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REVIEW ARTICLE

# Machine learning algorithms applied to weed management in integrated crop-livestock systems: a systematic literature review

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**Abstract:** In recent times, there has been an environmental pressure to reduce the amount of pesticides applied to crops and, consequently, the crop production costs. Therefore, investments have been made in technologies that could potentially reduce the usage of herbicides on weeds. Among such technologies, *Machine Learning* approaches are rising in number of applications and potential impact. Therefore, this article aims to identify the main machine learning algorithms used in integrated crop-livestock systems for weed management. Based on a systematic literature review, it was possible to determine where the selected studies were performed and which crop types were mostly used. The main research terms in this study were: "machine learning algorithms" + "weed management" + "integrated crop-livestock system". Although no results were found for the three terms altogether, the combinations involving "weed management" + "integrated crop-livestock system" and "machine learning algorithms" + "weed management" returned a significant number of studies which were subjected to a second layer of refinement by applying an eligibility criteria. The achieved results show that most of the studies were from the United States and from nations in Asia. Machine vision and deep learning were the most used machine learning models, representing 28% and 19% of all cases, respectively. These systems were applied to different practical solutions, the most prevalent being smart sprayers, which allow for a site-specific herbicide application.

**Keywords**: Weed control; Weed prevention; Artificial Intelligence; Image processing

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## 1. Introduction

Over the past few years, major investments have been made in the development of technologies to help reduce the use of herbicides on weed control. This reduction in the use of pesticides on agriculture is due to an environmental pressure, as well as aiming to diminish crop production costs. Such technologies make use of artificial intelligence, machine learning and analysis of great volumes of data (Big Data). The data used in such models can be classified as phytochemical, environmental, images, among others (Jha et al., 2019). Based on these approaches, new methods for dealing with invasive species have been developed. For instance, the automation of mechanical control and the use of smart sprayers allows the development of site-specific applications of herbicides (Oliveira et al., 2023). Furthermore, some studies demonstrated that in Integrated Crop-Livestock Systems (ICLS) the presence of weed is lower than in continuous tillage systems (Ikeda et al., 2007).

The objective of this study is to provide a systematic literature review of Machine Learning models applied in weed management in ICLS. The PRISMA methodology was used to identify previous studies relevant to the established goal (Snyder, 2019). The article is organized as follows: Section 2 presents the research methodology used in the systematic literature review, including its stages and objectives. Section 3 shows the results of the systematic literature review, as well as a critical analysis. Section 4 presents the conclusions based on the study findings and provides recommendations for future studies.

## 2. Material and Methods

A Systematic Literature Review (SLR) aims to identify and evaluate relevant articles, and also collect and analyze data from these selected studies. This SLR was based on the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, presented by Liberati et al. (2009). The process involved four stages: planning, conducting, analyzing the results and documenting. The objective is to identify the main Machine Learning models used in the context of weed management in ICL systems. Therefore, we have the following research questions: RQ1) Which machine learning algorithms are used in ICLS for weed control? RQ2) What are the solutions developed with the help of machine learning techniques for weed management in ICLS? RQ3) Is there any disparity in the number of studies found concerning the machine learning models used for weed management and the solutions developed?

The first stage consisted of extracting the keywords and their synonyms from the research questions, which are: Weed(s), Weed control, Weed management, Machine Learning, Artificial Intelligence, ICL system and ICLS. Based on the keywords, the following search string [(weed(s) OR weed control OR weed management) AND (machine learning OR artificial intelligence) AND (ICLS OR ICL system)] was elaborated to query the selected digital libraries. However, the composition of the three terms had no return in the databases, hence, the search had to be done in two parts. The two expressions were: [(weed(s) OR weed control OR weed management) AND (machine learning OR artificial intelligence)] and [(weed(s) OR weed control OR weed management) AND (ICL system OR ICLS)]. Table 1 shows the adaptations that needed to be done for each database.

In order to obtain more precise results on the studies that significantly contributed to the research field, it was necessary to define a set of inclusion and exclusion criteria (see Table 2). Along with the inclusion and exclusion criteria, the title, abstract and keywords of each study were also analyzed to verify whether they were in line with the desired search. This additional criterion was applied, since the query returned many articles that contained the usage of machine learning in agriculture but did not involve weed management.

The systematic literature review process was divided into three stages. The first consisted of identifying and removing duplicate articles, keeping only one version for analysis. In the second stage, the inclusion and exclusion criteria IC1, IC2 and EC3 were applied, in addition to the quality criteria. Finally, in the third stage, the EC2 criteria was used, that is, it was verified which of the articles had their full content available in the libraries. This procedure was done with the assistance of the tool Parsifal. Table 3 presents the quantity of studies selected in each stage, also, Figure 1 shows the process described above.

Altogether, there were 47 duplicates in all databases, most of which were from Science Direct. In the second

**Table 1** - Digital libraries: name, search string and website

| Data base | Search String | URL |
|---|---|---|
| IEEE Xplore | [TITLE-ABS-KEY(weed(s)) OR TITLE-ABS-KEY(weed control) OR TITLE-ABS-KEY(weed management) AND TITLE-ABS-KEY(machine learning) OR TITLE-ABS-KEY(artificial intelligence)] OR [TITLE-ABS-KEY(weed(s) OR TITLE-ABS-KEY(weed control) OR TITLE-ABS-KEY(weed management) AND TITLE-ABS-KEY(ICLS) OR TITLE-ABS-KEY(ICL system)]] | https://ieeexplore.ieee.org/Xplore/home.jsp/ (accessed on 26 May 2023) |
| Mendeley | [("weed(s)" OR "weed control" OR "weed management") AND ("machine learning" OR "artificial intelligence")] OR [("weed(s)" OR "weed control" OR "weed management") AND ("ICLS" OR "ICL system")] | https://www.mendeley.com/search/ (accessed on 23 May 2023) |
| Science Direct | [("weed(s)" OR "weed control" OR "weed management") AND ("machine learning" OR "artificial intelligence")] OR [("weed(s)" OR "weed control" OR "weed management") AND ("ICLS" OR "ICL system")] | https://www.sciencedirect.com/ (accessed on 26 May 2023) |
| Scopus | [(("All Metadata": "weed(s)") OR ("All Metadata": "weed control") OR ("All Metadata": "weed management")) AND (("All Metadata": "machine learning") OR ("All Metadata": "artificial intelligence"))] OR [(("All Metadata": "weed(s)") OR ("All Metadata": "weed control") OR ("All Metadata": "weed management")) AND (("All Metadata": "ICLS") OR ("All Metadata": "ICL system"))] | https://www.scopus.com/home.uri/ (accessed on 25 May 2023) |

**Table 2** - Inclusion and Exclusion criteria applied in the article's selection process

| Inclusion Criteria | Exclusion Criteria |
|---|---|
| IC1: Articles published in english. | EC1: Duplicated articles. |
| IC2: Articles published between January, 2013 and March, 2023. | EC2: Articles that do not allow access to their full content. |
| | EC3: Articles that do not have "weed management", "weed control" or "weed(s)" in the title, abstract or keywords. |

**Table 3** - Number of studies selected at each stage grouped by digital library

| Database | Studies found | Stage 1 | Stage 2 | Stage 3 |
|---|---|---|---|---|
| IEEE Xplore | 14 | 12 | 7 | 7 |
| Mendeley | 20 | 13 | 4 | 4 |
| Science Direct | 303 | 276 | 17 | 15 |
| Scopus | 159 | 148 | 35 | 14 |
| Total | 496 | 449 | 63 | 40 |

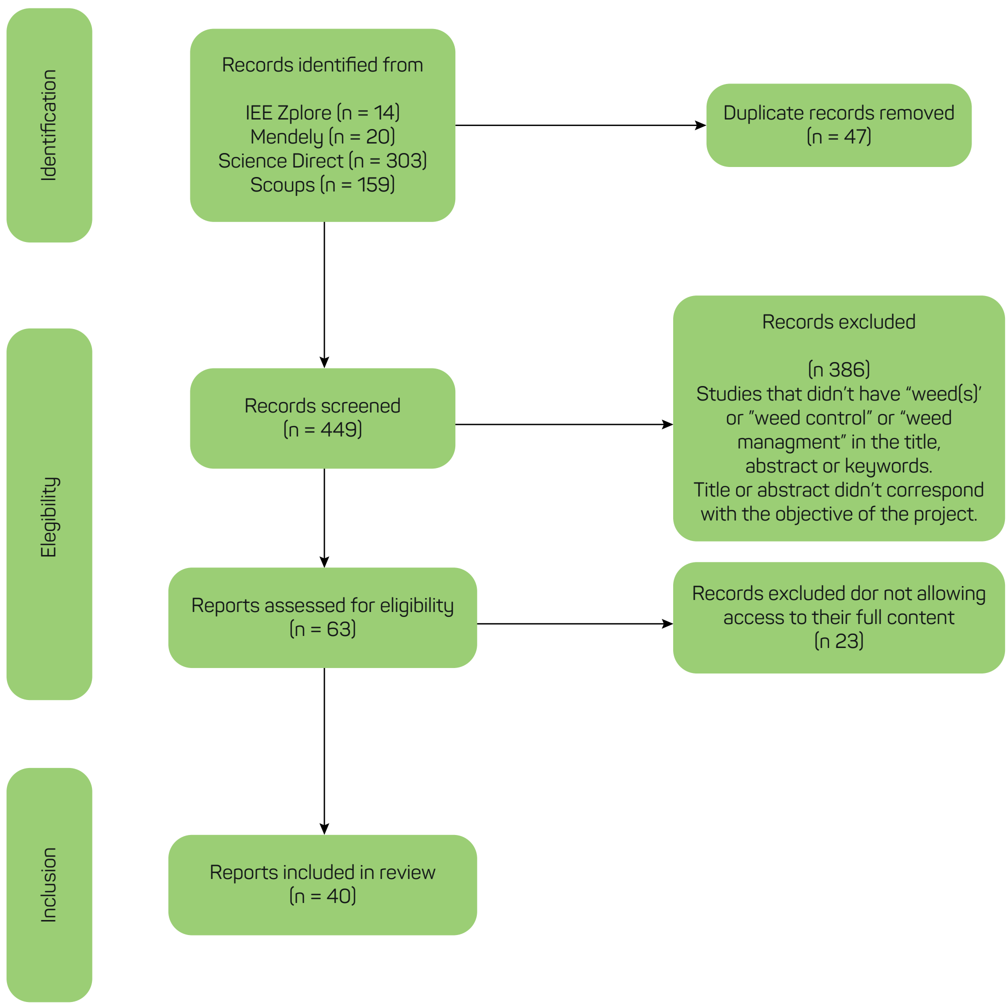


**Figure 1** - Systematic literature review process described in the PRISMA flowchart

stage, most of the results were removed because they did not have "weed(s)", "weed control" or "weed management" in the title, abstract or keywords. Also, for the IEEE Xplore and Mendeley libraries, it was possible to access the full content of all the studies. Meanwhile, the Scopus database presented the smallest number of studies with access to their full text. Therefore, at the end of the whole process, 40 articles were selected.

## 3. Results and Discussion

Table 4 presents the list of studies selected for analysis. The contributions of the selected articles are presented in Section 3.1. In Section 3.2, an analysis of the included studies is displayed. The research questions made in Section 2.1 are answered in Section 3.3.

### 3.1 Contributions of the Selected Articles

Since the search had to be done in two parts, the results returned from the bases are shown in separate subsections. Subsection 3.1.1 is dedicated to articles on weeds and ICLS. Subsection 3.1.2 is dedicated to articles on machine learning algorithms used for the weed control. Besides, the theoretical formalism of the methods presented in this review can be found in Hanson (2019) and Alpaydin (2020).

#### 3.1.1 *Selected articles regarding "weeds and ICLS"*

The effects of different grazing intensities on weed emergence and seed banks in ICLS are verified in southern Brazil by Schuster et al. (2016a). The authors conclude that decreasing the grazing intensity helps to reduce the number of weed species, the density of emerged weed seedlings and the weed seed bank density. Besides, the high reduction of pasture management increases weed density, as it is reported in Schuster et al. (2016b), which provides a description of the diversity and community structure of the weed flora due to changes on sward height in ICLS. Other aspects related to invasive species in ICLS are presented in Dominschek et al. (2022). The authors investigate the impacts in a traditional paddy field and in

**Table 4** - Selected studies: authors, title, and year

| Reference | Title | Year |
|---|---|---|
| Torres-Sospedra and Nebot (2014) | Two-stage procedure based on smoothed ensembles of neural networks applied to weed detection in orange groves | 2014 |
| Pérez-Ortiz et al. (2016) | Selecting patterns and features for between- and within- crop-row weed mapping using UAV-imagery | 2016 |
| Schuster et al. (2016a) | Grazing intensities affect weed seedling emergence and the seed bank in an integrated crop–livestock system | 2016 |
| Schuster et al. (2016b) | Floristic and phytosociology of weed in response to winter pasture sward height at Integrated Crop-Livestock in Southern Brazil | 2016 |
| Chavan and Nandedkar (2018) | AgroAVNET for crops and weeds classification: A step forward in automatic farmimg | 2018 |
| Sabzi and Abbaspour-Gilandeh (2018) | Using video processing to classify potato plant and three types of weed using hybrid of artificial neural network and partincle swarm algorithm | 2018 |
| Sandino and Gonzalez (2018) | A Novel Approach for Invasive Weeds and Vegetation Surveys using UAS and Artificial Intelligence | 2018 |
| Zhang et al. (2018) | Broad-Leaf Weed Detection in Pasture | 2018 |
| Abouzahir et al. (2018) | Enhanced Approach for Weeds Species Detection Using Machine Vision | 2018 |
| Gao et al. (2018) | Recognising weeds in a maize crop using a random forest machine-learning algorithm and near-infrared snapshot mosaic hyperspectral imagery | 2018 |
| Yu et al. (2019) | Weed Detection in Perennial Ryegrass With Deep Learning Convolutional Neural Network | 2019 |
| Partel et al. (2019) | Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence | 2019 |
| Sudars et al. (2020) | Dataset of annotated food crops and weed images for robotic computer vision control | 2020 |
| Qiao et al. (2020) | MmNet: Identifying Mikania micrantha Kunth in the wild via a deep Convolutional Neural Network | 2020 |
| Souza et al. (2020) | Spectral differentiation of sugarcane from weeds | 2020 |
| Yan et al. (2020) | Classification of weed species in the paddy field with DCNN-Learned features | 2020 |
| Wang et al. (2020) | Semantic Segmentation of Crop and Weed using an Encoder-Decoder Network and Image Enhancement Method under Uncontrolled Outdoor Illumination | 2020 |
| Yu et al. (2020) | Detection of grassy weeds in bermudagrass with deep convolutional neural networks | 2020 |
| Sabzi et al. (2020) | An automatic visible-range video weed detection, segmentation and classification prototype in potato field | 2020 |
| Hussain et al. (2021) | Application of deep learning to detect Lamb's quarters (Chenopodium álbum L.) in potato fields of Atlantic Canada | 2021 |
| Fawakherji et al. (2021) | Multi-Spectral Image Synthesis for Crop/Weed Segmentation in Precision Farming | 2021 |
| Siddiqui et al. (2021) | Neural Network based Smart Weed Detection System | 2021 |
| Monteiro et al. (2021) | A new alternative to determine weed control in agricultural systems based on artificial neural networks (ANNs) | 2021 |
| Etienne et al. (2021) | Deep Learning-Based Object Detection System for Identifying Weeds Using UAS Imagery | 2021 |
| Shorewala et al. (2021) | Weed Density and Distribution Estimation for Precision Agriculture Using Semi-Supervised Learning | 2021 |
| Subeesh et al. (2022) | Deep convolutional neural network models for weed detection in polyhouse grown bell peppers | 2022 |
| Nasiri et al. (2022) | Deep learning-based precision agriculture through weed recognition in sugar beet fields | 2022 |
| Alrowais et al. (2022) | Hybrid leader based optimization with deep learning driven weed detection on internet of things enabled smart agriculture environment | 2022 |
| Razfar et al. (2022) | Weed detection in soybean crops using custom lightweight deep learning models | 2022 |
| Costello et al. (2022) | Detection of Parthenium Weed (Parthenium hysterophorus L.) and Its Growth Stages Using Artificial Intelligence | 2022 |
| Dominschek et al. (2022) | Diversification of traditional paddy field impacts target species in weed seedbank | 2022 |
| Ni et al. (2022) | A deep convolutional neural network-based method for identifying weed seedlings in maize fields | 2022 |
| Ngo et al. (2022) | Automated Weed Detection System for Bokchoy Using Computer Vision | 2022 |
| Jose et al. (2022) | Classification of Weeds and Crops using Transfer Learning | 2022 |
| Wang and Leelapatra (2022) | Weeding Robot Based on Lightweight Platform and Dual Cameras | 2022 |
| Firmansyah et al. (2022) | Real-time Weed Identification Using Machine Learning and Image Processing in Oil Palm Plantations | 2022 |
| Meena et al. (2023) | Crop Yield Improvement with Weeds, Pest and Disease Detection | 2023 |
| Ajayi and Ashi (2023) | Effect of varying training epochs of a Faster Region-Based Convolutional Neural Network on the Accuracy of an Automatic Weed Classification Scheme | 2023 |
| Dang et al. (2023) | YOLOWeeds: A novel benchmark of YOLO object detectors for multi-class weed detection in cotton production systems | 2023 |
| Raja et al. (2023) | Real-time control of high-resolution micro-jet sprayer integrated with machine vision for precision weed control | 2023 |

four ICL systems, located in southern Brazil, to assess how the type of cultivation influences the weed seed banks. It was possible to verify that the decrease of the weed seed banks in ICLS was more noticeable.

### 3.1.2 *Selected articles regarding "machine learning for weed control"*

The usage of Unmanned Aerial Vehicle (UAV), to map and identify weeds, is explored in the studies of Pérez-Ortiz et al. (2016), which was performed in maize and sunflower fields and had a result that the proposed method is adequate to construct robust sets of data; Sandino and Gonzalez (2018), that achieved an accuracy of more than 96% to map invasive grasses; and Qiao et al. (2020), who proposed an identification model of the weed specie *M. micranta* utilizing deep convolutional neural networks (DCNN), based on the images captured by the UAV.

Different searches evolving images can also contribute to the development of other weed management technologies, like Etienne et al. (2021), which explores the need to develop larger databases to assess deep learning (DL) models to identify weeds under field conditions. Sudars et al. (2020) provided a dataset of images of crops and invasive species, which can be used to train convolutional neural networks (CNN) models to differentiate weeds from crops. Besides, Costello et al. (2022) utilized hyperspectral imagery and artificial intelligence to detect and map populations of the weed genus *Parthenium hysterophorus L*, their findings demonstrate the potential of collected images to be used in the preliminary design of weed detection strategies. Furthermore, Fawakherji et al. (2021) added synthetic images in the model training process to increase the performance of the weed/crop segmentation process in precision farming, utilizing a generative adversarial network (GAN).

Based on a similar approach, Torres-Sospedra and Nebot (2014) proposed a procedure for weed detection in orange groves. First, images are analyzed and identified as either trees, trunks, soil or sky. After that, images identified as soil are analyzed to detect invasive species. This procedure was done using ensembles of neural networks and multilayer perceptron (MLP), and it achieved suitable results for weed detection. The study of Dang et al. (2023) also approaches the weed problem from the perspective of image processing. The authors established benchmarks to verify which of the YOLO versions present the best accuracy in weed detection of an image dataset of invasive species in cotton fields in the United States, being the YOLOv5 the one with greater potential.

To classify images of invasive species, Yu et al. (2020) explored the feasibility of using DCNN. Their conclusion's showed that such thing is possible, and also, with excellent accuracy. In a similar research Hussain et al. (2021) used a database of images, trained by a DCNN, to detect the weed species lamb's quarter in potato fields in Canada, accomplishing excellent results, more than 90% of accuracy. Also, Yan et al. (2020) made an investigation over the results of different machine learning algorithms, like DCNN, K-nearerst neighbors (KNN) and support vector machine (SVM), regarding invasive species identification in paddy fields, being the DCNN the model that presented the best results.

Based on deep learning approaches, Subeesh et al. (2022) and Meena et al. (2023) assessed the feasibility of such techniques to identify invasive species and to classify images into weeds, pests, plant diseases and different crops, achieving 97% and 91% of accuracy, respectively. Moreover, Razfar et al. (2022) propose a weed detection system using CNN and DL models in soybean fields, which performed with 97% of accuracy. Using the same algorithm, CNN and DL, to detect and classify weeds, Wang and Leelapatra (2022), Ngo et al. (2022) and Jose et al. (2022), proposed, respectively: a weed robot with dual cameras; weed detection system, which distinguishes bok choy crops from non-crops; and an automatic classification method of images of tomato crops and weeds. Also, Zhang et al. (2018) proposed a method of recognizing broad-leaf weeds using conventional machine learning algorithms and DL, achieving an accuracy of 96%.

An automatic system of weed identification, which can be used to apply herbicides, is presented in Siddiqui et al. (2021). The developed model uses CNN to extract features from images and allow an early detection of weeds with better accuracy. Chavan and Nandedkar (2018) also utilize CNN for classification of weeds in the context of automatic farming, achieving an accuracy of 98%. With reasonable results, Nasiri et al. (2022) utilized CNN of pixel-wise segmentation of weeds, soil and sugar beet, which can be integrated in an autonomous weed control robot to make a selective herbicide application. Using algorithms like deep semi-supervised learning (DSSL), CNN and others, Shorewala et al. (2021) proposed an approach to estimate the weed density and distribution that can be useful in a site-specific weed management system. This procedure had a good performance, with 82% of accuracy.

A different approach to the weed problem is presented in the study of Alrowais et al. (2022), whose aim was to gather images, using IoT devices, to perform automatic weed recognition and classification. Their proposal was experimentally validated. Besides, Partel et al. (2019) designed a smart technology that can be used as a smart sprayer and also as a weed mapping system. Using machine vision (MV) and artificial intelligence, the authors achieved reasonable results. Other assessments of a practical solution can be found in Raja et al. (2023), which proposed a system that uses a crop signaling concept with MV and a precision micro-jet sprayer to apply herbicides accurately. The developed system had an excellent performance, with 98% of the weeds correctly sprayed.

Furthermore, Sabzi and Abbaspour-Gilandeh (2018) and Yu et al. (2019) also present systems that could be applied in site-specific smart sprayers. The first utilized MV techniques and artificial neural network (ANN) to localize and identify invasive species in potato fields and the second employed algorithms like DCNN and MV. Sabzi et al. (2020) also propose a prototype of a site-specific spraying, utilizing MV for identification and classification of five types of weeds in potato fields. Under field conditions, the prototype was able to detect, segment and classify weeds from potato plants accurately.

By the spectral behavior of the leaves, Souza et al. (2020) showed that it is possible to distinguish weeds from sugarcane plants. Wang et al. (2020) investigated how the lighting changes may affect the performance of certain machine learning models, like DL and MV, in weed detection, which can contribute to weed management. Moreover, Monteiro et al. (2021) analyzed the usage of ANN to estimate the beginning of the weed control and to model and predict the competition between the invasive species and the crops. Their results demonstrate that machine learning can be used in crop-weed competition modeling.

In the context of precision agriculture, Abouzahir et al. (2018) used back-propagation neural networks (BPNN) and SVM to distinguish soybean crops from weeds. The algorithms accomplished an accuracy of 96% and 95%, respectively. Ni et al. (2022) detect weeds in maize fields using DCNN to recognize the invasive species. Different algorithms, like KNN and random forest (RF) were used in the study of Gao et al. (2018), whose objective was to to classify weeds in maize fields. In conclusion, the RF performed better than the KNN model.

Employing machine learning techniques, Firmansyah et al. (2022) proposed an automatic weed identification system in oil palm plantations. It involves the description, naming, and tolerance class of the invasive species. Ajayi and Ashi (2023) implemented a faster region-based convolutional neural network (RCNN) to identify and classify different crops, like sugarcane, banana, spinach, pepper, and different types of weeds. The system was able to identify and classify invasive species in a mixed-crop farm.

### 3.2 Analysis of the Selected Articles

Regarding all the articles retrieved it is possible to observe that from 2020 onward there was an increase in the amount of research on this topic. It is particularly interesting to observe that, although the studies carried out in 2023 correspond only to those published between January and March, they represent 10% of all the selected articles. Furthermore, before 2014 there were no reports on the use of artificial intelligence in weed management. Figure 2 demonstrates that the use of machine learning techniques in weed control is a new and growing topic, mostly due to a greater availability of data on the subject, the evolution in machine learning models, as well as their increasing popularity. Another observation is that most of these studies have been carried out in the United States and in different countries of Asia. Few were carried out in Africa, Europe, and Latin America. It is relevant to point out that most of the selected Brazilian articles are about the ICLS and not about the usage of machine learning in weed management. Table 5 presents the main crops, machine learning algorithms, and developed solutions used in the studies.

Based on this table, it is possible to draw some insights for each of the aspects discussed. Concerning the crops, it follows that the classification "Types of grass" includes some varieties of grass mentioned in the papers, such as *Bermudagrass, Ryegrass, Desert bluegrass,* among others. Although it was the "crop" that most appeared in the studies, those plants do not refer to plantations for food production, but to golf course areas. Notably, maize is the crop with most retrieved record in this research. This can be due to the cultivated area of this crop being one of the largest, and because there are some difficulties in the control of narrow-leaf weeds in these plantations, since the herbicides supply of those species is lower and the cost is higher.

Furthermore, soybeans fields represent one of the largest cultivated areas, but it is possible to see that they are not much researched. The herbicides not sprayed in the soybean crops, by the developed technologies presented in the selected articles, can reduce the costs and negative impacts on the environment. For some articles, the crop was defined as "Not available", being only mentioned generically as "vegetables" or "crops". The reader could also refer to Figure 3 for a summary of the content described.

As for the algorithms, the most used is Machine Vision, followed by Deep Learning. The articles classified as "Not available" refer to studies on the ICLS and weeds, since they do not involve machine learning models. The higher concentration of studies on the use of Machine Vision in weed management is also evident in Figure 4. In some studies, these machine learning techniques were applied in practical solutions, which are presented in Figure 5 as well.

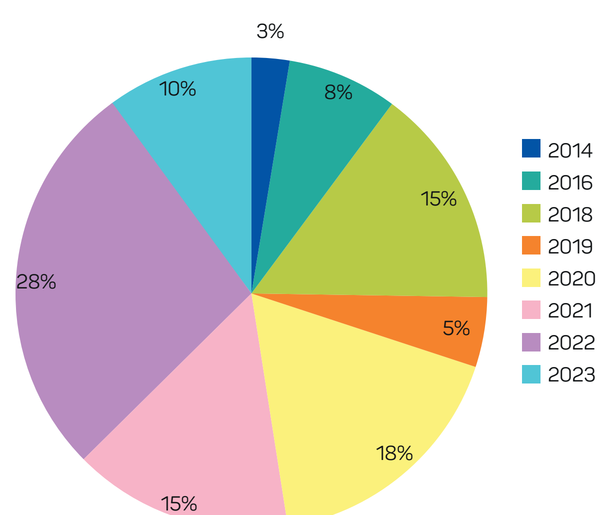


**Figure 2** - Publication year from the selected studies

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**Table 5** - Selected studies: crops, machine learning algorithms, and developed solutions

| Study | Crops | Machine Learning algorithms | Developed solutions |
|---|---|---|---|
| Torres-Sospedra and Nebot (2014) | Orange | SVM, ANN and MLP | Not available |
| Pérez-Ortiz et al. (2016) | Maize and Sunflower | MV | Not available |
| Schuster et al. (2016a) | Pasture | Not available | Not available |
| Schuster et al. (2016b) | Types of grass | Not available | Not available |
| Chavan and Nandedkar (2018) | Maize, Wheat, Sugar cane and Types of grass | CNN | Not available |
| Sabzi and Abbaspour- Gilandeh (2018) | Potato | ANN and MV | Smart sprayers |
| Sandino and Gonzalez (2018) | Types of grass | MV | Framework |
| Zhang et al. (2018) | Pasture | DL | Not available |
| Abouzahir et al. (2018) | Soy | SVM, MV and BPNN | Not available |
| Gao et al. (2018) | Maize | KNN | Hyperspectral cameras |
| Yu et al. (2019) | Types of grass | MV and DCNN | Smart sprayers |
| Partel et al. (2019) | Pepper | ANN and MV | Smart sprayers |
| Sudars et al. (2020) | Carrot, Pumpkin and Radish | MV | Dataset of images |
| Qiao et al. (2020) | Not available | CNN, MV and DL | Not available |
| Souza et al. (2020) | Sugar cane | RF | Not available |
| Yan et al. (2020) | Rice | SVM, DCNN and KNN | Not available |
| Wang et al. (2020) | Sugar beet | DL | Not available |
| Yu et al. (2020) | Types of grass | MV and DCNN | Smart sprayers |
| Sabzi et al. (2020) | Potato | MV | Smart sprayers |
| Hussain et al. (2021) | Potato | MV, DL and DCNN | Smart sprayers |
| Fawakherji et al. (2021) | Sugar beet and Sunflower | GAN | Farming robots |
| Siddiqui et al. (2021) | Maize | ANN and CNN | Smart sprayers |
| Monteiro et al. (2021) | Melon and Sesame | ANN | Not available |
| Etienne et al. (2021) | Soy | MV and DL | Dataset of images |
| Shorewala et al. (2021) | Not available | ANN, CNN, MV, DL and DSSL | Farming robots |
| Subeesh et al. (2022) | Bell pepper | CNN, MV, DL and DCNN | Not available |
| Nasiri et al. (2022) | Sugar beet | CNN and DL | Dataset of images |
| Alrowais et al. (2022) | Not available | MV and DL | Not available |
| Razfar et al. (2022) | Soy | CNN and DL | Not available |
| Costello et al. (2022) | Types of grass | CNN and MV | Not available |
| Dominschek et al. (2022) | Rice | Not available | Not available |
| Ni et al. (2022) | Maize | MV and DCNN | Not available |
| Ngo et al. (2022) | Bok choy (cabbage) | MV and RCNN | Smart lazer |
| Jose et al. (2022) | Tomato | CNN and DL | Not available |
| Wang and Leelapatra (2022) | Not available | CNN, MV and DL | Farming robots |
| Firmansyah et al. (2022) | Palm oil | CNN and MV | Mobile apps |
| Meena et al. (2023) | Not available | DL and DCNN | Not available |
| Ajayi and Ashi (2023) | Banana, Spinach, Sugar cane and Pepper | CNN, DL and RCNN | Not available |
| Dang et al. (2023) | Cotton | MV and DL | Dataset of images |
| Raja et al. (2023) | Lettuce | CNN, MV and DCNN | Smart sprayers |

In certain studies, the use-case application is not clearly defined. For the articles considered as "Not available", it can be assessed that, while few of them are about the ICLS, most of these studies explore the efficiency of machine learning models for identifying and classifying weeds, but do not apply them to any practical solutions. However, in some cases, the authors present possible applications to their systems, which are generally farming robots and smart sprayers, the latter being also called intelligent sprayers. Moreover, various studies rely on machine learning algorithms to improve these smart-sprayer systems.

### 3.3 Research Questions Answers

The articles concerning artificial intelligence and weed control show that the most used machine learning techniques are related to image processing. This happens because a major part of the studies is dedicated to detecting,

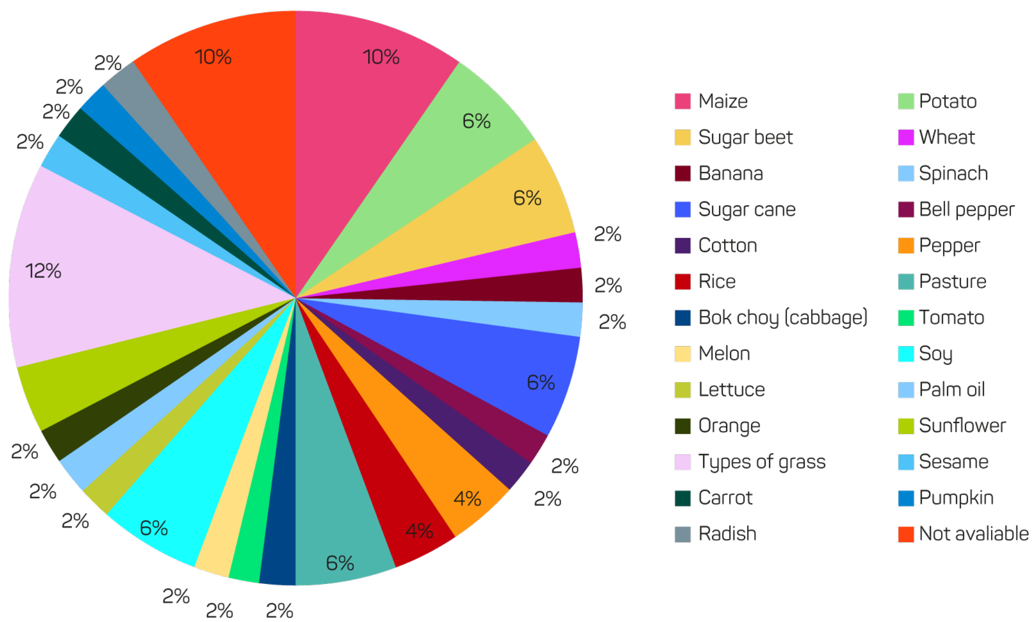


**Figure 3** - Crop types identified in the selected articles

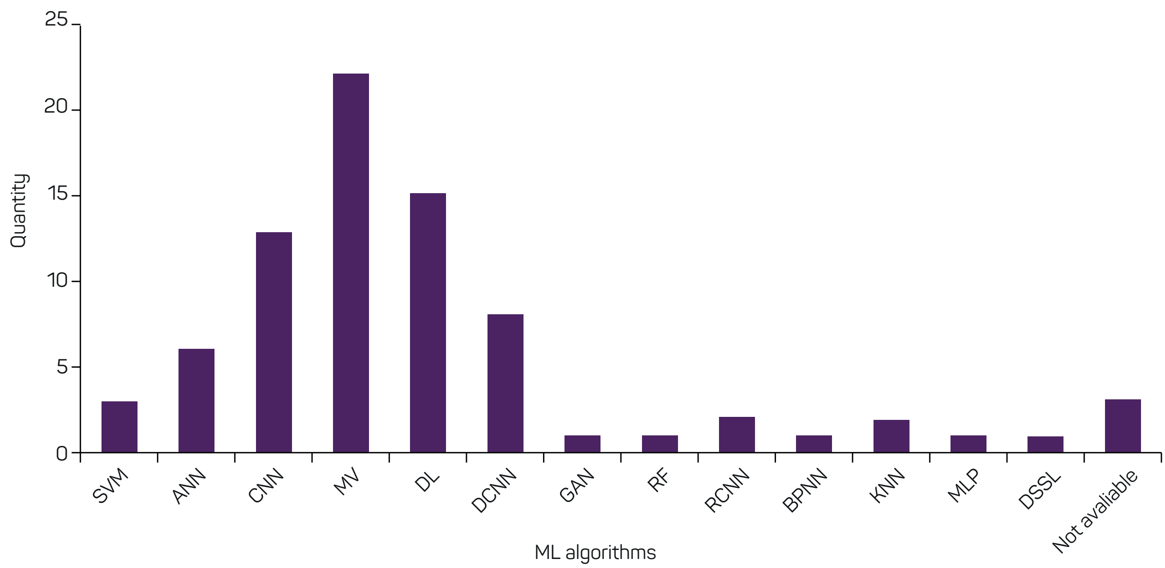


**Figure 4** - Machine Learning algorithms identified in the selected articles

identifying and classifying weeds, thus answering RQ1. As a result, the Machine Vision and Deep Learning algorithms are the most used (Table 5 and Figure 4). It was not possible to verify the machine learning models used in ICL systems for weed management, since there were no studies on this subject.

Other machine learning models like Convolutional Neural Networks, Support Vector Machine, Artificial Neural Networks and Deep Convolutional Neural Networks are also frequently featured in the studies. Generative Adversarial Networks, Random Forest, Region-based Convolutional Neural Networks, Back-propagation Neural Networks, K-Nearest Neighbors, Multilayer Perceptron and Deep semi-supervised Learning are other machine learning algorithms that appeared in some articles, but less often. Also 4% were “Not available”, since these studies were related to the weed control in ICLS.

For RQ2, the solutions presented are not related to the ICLS, since the included articles concerning this subject did not involve machine learning algorithms. But for the studies about artificial intelligence and weed control, some of the developed tools are frameworks, mobile apps, hyperspectral cameras, and smart lasers. One of the solutions that frequently appeared were datasets of images,

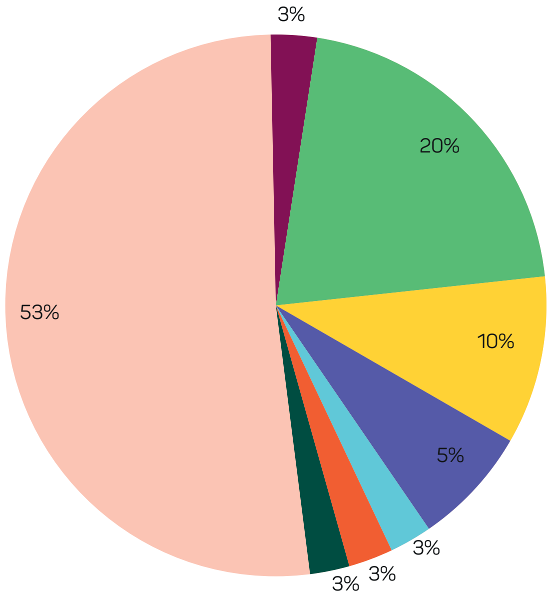


**Figure 5** - Developed solutions for weed control identified in the selected articles

containing pictures of weeds and crops, with the purpose to train and improve the performance of the machine learning models to correctly identify the invasive species.

Farming robots also represent a fair amount of the solutions, despite being less numerous, and in many studies, they are cited as possible applications for the artificial intelligence models. Those robots are created to remove weeds by themselves and, in some cases, apply agrochemicals in the plantations. The most common solutions are the smart sprayers, those are usually drones that make a site-specific application of the herbicides directly on the weeds. In the case of both smart sprayers and farming robots, drones and robots need to be capable of distinguishing crops and weeds to correctly perform their tasks, whether it is to remove the invasive species or apply herbicides on them. For that, machine learning algorithms for image processing are utilized, such as Deep Learning and Machine Vision.

The solutions described have their advantages since the accurate application of herbicides reduces the food and environment contamination and the costs. But it also has some disadvantages, given that the robots and drones are costly and not available yet. In addition, for countries with a skilled workforce, these technologies can make an effective contribution to weed control by working together with these professionals. But for countries where the rural workers do not have as many qualifications, there is no certainty as to how these solutions can impact work in the field and the labor market (Organisation for Economic Co-operation and Development, 2021).

The SLR shows that there is a disparity regarding the artificial intelligence models and the developed tools used for weed control. The Machine Vision algorithm represents 28% of all machine learning techniques presented in the studies, and the Deep Learning, 19%. Also, 28% of all solutions developed are smart sprayers and farming robots that make usage of such algorithms. This gives the answer to RQ3.

Hence, the focus of the use of technology in weed management is detection, identification, and classification of different types of weeds. Therefore, it is possible to see a lack of studies on the application of such models and algorithms to address applications such as: dataset for weed behavior patterns in cropping systems, morphological crop alteration due weed competition between crops and invasive species, identification of biotypes of herbicide resistant species, weed emergence prediction, early detection of herbicide resistant weeds, among other gaps.

## 4. Conclusions

This study presented a systematic review of the literature which identified articles related to the subjects of "machine-learning models", "weed management" and "integrated crop-livestock systems". Although none of the retrieved articles encompassed these three subjects mentioned above simultaneously, 496 studies concerning weed control and ICLS or artificial intelligence were pre-selected. After applying the eligibility criteria 40 research articles were chosen. These studies were submitted to a data extraction process, and the gathered information was further analyzed to answer the selected key questions.

An interesting finding is that the number of articles regarding artificial intelligence and weed management is increasing since 2020, but those related to ICLS not as much. Besides, maize was the crop that most appeared in the selected articles. This is probably due to the scarce and expensive treatment for narrow-leaf weeds. Moreover, it is evident from this review that the countries that invest the most in this type of research are the United States and some nations in Asia. Although Brazil is one of the few countries exploring the use of ICLS, the application of machine-learning models for weed control is still not widely seen. Future studies are important to monitor the trending in this field.

In terms of the actual application, the main finding was that 47% of all machine-learning studies and 28% of the developed solutions are related to image processing, demonstrating that there is a strong focus on developing technologies related to site-specific herbicide application. Consequently, many gaps related to weed management could be explored using these algorithms and models, such as weed behavior patterns, competition predictions between crops and weeds, weed emergence prediction, detection and identification of herbicide resistance species, and others.

### Author's contributions

All authors read and agreed to the published version of the manuscript. AG and AF: Conceptualization of the manuscript and development of the methodology. AG: data collection and curation. AG: data analysis. AG: data interpretation. AF and MO: funding acquisition and resources. AF: project administration. MO and BH: supervision. AG: writing the original draft of the manuscript. AF, BH, and MO: writing, review, and editing.

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### References

Abouzahir S, Sadik M, Sabir E. Enhanced approach for weeds species detection using machine vision. Proceedings of the 2018 International Conference on Electronics, Control, Optimization and Computer Science (ICECOCS); 2018; Kenitra, Morocco. New York: Institute of Electrical and Electronics Engineers; 2018[access May 25th, 2023]. Available from: https://doi.org/10.1109/icecocs.2018.8610505

Ajayi OG, Ashi J. Effect of varying training epochs of a faster region-based convolutional neural network on the accuracy of an automatic weed classification scheme. Smart Agric Technol. 2023;3:100-28. Available from: https://doi.org/10.1016/j.atech.2022.100128

Alpaydin E. Introduction to machine learning. 4th ed. Cambridge: Massachusetts Institute of Technology; 2020.

Alrowais F, Asiri MM, Alabdan R, Marzouk R, Hilal AM, Alkhayyat A et al. Hybrid leader based optimization with deep learning driven weed detection on internet of things enabled smart agriculture environment. Comput Electr Eng. 2022;104(4). Available from: https://doi.org/10.1016/j.compeleceng.2022.108411

Chavan TR, Nandedkar AV. AgroAVNET for crops and weeds classification: a step forward in automatic farming. Comput Electron Agric. 2018;154:361-72. Available from: https://doi.org/10.1016/j.compag.2018.09.021

Costello B, Osunkoya OO, Sandino J, Marinic W, Trotter P, Shi B et al. Detection of parthenium weed (*Parthenium hysterophorus* L.) and Its growth stages using artificial intelligence. Agriculture. 2022;12(11):1-23. Available from: https://doi.org/10.3390/agriculture12111838

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

Dominschek R, Schuster MZ, Barroso AAM, Moraes A, Anghinoni I, Carvalho PCF. Diversification of traditional paddy field impacts target species in weed seedbank. Rev Cienc Agron. 2022;53:1-10. Available from: https://doi.org/10.5935/1806-6690.20220030

Etienne A, Ahmad A, Aggarwal V, Saraswat D. Deep learning-based object detection system for identifying weeds using UAS imagery. Remote Sens. 2021;13(24):1-22. Available from: https://doi.org/10.3390/rs13245182

Fawakherji M, Potena C, Pretto A, Bloisi DD, Nsrdi D. Multi-spectral image synthesis for crop/weed segmentation in precision farming. Robot Auton Syst. 2021;146. Available from: https://doi.org/10.1016/j.robot.2021.103861

Firmansyah E, Suparyanto T, Hidayat AA, Pardamean B. Real-time weed identification using machine learning and image processing in oil palm plantations. IOP Conf Ser Earth Environ Sci. 2022;998:1-8.Available from: https://doi.org/10.1088/1755-1315/998/1/012046

Gao J, Nuyttens D, Lootens P, He Y, Pieters JG. Recognising weeds in a maize crop using a random forest machine-learning algorithm and near-infrared snapshot mosaic hyperspectral imagery. Biosyst Eng. 2018;170:39-50. Available from: https://doi.org/10.1016/j.biosystemseng.2018.03.006

Hanson B. Machine learning 2020: the ultimate guide to data science, artificial intelligence, and neural networks in modern business and marketing applications. San Francisco: databricks; 2019.

Hussain N, Farooque AA, Schumann AW, Abbas F, Acharya B, Mckenzie-Gopsill A et al. Application of deep learning to detect Lamb's quarters (*Chenopodium album* L.) in potato fields of Atlantic Canada. Comput Electr Eng. 2021;182. Available from: http://dx.doi.org/10.1016/j.compag.2021.106040

Ikeda FS, Mitja D, Vilela L, Carmona R. [Soil seedbank in integrated crop-pasture systems] Pesq Agropec Bras. 2007;42(11):1-7. Portuguese Available from: https://doi.org/10.1590/s0100-204x2007001100005

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

Jose JA, Sharma A, Sebastian M, Densil RVF. Classification of weeds and crops using transfer learning. Proceedings of the 2022 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI); 2022; Chennai, India. New York: Institute of Electrical and Electronics Engineers; 2022[access May 26th, 2023]. Available from: http://dx.doi.org/10.1109/accai53970.2022.9752477

Liberati A, Altman DG, Tetzlaff J, Mulrow C, Gøtzsche PC, Ioannidis JPA et al. The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: explanation and elaboration. J Clin Epidemiol. 2009;62(10):1-34. Available from: https://doi.org/10.1016/j.jclinepi.2009.06.006

Meena SD, Susank M, Guttula T, Chandana SH, Sheela J. Crop Yield Improvement with weeds, pest and disease detection. Procedia Comput Sci. 2023;218:2369-82. Available from: https://doi.org/10.1016/j.procs.2023.01.212

Monteiro AL, Souza MF, Lins HA, Teófilo TMS, Barros Júnior AP, Silva DV et al. A new alternative to determine weed control in agricultural systems based on artificial neural networks (ANNs). Field Crops Res. 2021;263. Available from: https://doi.org/10.1016/j.fcr.2021.108075

Nasiri A, Omid M, Taheri-Garavand A, Jafari A. Deep learning-based precision agriculture through weed recognition in sugar beet fields. Sustain Comput Informatics Systems. 2022;35. Available from: https://doi.org/10.1016/j.suscom.2022.100759

Ngo K, Chua J, Chun B, Ai RT. Automated weed detection system for bokchoy using computer vision. Proceedings of 2022 IEEE 14th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM); 2022; Boracay Island, Philippines. New York: Institute of Electrical and Electronics Engineers; 2022[access May 26th, 2023]. Available from: https://doi.org/10.1109/hnicem57413.2022.10109618

Ni C, Tian B, Wang X, Sun Y, Fei C. A deep convolutional neural network-based method for identifying weed seedlings in maize fields. Proceedings of 2022 IEEE 5th Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC); 2022; Chongqing, China. New York: Institute of Electrical and Electronics Engineers; 2022[access May 26th, 2023]. Available from: https://doi.org/10.1109/imcec55388.2022.10019943

Oliveira MF, Fernandes AMR, Moresco R. [Agriculture 5.0 perspectives for weed management]. Arinos: IFNM; 2023. Portuguese.

Organisation for Economic Co-operation and Development – OECD. Artificial intelligence and employment: new evidence from occupations most exposed to AI. Paris: Organisation for Economic Co-operation and Development; 2021[access September 08th, 2023]. Available from: https://www.oecd.org/future-of-work/

Partel V, Kakarla SC, Ampatzidis Y. Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence. Comput Electr Eng. 2019;157:339-50. Available from: https://doi.org/10.1016/j.compag.2018.12.048

Pérez-Ortiz M, Peña JM, Gutiérrez PA, Torres-Sánchez J, Hervás-Martínez C, López-Granados F. Selecting patterns and features for between- and within- crop-row weed mapping using UAV-imagery. Expert Syst Appl. 2016;47:85-94. Available from: https://doi.org/10.1016/j.eswa.2015.10.043

Qiao X, Li YZ, Su GY, Tian HK, Zhang S, Sun ZY et al. MmNet: identifying mikania micrantha kunth in the wild via a deep convolutional neural network. J Integr Agric. 2020;19(5):1292-300. Available from: https://doi.org/10.1016/s2095-3119(19)62829-7

Raja R, Slaughter DC, Fennimore SA, Siemens MC. Real-time control of high-resolution micro-jet sprayer integrated with machine vision for precision weed control. Biosyst Eng. 2023;228:31-48. Available from: https://doi.org/10.1016/j.biosystemseng.2023.02.006

Razfar N, True J, Bassiouny R, Venkatesh VI, Kashef R. Weed detection in soybean crops using custom lightweight deep learning models. J Agric Food Res. 2022;8. Available from: https://doi.org/10.1016/j.jafr.2022.100308

Sabzi S, Abbaspour-Gilandeh Y, Arribas JI. An automatic visible-range video weed detection, segmentation and classification prototype in potato field. Heliyon. 2020;6(5):1-17. Available from: https://doi.org/10.1016/j.heliyon.2020.e03685

Sabzi S, Abbaspour-Gilandeh Y. Using video processing to classify potato plant and three types of weed using hybrid of artificial neural network and particle swarm algorithm. Measurement. 2018;126:22-36. Available from: https://doi.org/10.1016/j.measurement.2018.05.037

Sandino J, Gonzalez F. A novel approach for invasive weeds and vegetation surveys using UAS and artificial intelligence. Proceedings of the 23rd International Conference on Methods & Models in Automation & Robotics (MMAR); 2018; Miedzyzdroje, Poland. New York: Institute of Electrical and Electronics Engineers; 2018[access May 25th, 2023]. Available from: https://doi.org/10.1109/mmar.2018.8485874

Schuster MZ, Martinichen D, Pelissari A, Lustosa SBC, Gazziero DLP. Floristic and phytosociology of weed in response to winter pasture sward height at Integrated Crop-Livestock in Southern Brazil. App Res Agrotechnol. 2016;9(2):19-26. Available from: https://doi.org/10.5935/10.5935/PAeT.V9.N2.02

Schuster MZ, Pelissari A, Moraes A, Harrison SK, Sulc RM, Lustosa SBC et al. Grazing intensities affect weed seedling emergence and the seed bank in an integrated crop–livestock system. Agric Ecosyst Environ. 2016;232:232-9. Available from: https://doi.org/10.1016/j.agee.2016.08.005

Shorewala S, Ashfaque A, Sidharth R, Verma U. Weed density and distribution estimation for precision agriculture using semi-supervised learning. IEEE Access. 2021;9:27971-86. Available from: https://doi.org/10.1109/access.2021.3057912

Siddiqui SA, Fatima N, Ahmad A. Neural network based smart weed detection system. Proceedings of the International Conference on Communication, Control and Information Sciences (ICCISc); 2021; Kerala, India. New York: Institute of Electrical and Electronics Engineers; 2021[access May 26th, 2023]. Available from: http://dx.doi.org/10.1109/iccisc52257.2021.9484925

Snyder, H. Literature review as a research methodology: an overview and guidelines. J Bus Res. 2019;104:333-9. Available from: https://doi.org/10.1016/j.jbusres.2019.07.039

Souza MF, Amaral LR, Oliveira SRM, Coutinho MAN, Netto, Camila Ferreira. Spectral differentiation of sugarcane from weeds. Biosyst Eng. 2020;190:41-6. Available from: https://doi.org/10.1016/j.biosystemseng.2019.11.023

Subeesh A, Bhole S, Singh K, Chandel NS, Rajwade YA, Rao KVR, Kumar SP et al. Deep convolutional neural network models for weed detection in polyhouse grown bell peppers. Artif Intell Agric. 2022;6:47-54. Available from: https://doi.org/10.1016/j.aiia.2022.01.002

Sudars K, Jasko J, Namatevs I, Ozola L, Badaukis N. Dataset of annotated food crops and weed images for robotic computer vision control. Data Br. 2020;31:105833. Available from: https://doi.org/10.1016/j.dib.2020.105833

Torres-Sospedra J, Nebot P. Two-stage procedure based on smoothed ensembles of neural networks applied to weed detection in orange groves. Biosyst Eng. 2014;123:40-55. Available from: https://doi.org/10.1016/j.biosystemseng.2014.05.005

Wang A, Xu Y, Wei X, Cui B. Semantic segmentation of crop and weed using an encoder-decoder network and image enhancement method under uncontrolled outdoor illumination. IEEE Access. 2020;8:81724-34. Available from: https://doi.org/10.1109/access.2020.2991354

Wang MY, Leelapatra W. Weeding robot based on lightweight platform and dual cameras. Skima. 2022;31:1-7. Available from: https://doi.org/10.1109/skima57145.2022.10029527

Yan X, Deng X, Jin J. Classification of weed species in the paddy field with DCNN-learned features. Proceedings of the IEEE 5th Information Technology and Mechatronics Engineering Conference (ITOEC); 2020; Chongqing, China. New York: Institute of Electrical and Electronics Engineers; 2020[access May 26th, 2023]. Available from: https://doi.org/10.1109/itoec49072.2020.9141894

Yu J, Schumann AW, Cao Z, Sharpe SM, Boyd NS. Weed detection in perennial ryegrass with deep learning convolutional neural network. Front Plant Sci. 2019;10. Available from: https://doi.org/10.3389/fpls.2019.01422

Yu J, Schumann AW, Sharpe SM, Li X, Boyd NS. Detection of grassy weeds in bermudagrass with deep convolutional neural networks. Weed Sci. 2020;68(5):545-52. Available from: https://doi.org/10.1017/wsc.2020.46

Zhang W, Hansen MF, Volonakis TN, Smith Melvyn, S Lyndon, Wilson J et al. Broad-leaf weed detection in pasture. Proceedings of the IEEE 3rd International Conference on Image, Vision and Computing (ICIVC); 2018; Chongqing, China. New York: Institute of Electrical and Electronics Engineers; 2018[access May 25th, 2023]. Available from: https://doi.org/10.1109/icivc.2018.8492831