

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

ARTICLE INFO

Keywords:

Weed management
Artificial intelligence
Deep learning
Precision agriculture
Agroecology
Sustainability

ABSTRACT

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

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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, Ace-moglu 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. • Provide an overview of DL models and the existing methodologies utilized for the detection of weeds. • 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. • Provides an overview of the management of herbicide-resistant weeds, including the problems and opportunities. • 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. • Examine diverse AI initiatives to accomplish sustainability goals for growth. • 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. • 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

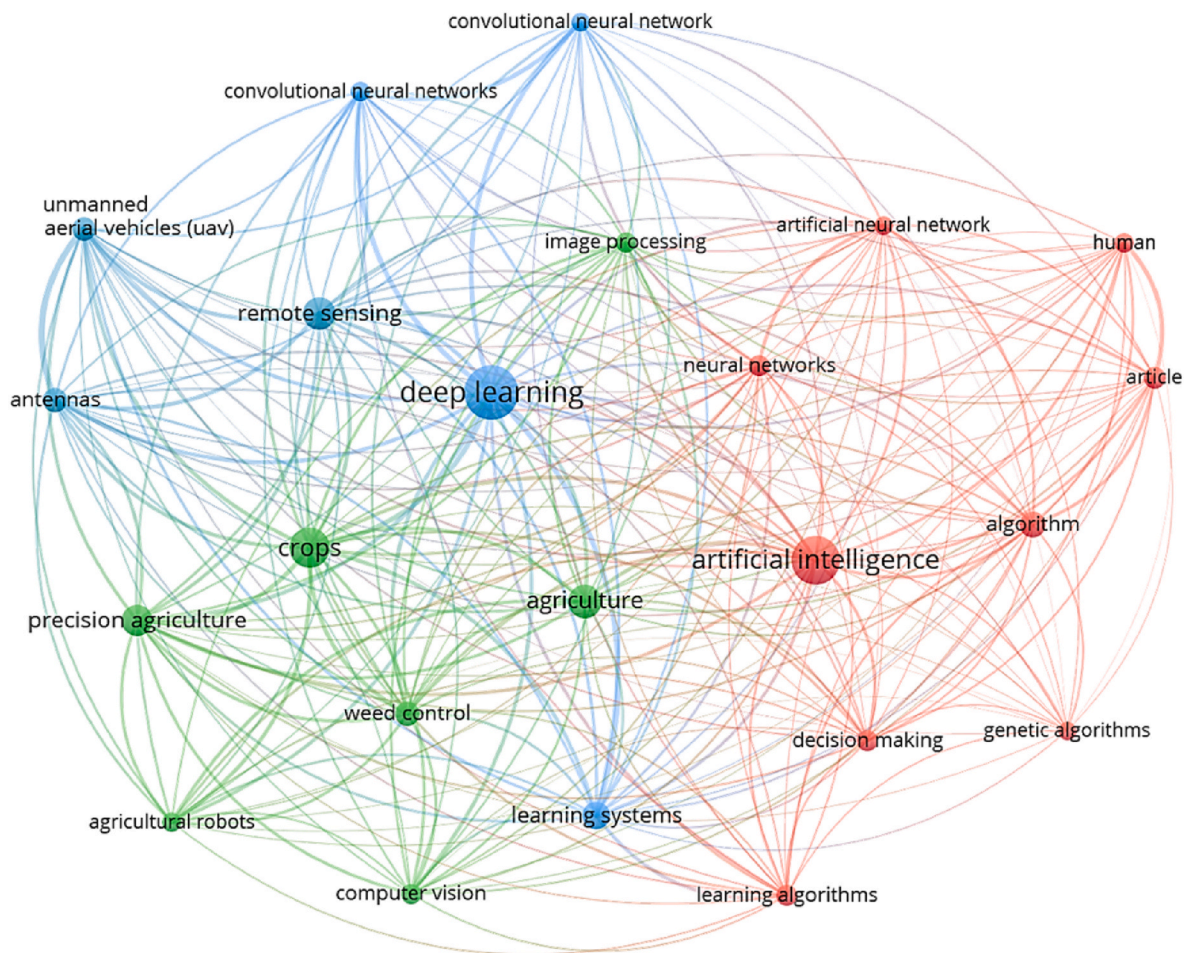


Fig. 1. Relationship of the keywords regarding “weed management”, and “artificial intelligence”.

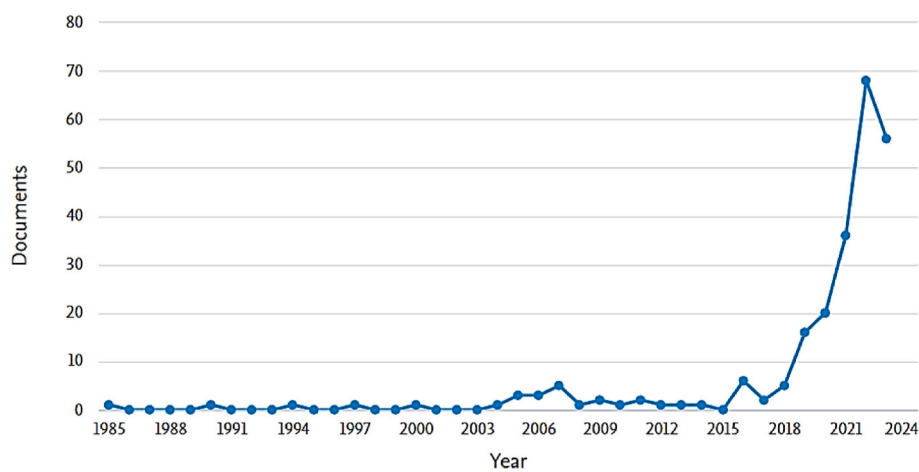


Fig. 2. Number of publications per year pertaining to the three terms in the final search query.

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

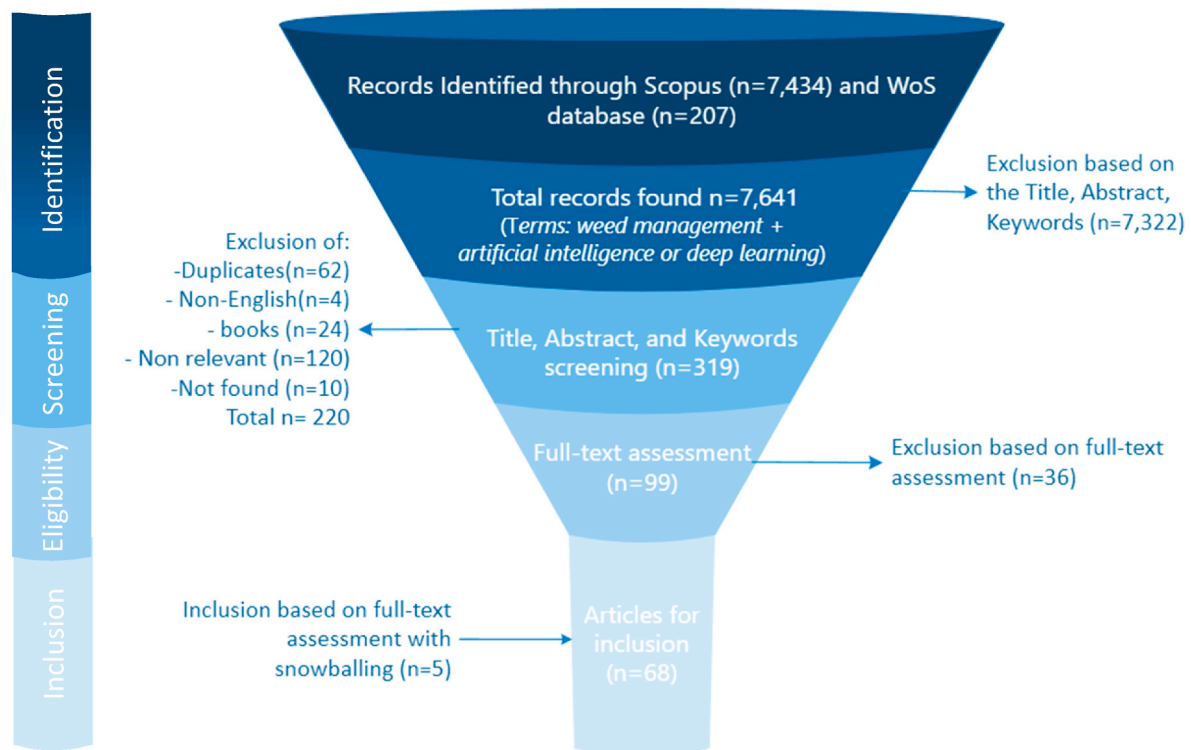


Fig. 3. Funnel diagram of SLR methodology using PRISMA guidelines.

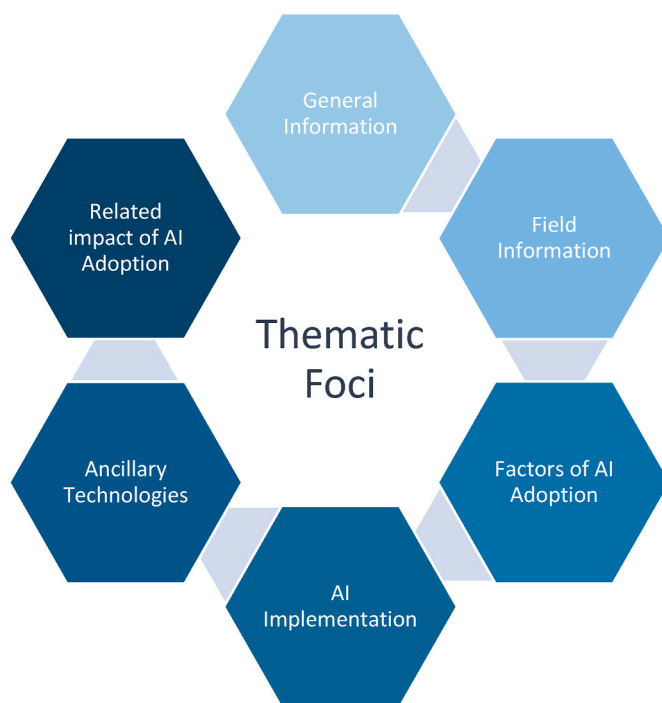


Fig. 4. SLR Thematic Foci of criteria.

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.

Table 2 (continued)

Category	Criteria	Description
	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.

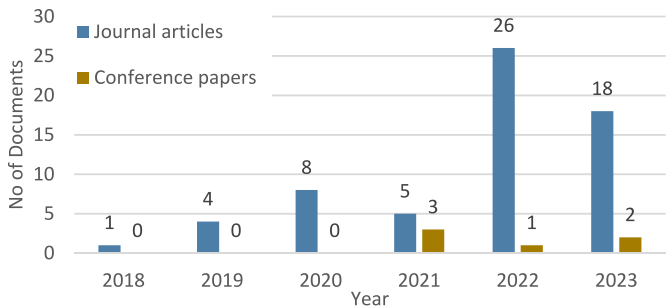


Fig. 5. Year-wise and source-type publications included in this analysis.

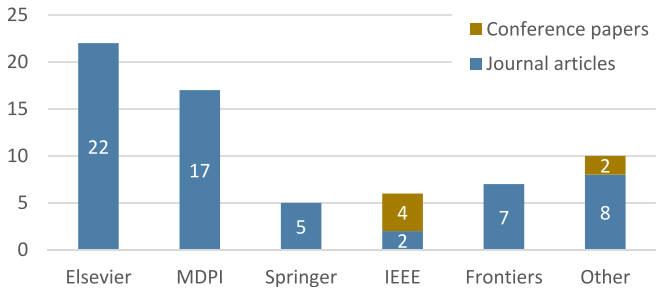


Fig. 6. Number of articles per publisher, categorized according to their respective source types.

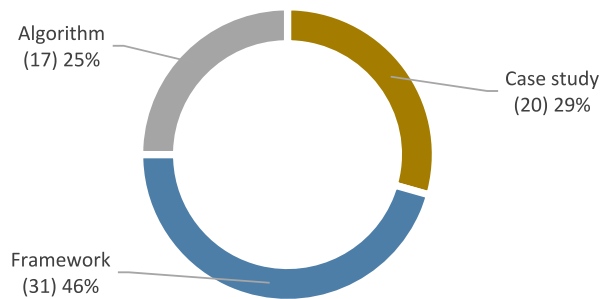


Fig. 7. Articles classified by their respective content type.

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.

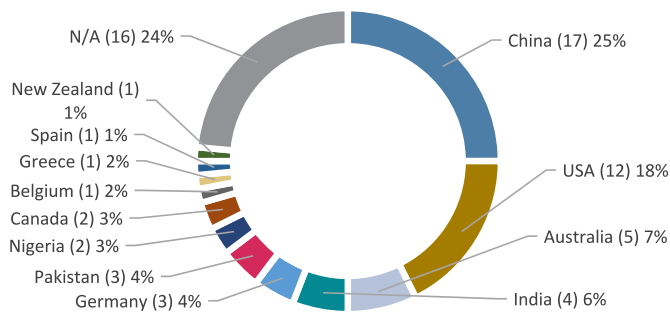


Fig. 8. Countries in which experimentations take place in this SLR.

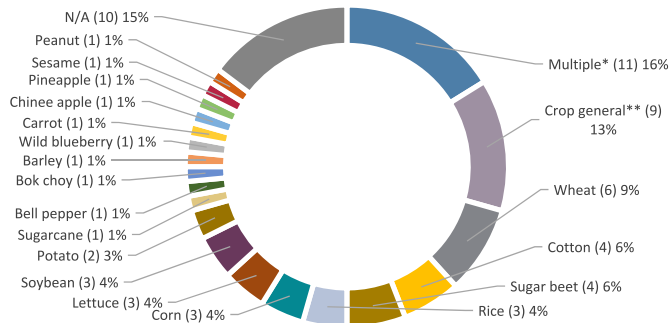


Fig. 9. Crops applied AI-enabled weed management. (* The article investigates more than one crops, ** The article refers crop in general).

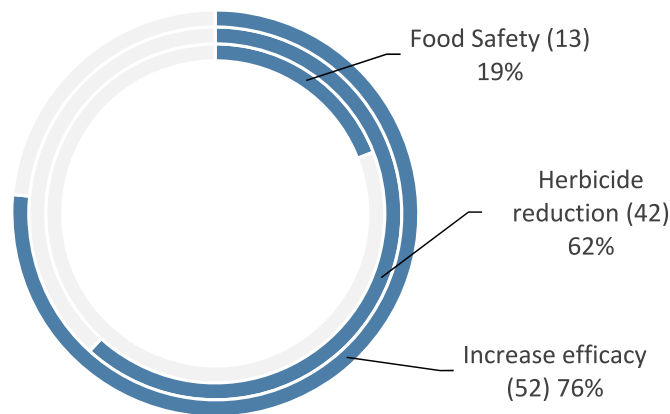


Fig. 10. Quantity of articles referring the three factors.

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, underlining 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 (Mivedi 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.

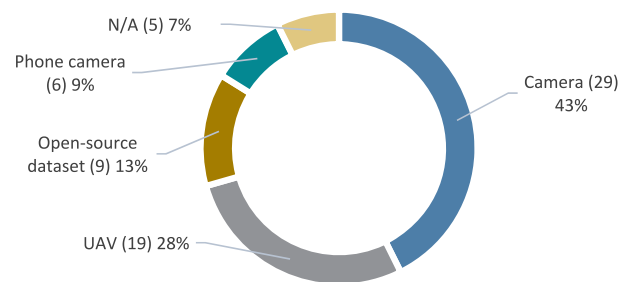


Fig. 11. Categorization of image acquisition technology for the training process.

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

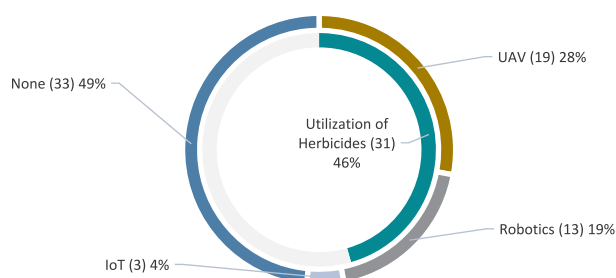


Fig. 12. Quantity of articles referring to the technologies used.

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).

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).

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

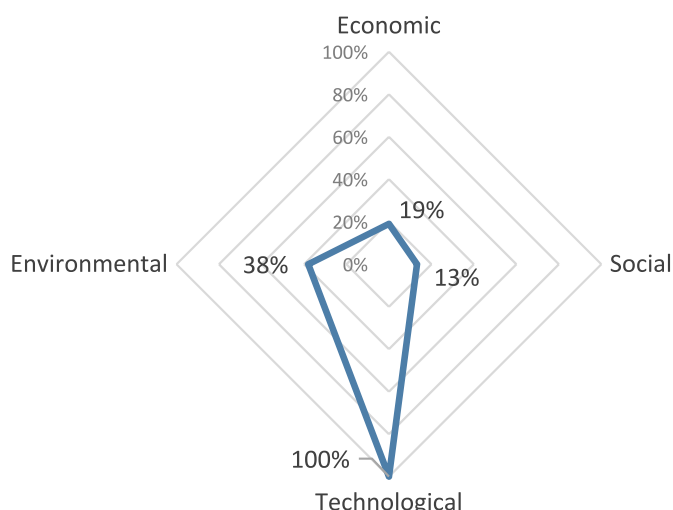


Fig. 13. Quantity of articles referring to the related impact.

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 as 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	<i>Chloris cucullata</i> (grass), <i>Cirsium arvense</i> (creeping thistle), <i>Convolvulus arvensis</i> (bindweed) and <i>Eschscholzia californica</i> (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	<i>Portulaca oleracea</i> , <i>Eleusine indica</i> , <i>Chenopodium album</i> , <i>Amaranth blitum</i> , <i>Abutilon theophrasti</i> , <i>Calystegia</i>	Peanut			●
Hussain et al. (2020)	N/A	lambquarters (<i>Chenopodium album</i>)	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 (<i>Ageratum conyzoides</i> L.), purple nutsedge (<i>Cyperus rotundus</i> L.), scarlet pimpernel (<i>Anagallis arvensis</i> L.), <i>Lepidium didymum</i> (<i>Coronopus didymus</i> L.), field bindweed (<i>Convolvulus arvensis</i> L.), ragweed parthenium (<i>Parthenium hysterophorus</i> L.), spiny sowthistle (<i>Sonchus asper</i> L.), corn spurry (<i>Spergula arvensis</i> L.) and asian scalystem (<i>Elytraria acaulis</i> L.)	Sugarcane		●	●
Sapkota et al. (2022)	USA	morningglories (<i>Ipomoea</i> spp.), johnsongrass (<i>Sorghum halepense</i> (L.) Pers.), Palmer amaranth (<i>Amaranthus palmeri</i> S. Watson), prostrate spurge (<i>Euphorbia humistrata</i> Engelm.), browntop panicum (<i>Panicum fasciculatum</i> 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 (<i>Amaranthus palmeri</i>)	Soybean		●	●
Valente et al. (2022)	Germany	<i>Rumex obtusifolius</i> (Rumex or broad leaved dock)	Crop general		●	
Danilevicz et al. (2023)	Australia	Lupin	Crop general			●
Gallo et al. (2023)	China	<i>Mercurialis annua</i> (French mercury)	Sugar beet			●
Costello et al. (2022)	Australia	Parthenium (<i>Parthenium hysterophorus</i> 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	<i>Echinochloa crusgalli</i> (L.) Beauv., <i>Solanum nigrum</i> L., <i>Chenopodium album</i> Linn, grass	Corn		●	
Wang et al. (2020)	China	N/A	Sugar beet		●	
Dang et al. (2023)	USA	12 weed species - unspecified	Cotton	●	●	●
Hennessey 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 (<i>Taraxacum officinale</i> Web.), ground ivy (<i>Glechoma hederacea</i> L.), and spotted spurge (<i>Euphorbia maculata</i> L.)	Crop general		●	●
Liu et al. (2023)	China	cleavers (<i>Galium aparine</i> L.), chickweed (<i>Malachium aquaticum</i> L.), Persian speedwell (<i>Veronica persica</i> Poir), shepherd's purse [<i>Capsella bursa-pastoris</i> (L.) Medik], and sweet woodruff [<i>Galium odoratum</i> (L.) Scop.].	Wheat		●	●

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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 (<i>Pilosella officinarum</i>)	N/A		●	
Zou et al. (2022)	China	<i>Trigonotis peduncularis</i> , <i>Rorippa indica</i> (L.) Hiern, <i>Cirsium setosum</i> , <i>Chenopodium album</i> L.	Wheat		●	
Rahman et al. (2023)	USA	Carpetweed (<i>Mollugo verticillata</i>), Morningglory (<i>Ipomoea</i> genus), and Palmer Amaranth (<i>Amaranthus palmeri</i>)	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 (<i>Chenopodium album</i> L.), and corn spurry (<i>Spergula arvensis</i> L.)	Potato		●	●
Cai et al. (2023)	China	N/A	Pineapple			●
Saleem et al. (2022)	Australia	8 types	Chinese apple		●	●
Jin et al. (2022a)	USA	dallisgrass, goosegrass, Virginia buttonweed	N/A		●	●
Gao et al. (2020)	Belgium	Hedge bindweed (<i>Convolvulus sepium</i>)	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	<i>L. chinensis</i> , <i>Cyperus iric</i> , <i>Digitaria sanguinalis</i> (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 (<i>Papaver rhoeas</i>)	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 (<i>Chenopodium album</i> L.), Field pennycress (<i>Thlaspi arvense</i>), Wild chamomile (<i>Matricaria chamomilla</i>), Common gypsyweed (<i>Veronica officinalis</i>) and Cotton thistle (<i>Onopordum acanthium</i>)	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

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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-USBFD01M-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

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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 classification 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, ShufNet-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

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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	●		●	

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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	●			

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