camera | Resnet18 | average precision = 0.86, intersection over union = 0.60, and F1 score = 0.70 | UAV | Yes |
| Gallo et al. (2023) | Weed detection | 4405 | DJI phantom4 pro camera, and open-source dataset | YOLOv7 | precision = 61.3%, mAP 56.66, recall = 62.1% | UAV | Yes |
| Costello et al. (2022) | Weed detection | 21784 | Nikon D2 with a 24–70 mm lens and a focal length of 70 mm | Yolov4 | detection accuracy = 94% | None | No |
| Sapkota et al. (2020) | Weed detection | N/A | DJI Phantom 4 Pro with RGB sensor (12 megapixels) | deep learning-based estimation | precision = 95.44 ± 4.27%, recall = 95.48 ± 5.05%, F-score = 95.56 ± 4.11% | UAV | No |
| Moraitis et al. (2022) | Weed detection | 400 | OV2640 camera | Faster-RCNN-Inception-V2 | maximum accuracy 92% | Robotics | No |
| (G C et al., 2022) | Weeds and crops identification | 3792 | Google Pixel 5 mobile camera | SVM and VGG16 | average f1-score >93% | None | Yes |
| Hu et al. (2020) | Weed identification | 17509 | Open-source dataset | Graph Weeds Net (GWN) | top-1 accuracy 98.1% | None | No |
| Jin et al. (2022b) | Weeds and crops identification | 11339 | HV1300FC, DaHeng Image | YOLO-v3, CenterNet, and Faster R–CNN | F1 score = 97.1%, precision = 97.1%, recall = 97.0% | None | No |
| Lou et al. (2022) | Weeds and crops identification | 1500 | LR1601-IRIS LIDAR and Pika L hyperspectral system | 3D-CNN | accuracy = 83.32% | Robotics | No |
| Wang et al. (2020) | Weeds and crops detection | 11780 | open-source dataset, Canon 60D | encoder-decoder network, transfer learning | MIoU = 88.91%, mean accuracy = 96.12% | None | No |
| Dang et al. (2023) | Weeds and crops detection | 5648 | Mobile phones >10 megapixels | YOLOv3-YOLOv7 | max mAP = 95,22 | UAV | No |
| Hennessy et al. (2022) | Weed detection | N/A | Canon T6 DSLR camera, LG G6 smartphone, Logitech c920 | YOLOv3-Tiny | F1-scores of up to 0.97 | None | Yes |
| (P. Wang et al., 2022) | Weed identification | 14035 | Nikon D5300 SLR | YOLOv3, YOLOv5, and Faster R–CNN | average accuracy: 91.8%, 92.4%, and 92.15% respectively | None | No |
| Subeesh et al. (2022) | Weed detection | 1106 | Xiaomi Mi 11 × mobile device's rear camera | Alexnet, GoogLeNet, InceptionV3, Xception | InceptionV3: accuracy = 97.7%, precision = 98.5%, recall = 97.8% | None | Yes |
| Thanh Le et al. (2021) | Weed detection | 3380 | VITA 2000 | Faster RCNN, Inception-ResNet-V2 | mAP = 0,555 | None | No |
| (A. Wang et al., 2022) | Weeds and crops detection | 5536 | Open-source dataset | TIA-YOLOv5 | F1-scoreweed = 70.0%, Apweed = 80.8%, mAP = 90.0% | None | No |

(continued on next page)

**Table B2** (*continued*)

| Source | Functionality | Training Dataset | Capture Technology for dataset and testing | AI model | Outcomes and Accuracy | Auxiliary technologies | Herbicide |
|---|---|---|---|---|---|---|---|
| (A. Farooq et al., 2022) | Weed detection and mapping | 1158 | 16-band XIMEA SNm 4 × 4 camera, four-band Sequoia multispectral camera | Transferable CNN | F1 score = 77.7%, precision = 77.45%, recall = 77.9% | IoT | No |
| Olsen et al. (2019) | Weed identification | 17509 | 1920 × 1200 px camera | Inception-v3 and ResNet-50 | average classifcation accuracy: 95.1% and 95.7% | Robotics | Yes |
| Yu et al. (2019a) | Weed detection | 33086 | Sony® Cyber-Shot, Canon® EOS Rebel T6 digital camera | VGGNet, AlexNet, DetectNet | F1 scores ≥92.78% recall values ≥ 99.52% | None | Yes |
| Liu et al. (2023) | Weed detection | 424 | Panasonic® DMC-ZS110 | SSL algorithm, CBAM, ResNet50 | accuracy ≥94.7% and ≥96% | Robotics | Yes |
| Chen et al. (2022) | Weed identification | 5187 | N/A | DTL, ResNeXt101 | F1 scores >95% | None | No |
| Amarasingam et al. (2023) | Weed detection | N/A | Micasense Altum multispectral camera | eXtreme Gradient Boosting (XGB), Support Vector Machine (SVM), Random Forest (RF), and K-nearest neighbours (KNN) | testing accuracy >96%, validation accuracy> 97% | UAV | No |
| Zou et al. (2022) | Weeds and crops detection | 1200 | RERVISION USB8MP02G | U-net | IoU≤88.98% | None | Yes |
| Rahman et al. (2023) | Weeds and crops detection | 848 | 4442 × 4335 pixels camera | YOLOv5, RetinaNet, EfficientDet, Fast RCNN and Faster RCNN | Highest accuracy mAP = 79.98% | None | No |
| Fathipoor et al. (2023) | Weed detection | N/A | Open-source dataset | U-net | IoU = 65% | None | No |
| (J.-L. Zhang et al., 2022) | Weeds and crops identification | 1918 | N/A | SE-YOLOv5x | precision = 97.6%, recall = 95.6%, mAP = 97.1%, F1-score = 97.3% | None | No |
| Nasiri et al. (2022) | Weed detection | 1385 | FotoClip, 2164 | U-net, ResNet50 | accuracy = 99.06, IoU = 84.23 | None | Yes |
| Ajayi and Ashi (2023) | Weed detection | 254 | N/A | Inception V2, faster RCNN | classification accuracy = 97.2%, weed precision = 96.2%, weed recall = 97.5% and a F1 score = 99% | UAV | No |
| Farooque et al. (2023) | Weed detection and spray | 2000 | Canon PowerShot SX540 HS camera, Logitech C270 HD Webcam | YOLOv3-tiny | precision = 87%, recall = 75%, mAP = 76.4%, Reduction in spraying liquid of 47 and 51% for weed and diseased plant detection | Robotics | Yes |
| Cai et al. (2023) | Weed identification | 2176 | DJI mavic 12 megapixels camera | ResNet50 | F-score = 87.79% | UAV | Yes |
| Saleem et al. (2022) | Weed identification | 17509 | N/A | SSD, YOLO-v4, EfficientDet, CenterNet, RetinaNet, Faster RCNN, and RFCN, | highest mAP = 87.64% | None | No |
| Jin et al. (2022a) | Weed identification | 24000 | DSC-HX1, SONY® | GoogLeNet, MobileNet-v3, ShufeNet-v2, and VGGNet | accuracy≥0.999, F1 scores≥0.998 | Robotics | Yes |
| Gao et al. (2020) | Weeds and crops detection | 2723 | Nikon D7200 | tiny-YOLOv3 | mAP = 0.829 | None | No |
| Xu et al. (2021) | Weeds and crops detection | 4750 | Open-source dataset | Xception, ImageNet, XGBoost | accuracy = 99.63% | None | No |
| Ma et al. (2019) | Weeds and crops identification | N/A | Canon IXUS 1000 HS | SegNet, FCN, U-Net | accuracy = 92.7%, 89.5% and 70.8% respectively | None | No |
| Huang et al. (2020) | Weed detection and mapping | 604 | SZ DJI drone camera | OBIA method | accuracy = 66.6% | UAV | Yes |
| Li et al. (2021) | Weeds and crops detection, and planting | 180 | N/A | MobileNetV2-SSD | accuracy = 94% | Robotics | No |
| Kamath et al. (2022b) | Weed identification | 4950 | Canon PowerShot SD3500 IS, Sony Cybershot (DSC-W220) | YOLO-v2 | accuracy = 90% | None | Yes |
| Peteinatos et al. (2020) | Weeds and crops identification | 93000 | Sony Alpha 7R Mark4 | VGG16, ResNet–50, and Xception | plant accuracy = 77%, weed accuracy = 98% | None | Yes |
| Xia et al. (2022) | Weed identification | N/A | DJI Phantom camera | N/A | barnyardgrass accuracy = 81.1% velvetleaf accuracy = 92.4% | UAV | Yes |
| Ajayi et al. (2023) | Weeds and crops identification | 254 | DJI Phantom 4 drone camera | YOLOv5 | accuracy = 65, precision = 43, recal = 43% | UAV | No |
| de Camargo et al. (2021) | Weeds and crops detection | N/A | Sony NEX 5N | ResNet-18 | accuracy = 94% | UAV | Yes |
| Ofori and Omar (2021) | Weeds and crops detection | 5539 | Open-source dataset | EfficientNet, transfer learning | accuracy = 95.44% | None | No |
| Pérez-Porras et al. (2023) | Weed detection | 6319 | Sony FDR-AX100E | YOLOv5 | accuracy = 77%, mAP = 76.2%, F1-score = 75.3% | None | Yes |
| Bah et al. (2018) | Weed detection | 5534 | DJI Phantom 3 Pro drone camera | ResNet18 | AUCs>82% | UAV | Yes |

(continued on next page)

**Table B2** (*continued*)

| Source | Functionality | Training Dataset | Capture Technology for dataset and testing | AI model | Outcomes and Accuracy | Auxiliary technologies | Herbicide |
|---|---|---|---|---|---|---|---|
| Osorio et al. (2020) | Weed detection | 100 | Mavic Pro with the Parrot Sequoia multispectral camera | SVM, YOLOv3, n Mask R–CNN | F1-scores of 88%, 94%, and 94% respectively | UAV | Yes |
| Partel et al. (2019b) | Weed detection and spray | 1000 | Webcam Logitech c920 | YOLOv3 | precision = 71%, recall = 78% | Robotics | Yes |
| Etienne et al. (2021) | Weed identification | 374 | a DJI Matrice 600 Pro hexacopter camera | YOLOv3 | AP = 91.48% | UAV | Yes |
| Halstead et al. (2021) | Weed and crop detection and removal | 2961 | PATHoBot camera | Mask-RCNN | precision = 86.5%, recall = 75.2, F1-score = 80.4 | Robotics | Yes |
| Khan et al. (2021) | Weed and crop detection and spray | 5400 | DJI Spark camera | faster R–CNN | accuracy = 94.7% | UAV | Yes |
| Quan et al. (2023) | weed competition analysis | 1855 | Pika L hyperspectral camera | CCI-A | prediction accuracy = 85% | IoT | No |
| Kamath et al. (2022a) | Weed detection | 2345 | Canon Power shot SD3500 IS and Sony DSLR | PSPNet, UNet, and SegNet | IoU>70%, accuracy>90% | None | Yes |
| Genze et al. (2022) | Weed identification | N/A | DJI Mavic 2 Pro camera | UNet-like, ResNet34 | F1-score>89% | UAV | Yes |

**Table B3**
Classification of the articles reviewed in this study pertaining to the related impact

| Source | Document Type | Technological | Social | Economic | Environmental |
|---|---|---|---|---|---|
| Quan et al. (2022) | Case study | ● | | | |
| Jiang et al. (2023) | Algorithm | ● | | | |
| Albraikan et al. (2022) | Case study | ● | | ● | ● |
| (H. Zhang et al., 2022) | Case study | ● | | | ● |
| Hussain et al. (2020) | Framework | ● | | | |
| (U. Farooq et al., 2022) | Algorithm | ● | | | |
| Fatima et al. (2023) | Framework | ● | | ● | ● |
| Modi et al. (2023) | Algorithm | ● | ● | | ● |
| Sapkota et al. (2022) | Framework | ● | | | |
| Xu et al. (2023) | Framework | ● | | ● | ● |
| Kong et al. (2023) | Framework | ● | | | |
| Barnhart et al. (2022) | Algorithm | ● | | | |
| Valente et al. (2022) | Framework | ● | | ● | |
| Danilevicz et al. (2023) | Framework | ● | | | |
| Gallo et al. (2023) | Case study | ● | | | |
| Costello et al. (2022) | Case study | ● | | | ● |
| Sapkota et al. (2020) | Framework | ● | ● | | ● |
| Moraitis et al. (2022) | Framework | ● | | | |
| (G C et al., 2022) | Framework | ● | | | |
| Hu et al. (2020) | Framework | ● | | | |
| Jin et al. (2022b) | Framework | ● | | | ● |
| Lou et al. (2022) | Algorithm | ● | | | |
| Wang et al. (2020) | Framework | ● | | | |
| Dang et al. (2023) | Framework | ● | | ● | |
| Hennessy et al. (2022) | Framework | ● | | | |
| (P. Wang et al., 2022) | Framework | ● | ● | | ● |
| Subeesh et al. (2022) | Case study | ● | | | ● |
| Thanh Le et al. (2021) | Case study | ● | | | ● |
| (A. Wang et al., 2022) | Case study | ● | ● | | ● |
| (A. Farooq et al., 2022) | Case study | ● | | ● | |
| Olsen et al. (2019) | Algorithm | ● | | | ● |
| Yu et al. (2019a) | Algorithm | ● | | | |
| Liu et al. (2023) | Case study | ● | | | |
| Chen et al. (2022) | Case study | ● | | ● | |
| Amarasingam et al. (2023) | Framework | ● | | | |
| Zou et al. (2022) | Case study | ● | | | |
| Rahman et al. (2023) | Framework | ● | | | |
| Fathipoor et al. (2023) | Framework | ● | | ● | ● |
| (J.-L. Zhang et al., 2022) | Case study | ● | | | |
| Nasiri et al. (2022) | Algorithm | ● | | | |
| Ajayi and Ashi (2023) | Algorithm | ● | ● | | ● |
| Farooque et al. (2023) | Framework | ● | ● | | |
| Cai et al. (2023) | Algorithm | ● | ● | | ● |
| Saleem et al. (2022) | Case study | ● | | ● | |

(*continued on next page*)

**Table B3** (*continued*)

| Source | Document Type | Technological | Social | Economic | Environmental |
|---|---|---|---|---|---|
| Jin et al. (2022a) | Framework | ● | | | |
| Gao et al. (2020) | Algorithm | ● | | | |
| Xu et al. (2021) | Framework | ● | | | |
| Ma et al. (2019) | Algorithm | ● | | | |
| Huang et al. (2020) | Case study | ● | | | |
| Li et al. (2021) | Case study | ● | | | |
| Kamath et al. (2022b) | Algorithm | ● | | | ● |
| Peteinatos et al. (2020) | Framework | ● | | | |
| Xia et al. (2022) | Algorithm | ● | | | ● |
| Ajayi et al. (2023) | Framework | ● | ● | | |
| de Camargo et al. (2021) | Framework | ● | | | |
| Ofori and Omar (2021) | Case study | ● | | | |
| Pérez-Porras et al. (2023) | Algorithm | ● | | | ● |
| Bah et al. (2018) | Algorithm | ● | | | |
| Osorio et al. (2020) | Case study | ● | | ● | ● |
| Partel et al. (2019b) | Framework | ● | | ● | ● |
| Etienne et al. (2021) | Case study | ● | | | |
| Halstead et al. (2021) | Framework | ● | | ● | ● |
| Khan et al. (2021) | Case study | ● | | ● | ● |
| Quan et al. (2023) | Framework | ● | | | |
| Kamath et al. (2022a) | Framework | ● | | | ● |
| Genze et al. (2022) | Algorithm | ● | | | |
| Quan et al. (2022) | Framework | ● | ● | | ● |
| Jiang et al. (2023) | Framework | ● | | | |

## References


Acemoglu, D., Restrepo, P., 2019. Automation and new tasks: how technology displaces and reinstates labor. J. Econ. Perspect. 33, 3–30. https://doi.org/10.1257/jep.33.2.3.

Adeux, G., Vieren, E., Carlesi, S., Bàrberi, P., Munier-Jolain, N., Cordeau, S., 2019. Mitigating crop yield losses through weed diversity. Nat. Sustain. 2, 1018–1026. https://doi.org/10.1038/s41893-019-0415-y.

Ahmad Loti, N.N., Mohd Noor, M.R., Chang, S., 2021. Integrated analysis of machine learning and deep learning in chili pest and disease identification. J. Sci. Food Agric. 101, 3582–3594. https://doi.org/10.1002/jsfa.10987.

Ajayi, O.G., Ashi, J., 2023. Effect of varying training epochs of a faster region-based convolutional neural network on the accuracy of an automatic weed classification scheme. Smart Agricultural Technology 3, 100128. https://doi.org/10.1016/j.atech.2022.100128.

Ajayi, O.G., Ashi, J., Guda, B., 2023. Performance evaluation of YOLO v5 model for automatic crop and weed classification on UAV images. Smart Agricultural Technology 5, 100231. https://doi.org/10.1016/j.atech.2023.100231.

Albraikan, A.A., Aljebreen, M., Alzahrani, J.S., Othman, M., Mohammed, G.P., Ibrahim Alsaid, M., 2022. Modified barnacles mating optimization with deep learning based weed detection model for smart agriculture. Appl. Sci. 12, 12828 https://doi.org/10.3390/app122412828.

Amarasingam, N., Hamilton, M., Kelly, J.E., Zheng, L., Sandino, J., Gonzalez, F., Dehaan, R.L., Cherry, H., 2023. Autonomous detection of mouse-ear hawkweed using drones, multispectral imagery and supervised machine learning. Remote Sens (Basel) 15, 1633. https://doi.org/10.3390/rs15061633.

Asghar, U., Malik, M., 2016. Pesticide exposure and human health: a review. J. Ecosyst. Ecography 1. https://doi.org/10.4172/2157-7625.S5-005.

Bah, M., Hafiane, A., Canals, R., 2018. Deep learning with unsupervised data labeling for weed detection in line crops in UAV images. Remote Sens (Basel) 10, 1690. https://doi.org/10.3390/rs10111690.

Bah, M.D., Hafiane, A., Canals, R., 2020. CRowNet: deep network for crop row detection in UAV images. IEEE Access 8, 5189–5200. https://doi.org/10.1109/ACCESS.2019.2960873.

Bakhshipour, A., Jafari, A., 2018. Evaluation of support vector machine and artificial neural networks in weed detection using shape features. Comput. Electron. Agric. 145, 153–160. https://doi.org/10.1016/j.compag.2017.12.032.

Bakhshipour, A., Jafari, A., Nassiri, S.M., Zare, D., 2017. Weed segmentation using texture features extracted from wavelet sub-images. Biosyst. Eng. 157, 1–12. https://doi.org/10.1016/j.biosystemseng.2017.02.002.

Barnhart, I.H., Lancaster, S., Goodin, D., Spotanski, J., Dille, J.A., 2022. Use of open-source object detection algorithms to detect Palmer amaranth (Amaranthus palmeri) in soybean. Weed Sci. 70, 648–662. https://doi.org/10.1017/wsc.2022.53.

Bochtis, D.D., Lampridi, M., Petropoulos, G.P., Ampatzidis, Y., Pardalos, P. (Eds.), 2022a. Information and Communication Technologies for Agriculture—Theme I: Sensors. Springer International Publishing, Cham. https://doi.org/10.1007/978-3-030-84144-7.

Bochtis, D.D., Moshou, D.E., Vasileiadis, G., Balafoutis, A., Pardalos, P.M. (Eds.), 2022b. Information and Communication Technologies for Agriculture—Theme II: Data. Springer International Publishing, Cham. https://doi.org/10.1007/978-3-030-84148-5.

Bochtis, D.D., Pearson, S., Lampridi, M., Marinoudi, V., Pardalos, P.M. (Eds.), 2021. Information and Communication Technologies for Agriculture—Theme IV: Actions. Springer International Publishing, Cham. https://doi.org/10.1007/978-3-030-84156-0.

Bochtis, D.D., Sørensen, C.G., Fountas, S., Moysiadis, V., Pardalos, P.M. (Eds.), 2022c. Information and Communication Technologies for Agriculture—Theme III: Decision. Springer International Publishing, Cham. https://doi.org/10.1007/978-3-030-84152-2.

Butte, S., Vakanski, A., Duellman, K., Wang, H., Mirkouei, A., 2021. Potato crop stress identification in aerial images using deep learning-based object detection. Agron. J. 113, 3991–4002. https://doi.org/10.1002/agj2.20841.

Cai, Y., Zeng, F., Xiao, J., Ai, W., Kang, G., Lin, Y., Cai, Z., Shi, H., Zhong, S., Yue, X., 2023. Attention-aided semantic segmentation network for weed identification in pineapple field. Comput. Electron. Agric. 210, 107881 https://doi.org/10.1016/j.compag.2023.107881.

Canadian Food Inspection Agency, 2020. National Chemical Residue Monitoring Program and Chemistry Food Safety Oversight Program Annual Report 2017-2018.

Chen, D., Lu, Y., Li, Z., Young, S., 2022. Performance evaluation of deep transfer learning on multi-class identification of common weed species in cotton production systems. Comput. Electron. Agric. 198, 107091 https://doi.org/10.1016/j.compag.2022.107091.

Chu, L., Liu, H., Zhang, Z., Zhan, Y., Wang, K., Yang, D., Liu, Z., Yu, J., 2022. Evaluation of wood vinegar as an herbicide for weed control. Agronomy 12, 3120. https://doi.org/10.3390/agronomy12123120.

Consumer Report, 2022. Which food to buy organic [WWW document]. URL. https://www.consumerreports.org/health/organic-foods/which-food-to-buy-organic-and-how-to-spend-less-when-you-do-a5815536309/, 9.19.23.

Consumer Reports, 2015. Pesticides in produce [WWW document]. Special Report. URL. https://www.consumerreports.org/cro/health/natural-health/pesticides/index.htm, 9.19.23.

Costello, B., Osunkoya, O.O., Sandino, J., Marinic, W., Trotter, P., Shi, B., Gonzalez, F., Dhileepan, K., 2022. Detection of parthenium weed (parthenium hysterophorus L.) and its growth stages using artificial intelligence. Agriculture (Switzerland) 12. https://doi.org/10.3390/agriculture12111838.

Dang, F., Chen, D., Lu, Y., Li, Z., 2023. YOLOWeeds: a novel benchmark of YOLO object detectors for multi-class weed detection in cotton production systems. Comput. Electron. Agric. 205 https://doi.org/10.1016/j.compag.2023.107655.

Danilevicz, M.F., Rocha, R.L., Batley, J., Bayer, P.E., Bennamoun, M., Edwards, D., Ashworth, M.B., 2023. Segmentation of sandplain lupin weeds from morphologically similar narrow-leafed lupins in the field. Remote Sens (Basel) 15, 1817. https://doi.org/10.3390/rs15071817.

de Camargo, T., Schirrmann, M., Landwehr, N., Dammer, K.-H., Pflanz, M., 2021. Optimized deep learning model as a basis for fast UAV mapping of weed species in winter wheat crops. Remote Sens (Basel) 13, 1704. https://doi.org/10.3390/rs13091704.

Du, X., Wang, X., Hatzenbuehler, P., 2023. Digital technology in agriculture: a review of issues, applications and methodologies. China Agric. Econ. Rev. 15, 95–108. https://doi.org/10.1108/CAER-01-2022-0009.

Duke, S.O., Dayan, F.E., 2022. The search for new herbicide mechanisms of action: is there a 'holy grail'? Pest Manag. Sci. 78, 1303–1313. https://doi.org/10.1002/ps.6726.

Dyrmann, M., Midtiby, H.S., Mortensen, A.K., 2016. Pixel-wise classification of weeds and crops in images by using a Fully Convolutional neural network. In: Proceedings of the International Conference on Agricultural Engineering. Aarhus, Denmark.

Environmental Working Group, 2023. EWG's 2023 shopper's guide to pesticides in produce [WWW document]. URL. https://www.ewg.org/foodnews/summary.php, 9.19.23.

Etienne, A., Ahmad, A., Aggarwal, V., Saraswat, D., 2021. Deep learning-based object detection system for identifying weeds using UAS imagery. Remote Sens (Basel) 13, 5182. https://doi.org/10.3390/rs13245182.

European Commission, 2023. Common agricultural policy [WWW Document]. Agriculture and rural development, EU. URL. https://agriculture.ec.europa.eu/common-agricultural-policy_en, 9.19.23.

European Food Safety Authority (Efsa), 2015. Conclusion on the peer review of the pesticide risk assessment of the active substance glyphosate. EFSA J. 13 https://doi.org/10.2903/j.efsa.2015.4302.

Farooq, A., Jia, X., Hu, J., Zhou, J., 2022. Transferable convolutional neural network for weed mapping with multisensor imagery. IEEE Trans. Geosci. Rem. Sens. 60, 1–16. https://doi.org/10.1109/TGRS.2021.3102243.

Farooq, U., Rehman, A., Khanam, T., Amtullah, A., Bou-Rabee, M.A., Tariq, M., 2022. Lightweight deep learning model for weed detection for IoT devices. In: 2022 2nd International Conference on Emerging Frontiers in Electrical and Electronic Technologies (ICEFEET). IEEE, pp. 1–5. https://doi.org/10.1109/ICEFEET51821.2022.9847812.

Farooque, A.A., Hussain, N., Schumann, A.W., Abbas, F., Afzaal, H., McKenzie-Gopsill, A., Esau, T., Zaman, Q., Wang, X., 2023. Field evaluation of a deep learning-based smart variable-rate sprayer for targeted application of agrochemicals. Smart Agricultural Technology 3, 100073. https://doi.org/10.1016/j.atech.2022.100073.

Fathipoor, H., Shah-Hosseini, R., Arefi, H., 2023. Crop and weed segmentation on ground-based images using deep convolutional neural network. In: ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences X-4/W1-2022, pp. 195–200. https://doi.org/10.5194/isprs-annals-X-4-W1-2022-195-2023.

Fatima, H.S., ul Hassan, I., Hasan, S., Khurram, M., Stricker, D., Afzal, M.Z., 2023. Formation of a lightweight, deep learning-based weed detection system for a commercial autonomous laser weeding robot. Appl. Sci. 13, 3997. https://doi.org/10.3390/app13063997.

G C, S., Zhang, Y., Koparan, C., Ahmed, M.R., Howatt, K., Sun, X., 2022. Weed and crop species classification using computer vision and deep learning technologies in greenhouse conditions. J Agric Food Res 9, 100325. https://doi.org/10.1016/j.jafr.2022.100325.

Gallardo, R.K., Sauer, J., 2018. Adoption of labor-saving technologies in agriculture. Annu Rev Resour Economics 10, 185–206. https://doi.org/10.1146/annurev-resource-100517-023018.

Gallo, I., Rehman, A.U., Dehkordi, R.H., Landro, N., La Grassa, R., Boschetti, M., 2023. Deep object detection of crop weeds: performance of YOLOv7 on a real case dataset from UAV images. Remote Sens (Basel) 15, 539. https://doi.org/10.3390/rs15020539.

Gao, J., French, A.P., Pound, M.P., He, Y., Pridmore, T.P., Pieters, J.G., 2020. Deep convolutional neural networks for image-based Convolvulus sepium detection in sugar beet fields. Plant Methods 16, 29. https://doi.org/10.1186/s13007-020-00570-z.

Genze, N., Ajekwe, R., Güreli, Z., Haselbeck, F., Grieb, M., Grimm, D.G., 2022. Deep learning-based early weed segmentation using motion blurred UAV images of sorghum fields. Comput. Electron. Agric. 202, 107388 https://doi.org/10.1016/j.compag.2022.107388.

Gerhards, R., Andújar Sanchez, D., Hamouz, P., Peteinatos, G.G., Christensen, S., Fernandez-Quintanilla, C., 2022. Advances in site-specific weed management in agriculture—a review. Weed Res. 62, 123–133. https://doi.org/10.1111/wre.12526.

Ghatrehsamani, S., Jha, G., Dutta, W., Molaei, F., Nazrul, F., Fortin, M., Bansal, S., Debangshi, U., Neupane, J., 2023. Artificial intelligence tools and techniques to combat herbicide resistant weeds—a review. Sustainability 15. https://doi.org/10.3390/su15031843.

Gutiérrez, P.A., López-Granados, F., Peña-Barragán, J.M., Jurado-Expósito, M., Hervás-Martínez, C., 2008. Logistic regression product-unit neural networks for mapping Ridolfia segetum infestations in sunflower crop using multitemporal remote sensed data. Comput. Electron. Agric. 64, 293–306. https://doi.org/10.1016/j.compag.2008.06.001.

Hakme, E., Herrmann, S., S., E. Poulsen, M., 2020. Data processing approach for the screening and quantification of pesticide residues in food matrices for early-generation GC-TOFMS. Brazilian J. Anal. Chem. 7 https://doi.org/10.30744/brjac.2179-3425.AR-36-2019.

Halstead, M., Ahmadi, A., Smitt, C., Schmittmann, O., McCool, C., 2021. Crop agnostic monitoring driven by deep learning. Front. Plant Sci. 12 https://doi.org/10.3389/fpls.2021.786702.

Hassan, S.I., Alam, M.M., Illahi, U., Al Ghamdi, M.A., Almotiri, S.H., Su'ud, M.M., 2021. A systematic review on monitoring and advanced control strategies in smart agriculture. IEEE Access 9, 32517–32548. https://doi.org/10.1109/ACCESS.2021.3057865.

Hennessy, P.J., Esau, T.J., Schumann, A.W., Zaman, Q.U., Corscadden, K.W., Farooque, A.A., 2022. Evaluation of cameras and image distance for CNN-based weed detection in wild blueberry. Smart Agricultural Technology 2, 100030. https://doi.org/10.1016/j.atech.2021.100030.

Hu, K., Coleman, G., Zeng, S., Wang, Z., Walsh, M., 2020. Graph weeds net: a graph-based deep learning method for weed recognition. Comput. Electron. Agric. 174, 105520 https://doi.org/10.1016/j.compag.2020.105520.

Huang, H., Lan, Y., Yang, A., Zhang, Y., Wen, S., Deng, J., 2020. Deep learning versus Object-based Image Analysis (OBIA) in weed mapping of UAV imagery. Int. J. Rem. Sens. 41, 3446–3479. https://doi.org/10.1080/01431161.2019.1706112.

Hussain, N., Farooque, A., Schumann, A., McKenzie-Gopsill, A., Esau, T., Abbas, F., Acharya, B., Zaman, Q., 2020. Design and development of a smart variable rate sprayer using deep learning. Remote Sens (Basel) 12, 4091. https://doi.org/10.3390/rs12244091.

Ismail, N., Malik, O.A., 2022. Real-time visual inspection system for grading fruits using computer vision and deep learning techniques. Information Process. Agric. 9, 24–37. https://doi.org/10.1016/j.inpa.2021.01.005.

Jha, Kirtan, Doshi, A., Patel, P., Shah, M., 2019. A comprehensive review on automation in agriculture using artificial intelligence. Artificial Intell. Agric. 2, 1–12. https://doi.org/10.1016/j.aiia.2019.05.004.

Jha, K., Doshi, A., Patel, P., Shah, M., 2019. A comprehensive review on automation in agriculture using artificial intelligence. Artificial Intell. Agric. 2, 1–12. https://doi.org/10.1016/j.aiia.2019.05.004.

Jiang, W., Quan, L., Wei, G., Chang, C., Geng, T., 2023. A conceptual evaluation of a weed control method with post-damage application of herbicides: a composite intelligent intra-row weeding robot. Soil Tillage Res. 234, 105837 https://doi.org/10.1016/j.still.2023.105837.

Jin, X., Bagavathiannan, M., Maity, A., Chen, Y., Yu, J., 2022a. Deep learning for detecting herbicide weed control spectrum in turfgrass. Plant Methods 18, 94. https://doi.org/10.1186/s13007-022-00929-4.

Jin, X., Liu, T., Yang, Z., Xie, J., Bagavathiannan, M., Hong, X., Xu, Z., Chen, X., Yu, J., Chen, Y., 2023. Precision weed control using a smart sprayer in dormant bermudagrass turf. Crop Protect. 172, 106302 https://doi.org/10.1016/j.cropro.2023.106302.

Jin, X., Sun, Y., Che, J., Bagavathiannan, M., Yu, J., Chen, Y., 2022b. A novel deep <scp>learning-based</scp> method for detection of weeds in vegetables. Pest Manag. Sci. 78, 1861–1869. https://doi.org/10.1002/ps.6804.

Johansson, D., Juell, J.-E., Oppedal, F., Stiansen, J.-E., Ruohonen, K., 2007. The influence of the pycnocline and cage resistance on current flow, oxygen flux and swimming behaviour of Atlantic salmon (Salmo salar L.) in production cages. Aquaculture 265, 271–287. https://doi.org/10.1016/j.aquaculture.2006.12.047.

Kamath, R., Balachandra, M., Vardhan, A., Maheshwari, U., 2022a. Classification of paddy crop and weeds using semantic segmentation. Cogent Eng 9. https://doi.org/10.1080/23311916.2021.2018791.

Kamath, R., Balachandra, M., Vardhan, A., Maheshwari, U., 2022b. Classification of weeds of paddy fields using deep learning. ECTI Trans. Comput. Information Technol.(ECTI-CIT) 16, 365–377. https://doi.org/10.37936/ecti-cit.2022164.246857.

Khan, S., Hussain, Z., Khan, H., Uslu, O.S., 2023. Comparison of artificial intelligence and synthetic herbicides for weed control in wheat crop. Pakistan J. Weed Sci. Res. 29, 81–87.

Khan, S., Tufail, M., Khan, M.T., Khan, Z.A., Anwar, S., 2021. Deep learning-based identification system of weeds and crops in strawberry and pea fields for a precision agriculture sprayer. Precis. Agric. 22, 1711–1727. https://doi.org/10.1007/s11119-021-09808-9.

Kitchenham, B., Charters, S., 2007. Guidelines for Performing Systematic Literature Reviews in Software Engineering.

Kong, S., Li, J., Zhai, Y., Gao, Z., Zhou, Y., Xu, Y., 2023. Real-time detection of crops with dense planting using deep learning at seedling stage. Agronomy 13, 1503. https://doi.org/10.3390/agronomy13061503.

Kopittke, P.M., Menzies, N.W., Wang, P., McKenna, B.A., Lombi, E., 2019. Soil and the intensification of agriculture for global food security. Environ. Int. 132, 105078 https://doi.org/10.1016/j.envint.2019.105078.

Kulkarni, A.A., Dhanush, P., Chethan, B.S., Thammegowda, C.S., Shrivastava, P.K., 2020. Recent development of AI and IoT in the field of agriculture industries: a review. In: Advances in Intelligent Systems and Computing. Springer, pp. 793–798. https://doi.org/10.1007/978-981-15-4032-5_71.

Kyrgiakos, L.S., Kleftodimos, G., Vlontzos, G., Pardalos, P.M., 2023. A systematic literature review of data envelopment analysis implementation in agriculture under the prism of sustainability. Operational Res. 23, 7. https://doi.org/10.1007/s12351-023-00741-5.

Li, X., Du, X., Chen, B., Gong, L., Liu, C., Zhou, Q., He, L., 2021. Design of multifunctional seedbed planting robot based on MobileNetV2-SSD. In: 2021 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA). IEEE, pp. 272–278. https://doi.org/10.1109/ICAICA52286.2021.9498205.

Liu, J., Abbas, I., Noor, R.S., 2021. Development of deep learning-based variable rate agrochemical spraying system for targeted weeds control in strawberry crop. Agronomy 11, 1480. https://doi.org/10.3390/agronomy11081480.

Liu, J., Wang, X., 2021. Plant diseases and pests detection based on deep learning: a review. Plant Methods 17, 22. https://doi.org/10.1186/s13007-021-00722-9.

Liu, T., Jin, X., Zhang, L., Wang, J., Chen, Y., Hu, C., Yu, J., 2023. Semi-supervised learning and attention mechanism for weed detection in wheat. Crop Protect. 174, 106389 https://doi.org/10.1016/j.cropro.2023.106389.

Lottes, P., Behley, J., Milioto, A., Stachniss, C., 2018. Fully convolutional networks with sequential information for robust crop and weed detection in precision farming. IEEE Rob. Autom. Lett. 3, 2870–2877. https://doi.org/10.1109/LRA.2018.2846289.

Lou, Z., Quan, L., Sun, D., Li, H., Xia, F., 2022. Hyperspectral remote sensing to assess weed competitiveness in maize farmland ecosystems. Sci. Total Environ. 844, 157071 https://doi.org/10.1016/j.scitotenv.2022.157071.

Lv, J., Xu, H., Xu, L., Zou, L., Rong, H., Yang, B., Niu, L., Ma, Z., 2022. Recognition of fruits and vegetables with similar-color background in natural environment: a survey. J. Field Robot. 39, 888–904. https://doi.org/10.1002/rob.22074.

Ma, X., Deng, X., Qi, L., Jiang, Y., Li, H., Wang, Y., Xing, X., 2019. Fully convolutional network for rice seedling and weed image segmentation at the seedling stage in paddy fields. PLoS One 14, e0215676. https://doi.org/10.1371/journal.pone.0215676.

Mishra, A.M., Gautam, V., 2021. Weed species identification in different crops using precision weed management: a review. In: CEUR Workshop Proceedings. CEUR-WS, pp. 180–194.

Modi, R.U., Kancheti, M., Subeesh, A., Raj, C., Singh, A.K., Chandel, N.S., Dhimate, A.S., Singh, M.K., Singh, S., 2023. An automated weed identification framework for sugarcane crop: a deep learning approach. Crop Protect. 173, 106360 https://doi.org/10.1016/j.cropro.2023.106360.

Molinari, F.A., Blanco, A.M., Vigna, M.R., Chantre, G.R., 2020. Towards an integrated weed management decision support system: a simulation model for weed-crop competition and control. Comput. Electron. Agric. 175 https://doi.org/10.1016/j.compag.2020.105597.

Moraitis, M., Vaiopoulos, K., Balafoutis, A.T., 2022. Design and implementation of an urban farming robot. Micromachines 13, 250. https://doi.org/10.3390/mi13020250.

Movedi, E., Valiante, D., Colosio, A., Corengia, L., Cossa, S., Confalonieri, R., 2022. A new approach for modeling crop-weed interaction targeting management support in operational contexts: a case study on the rice weeds barnyardgrass and red rice. Ecol. Model. 463 https://doi.org/10.1016/j.ecolmodel.2021.109797.

Nasiri, A., Omid, M., Taheri-Garavand, A., Jafari, A., 2022. Deep learning-based precision agriculture through weed recognition in sugar beet fields. Sustainable Computing: Informatics and Systems 35, 100759. https://doi.org/10.1016/j.suscom.2022.100759.

NATAE, 2023. Foster agroecological transition in North Africa [WWW document]. URL. https://www.natae-agroecology.eu/, 10.30.23.

Ofori, M., Omar, E.-G., 2021. An approach for weed detection using CNNs and transfer learning. In: Annual Hawaii International Conference on System Sciences.

Olsen, A., Konovalov, D.A., Philippa, B., Ridd, P., Wood, J.C., Johns, J., Banks, W., Girgenti, B., Kenny, O., Whinney, J., Calvert, B., Azghadi, M.R., White, R.D., 2019. DeepWeeds: a multiclass weed species image dataset for deep learning. Sci. Rep. 9, 2058. https://doi.org/10.1038/s41598-018-38343-3.

Ong, K., Haw, S.-C., Ng, K.-W., 2019. Deep learning based-recommendation system. In: Proceedings of the 2019 2nd International Conference on Computational Intelligence and Intelligent Systems. ACM, New York, NY, USA, pp. 6–11. https://doi.org/10.1145/3372422.3372444.

Onishi, Y., Yoshida, T., Kurita, H., Fukao, T., Arihara, H., Iwai, A., 2019. An automated fruit harvesting robot by using deep learning. ROBOMECH Journal 6, 13. https://doi.org/10.1186/s40648-019-0141-2.

Osorio, K., Puerto, A., Pedraza, C., Jamaica, D., Rodríguez, L., 2020. A deep learning approach for weed detection in lettuce crops using multispectral images. AgriEngineering 2, 471–488. https://doi.org/10.3390/agriengineering2030032.

Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D., Shamseer, L., Tetzlaff, J.M., Akl, E.A., Brennan, S.E., Chou, R., Glanville, J., Grimshaw, J.M., Hróbjartsson, A., Lalu, M.M., Li, T., Loder, E.W., Mayo-Wilson, E., McDonald, S., McGuinness, L.A., Stewart, L.A., Thomas, J., Tricco, A.C., Welch, V.A., Whiting, P., Moher, D., 2021a. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ n71. https://doi.org/10.1136/bmj.n71.

Page, M.J., Moher, D., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D., Shamseer, L., Tetzlaff, J.M., Akl, E.A., Brennan, S.E., Chou, R., Glanville, J., Grimshaw, J.M., Hróbjartsson, A., Lalu, M.M., Li, T., Loder, E.W., Mayo-Wilson, E., McDonald, S., McGuinness, L.A., Stewart, L.A., Thomas, J., Tricco, A.C., Welch, V.A., Whiting, P., McKenzie, J.E., 2021b. PRISMA 2020 explanation and elaboration: updated guidance and exemplars for reporting systematic reviews. BMJ n160. https://doi.org/10.1136/bmj.n160.

Panati, H.S., P, G., A, D.A., T, M.N., 2023. Weeds and crop image classification using deep learning technique. In: 2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS). IEEE, pp. 117–122. https://doi.org/10.1109/ICACCS57279.2023.10112958.

Partel, V., Charan Kakarla, S., Ampatzidis, Y., 2019a. Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence. Comput. Electron. Agric. 157, 339–350. https://doi.org/10.1016/j.compag.2018.12.048.

Partel, V., Charan Kakarla, S., Ampatzidis, Y., 2019b. Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence. Comput. Electron. Agric. 157, 339–350. https://doi.org/10.1016/j.compag.2018.12.048.

Pérez-Porras, F.J., Torres-Sánchez, J., López-Granados, F., Mesas-Carrascosa, F.J., 2023. Early and on-ground image-based detection of poppy (*Papaver rhoeas*) in wheat using YOLO architectures. Weed Sci. 71, 50–58. https://doi.org/10.1017/wsc.2022.64.

Peteinatos, G.G., Reichel, P., Karouta, J., Andújar, D., Gerhards, R., 2020. Weed identification in maize, sunflower, and potatoes with the aid of convolutional neural networks. Remote Sens (Basel) 12, 4185. https://doi.org/10.3390/rs12244185.

Quan, L., Jiang, W., Li, Hailong, Li, Hengda, Wang, Q., Chen, L., 2022. Intelligent intra-row robotic weeding system combining deep learning technology with a targeted weeding mode. Biosyst. Eng. 216, 13–31. https://doi.org/10.1016/j.biosystemseng.2022.01.019.

Quan, L., Lou, Z., Lv, X., Sun, D., Xia, F., Li, H., Sun, W., 2023. Multimodal remote sensing application for weed competition time series analysis in maize farmland ecosystems. J. Environ. Manag. 344, 118376 https://doi.org/10.1016/j.jenvman.2023.118376.

Rahman, A., Lu, Y., Wang, H., 2023. Performance evaluation of deep learning object detectors for weed detection for cotton. Smart Agricultural Technology 3, 100126. https://doi.org/10.1016/j.atech.2022.100126.

Rai, N., Flores, P., 2021. Leveraging transfer learning in ArcGIS Pro to detect “doubles” in a sunflower field. In: 2021 ASABE Annual International Virtual Meeting, July 12-16, 2021. American Society of Agricultural and Biological Engineers, St. Joseph, MI. https://doi.org/10.13031/aim.202100742.

Rai, N., Zhang, Y., Ram, B.G., Schumacher, L., Yellavajjala, R.K., Bajwa, S., Sun, X., 2023. Applications of deep learning in precision weed management: a review. Comput. Electron. Agric. 206, 107698 https://doi.org/10.1016/j.compag.2023.107698.

Ramankutty, N., Mehrabi, Z., Waha, K., Jarvis, L., Kremen, C., Herrero, M., Rieseberg, L. H., 2018. Trends in global agricultural land use: implications for environmental health and food security. Annu. Rev. Plant Biol. 69, 789–815. https://doi.org/10.1146/annurev-arplant-042817-040256.

Roslim, M.H.M., Juraimi, A.S., Che'ya, N.N., Sulaiman, N., Manaf, M.N.H.A., Ramli, Z., Motmainna, M., 2021. Using remote sensing and an unmanned aerial system for weed management in agricultural crops: a review. Agronomy 11. https://doi.org/10.3390/agronomy11091809.

Sachithra, V., Subhashini, L.D.C.S., 2023. How artificial intelligence uses to achieve the agriculture sustainability: systematic review. Artificial Intell. Agric. 8, 46–59. https://doi.org/10.1016/j.aiia.2023.04.002.

Saleem, M.H., Velayudhan, K.K., Potgieter, J., Arif, K.M., 2022. Weed identification by single-stage and two-stage neural networks: a study on the impact of image resizers and weights optimization algorithms. Front. Plant Sci. 13 https://doi.org/10.3389/fpls.2022.850666.

Sapkota, B., Singh, V., Neely, C., Rajan, N., Bagavathiannan, M., 2020. Detection of Italian ryegrass in wheat and prediction of competitive interactions using remote-sensing and machine-learning techniques. Remote Sens (Basel) 12, 2977. https://doi.org/10.3390/rs12182977.

Sapkota, B.B., Popescu, S., Rajan, N., Leon, R.G., Reberg-Horton, C., Mirsky, S., Bagavathiannan, M.V., 2022. Use of synthetic images for training a deep learning model for weed detection and biomass estimation in cotton. Sci. Rep. 12, 19580 https://doi.org/10.1038/s41598-022-23399-z.

Saqib, M.A., Aqib, M., Tahir, M.N., Hafeez, Y., 2023. Towards deep learning based smart farming for intelligent weeds management in crops. Front. Plant Sci. 14 https://doi.org/10.3389/fpls.2023.1211235.

Shirzadifar, A., Bajwa, S., Nowatzki, J., Shojaeiarani, J., 2020. Development of spectral indices for identifying glyphosate-resistant weeds. Comput. Electron. Agric. 170, 105276 https://doi.org/10.1016/j.compag.2020.105276.

Shorewala, S., Ashfaque, A., Sidharth, R., Verma, U., 2021. Weed density and distribution estimation for precision agriculture using semi-supervised learning. IEEE Access 9, 27971–27986. https://doi.org/10.1109/ACCESS.2021.3057912.

Snyder, H., 2019. Literature review as a research methodology: an overview and guidelines. J. Bus. Res. 104, 333–339. https://doi.org/10.1016/j.jbusres.2019.07.039.

Subeesh, A., Bhole, S., Singh, K., Chandel, N.S., Rajwade, Y.A., Rao, K.V.R., Kumar, S.P., Jat, D., 2022. Deep convolutional neural network models for weed detection in polyhouse grown bell peppers. Artificial Intell. Agric. 6, 47–54. https://doi.org/10.1016/j.aiia.2022.01.002.

Sudars, K., Jasko, J., Namatevs, I., Ozola, L., Badaukis, N., 2020. Dataset of annotated food crops and weed images for robotic computer vision control. Data Brief 31. https://doi.org/10.1016/j.dib.2020.105833.

Swain, K.C., Nørremark, M., Jørgensen, R.N., Midtiby, H.S., Green, O., 2011. Weed identification using an automated active shape matching (AASM) technique. Biosyst. Eng. 110, 450–457. https://doi.org/10.1016/j.biosystemseng.2011.09.011.

Tang, J., Wang, D., Zhang, Z., He, L., Xin, J., Xu, Y., 2017. Weed identification based on K-means feature learning combined with convolutional neural network. Comput. Electron. Agric. 135, 63–70. https://doi.org/10.1016/j.compag.2017.01.001.

Tanveer, U., Kremantzis, M.D., Roussinos, N., Ishaq, S., Kyrgiakos, L.S., Vlontzos, G., 2023. A fuzzy TOPSIS model for selecting digital technologies in circular supply chains. Supply Chain Analytics 4, 100038. https://doi.org/10.1016/j.sca.2023.100038.

Thanh Le, V.N., Truong, G., Alameh, K., 2021. Detecting weeds from crops under complex field environments based on Faster RCNN. In: 2020 IEEE Eighth International Conference on Communications and Electronics (ICCE). IEEE, pp. 350–355. https://doi.org/10.1109/ICCE48956.2021.9352073.

Thompson, D., Chartrand, D., Staznik, B., Leach, J., Hodgins, P., 2010. Integrating advanced technologies for optimization of aerial herbicide applications. New For (Dordr) 40, 45–66. https://doi.org/10.1007/s11056-009-9181-4.

Tshewang, S., Sindel, B.M., Ghimiray, M., Chauhan, B.S., 2016. Weed management challenges in rice (Oryza sativa L.) for food security in Bhutan: a review. Crop Protect. 90, 117–124. https://doi.org/10.1016/j.cropro.2016.08.031.

Valente, J., Hiremath, S., Ariza-Sentís, M., Doldersum, M., Kooistra, L., 2022. Mapping of Rumex obtusifolius in nature conservation areas using very high resolution UAV imagery and deep learning. Int. J. Appl. Earth Obs. Geoinf. 112, 102864 https://doi.org/10.1016/j.jag.2022.102864.

van Klompenburg, T., Kassahun, A., Catal, C., 2020. Crop yield prediction using machine learning: a systematic literature review. Comput. Electron. Agric. 177, 105709 https://doi.org/10.1016/j.compag.2020.105709.

Waltman, L., Ecken, N., 2010. VOSViewer: visualizing scientifc landscapes. https://www.vosviewer.com/.

Wang, A., Peng, T., Cao, H., Xu, Y., Wei, X., Cui, B., 2022. TIA-YOLOv5: an improved YOLOv5 network for real-time detection of crop and weed in the field. Front. Plant Sci. 13 https://doi.org/10.3389/fpls.2022.1091655.

Wang, A., Xu, Y., Wei, X., Cui, B., 2020. Semantic segmentation of crop and weed using an encoder-decoder network and image enhancement method under uncontrolled outdoor illumination. IEEE Access 8, 81724–81734. https://doi.org/10.1109/ACCESS.2020.2991354.

Wang, P., Tang, Y., Luo, F., Wang, L., Li, C., Niu, Q., Li, H., 2022. Weed25: a deep learning dataset for weed identification. Front. Plant Sci. 13 https://doi.org/10.3389/fpls.2022.1053329.

Wohlin, C., 2014. Guidelines for snowballing in systematic literature studies and a replication in software engineering. In: Proceedings of the 18th International Conference on Evaluation and Assessment in Software Engineering. ACM, New York, NY, USA, pp. 1–10. https://doi.org/10.1145/2601248.2601268.

World Health Organization, 2022. Pesticide residues in food [WWW Document]. Pesticide residues in food. URL. https://www.who.int/news-room/fact-sheets/detail/pesticide-residues-in-food, 9.19.23.

Wu, Z., Chen, Y., Zhao, B., Kang, X., Ding, Y., 2021. Review of weed detection methods based on computer vision. Sensors 21, 3647. https://doi.org/10.3390/s21113647.

Xia, F., Quan, L., Lou, Z., Sun, D., Li, H., Lv, X., 2022. Identification and comprehensive evaluation of resistant weeds using unmanned aerial vehicle-based multispectral imagery. Front. Plant Sci. 13 https://doi.org/10.3389/fpls.2022.938604.

Xiao, Y., Watson, M., 2019. Guidance on conducting a systematic literature review. J. Plann. Educ. Res. 39, 93–112. https://doi.org/10.1177/0739456X17723971.

Xu, B., Fan, J., Chao, J., Arsenijevic, N., Werle, R., Zhang, Z., 2023. Instance segmentation method for weed detection using UAV imagery in soybean fields. Comput. Electron. Agric. 211, 107994 https://doi.org/10.1016/j.compag.2023.107994.

Xu, Y., Zhai, Y., Zhao, B., Jiao, Y., Kong, S., Zhou, Y., Gao, Z., 2021. Weed recognition for depthwise separable network based on transfer learning. Intelligent Automation & Soft Computing 27, 669–682. https://doi.org/10.32604/iasc.2021.015225.

Yasrab, R., Zhang, J., Smyth, P., Pound, M.P., 2021. Predicting plant growth from time-series data using deep learning. Remote Sens (Basel) 13, 331. https://doi.org/10.3390/rs13030331.

Yu, J., Schumann, A.W., Cao, Z., Sharpe, S.M., Boyd, N.S., 2019a. Weed detection in perennial ryegrass with deep learning convolutional neural network. Front. Plant Sci. 10 https://doi.org/10.3389/fpls.2019.01422.

Yu, J., Sharpe, S.M., Boyd, N.S., 2019b. Fumigants alone or in combination with herbicide for weed management in bell pepper (Capsicum annuum). Crop Protect. 118, 31–35. https://doi.org/10.1016/j.cropro.2018.12.010.

Zhang, H., Wang, Z., Guo, Y., Ma, Y., Cao, W., Chen, D., Yang, S., Gao, R., 2022. Weed detection in peanut fields based on machine vision. Agriculture 12, 1541. https://doi.org/10.3390/agriculture12101541.

Zhang, J.-L., Su, W.-H., Zhang, H.-Y., Peng, Y., 2022. SE-YOLOv5x: an optimized model based on transfer learning and visual attention mechanism for identifying and localizing weeds and vegetables. Agronomy 12, 2061. https://doi.org/10.3390/agronomy12092061.

Zou, K., Liao, Q., Zhang, F., Che, X., Zhang, C., 2022. A segmentation network for smart weed management in wheat fields. Comput. Electron. Agric. 202, 107303 https://doi.org/10.1016/j.compag.2022.107303.