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COMPUTER VISION IN PRECISION AGRICULTURE FOR WEED CONTROL: A SYSTEMATIC LITERATURE REVIEW

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Highlights

- Identify popular computer vision approaches for weed control
- Determine which approaches worked best in which situations
- Approaches that were combined with Machine Learning were preferred

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ABSTRACT: The paper aims to carry out a systematic literature review to determine what computer vision techniques are prevalent in the field of precision agriculture, specifically for weed control. The review also noted what situations the techniques were best suited to and compared their various efficacy rates. The review covered a period between the years 2011 to 2022. The study findings indicate that computer vision in conjunction with machine learning and particularly Convolutional Neural Networks were the preferred options for most researchers. The techniques were generally applicable to all situations farmers may face themselves with a few exceptions, and they showed high efficacy rates across the board when it came to weed detection and control.

Keywords: *Computer Vision, Machine Vision, Precision Agriculture, Smart Farming, Weed Control*

1. INTRODUCTION

The agricultural sector grapples with the dual tasks of maintaining a high crop yield from farms and doing so in a sustainable way, such that resources are utilized efficiently for costs and environmental friendliness [1]. Weeds refer to plants that are invasive in some way and are unwanted in a particular situation. The unmitigated proliferation of weeds in a farm setting can have a severe negative impact on crop yields, resulting in diminished yields, poorly utilized resources, and environmental degradation, particularly with respect to herbicides and farmer labour efforts. Traditional measures currently employed when dealing with weeds include the blanket use of herbicides over large tracts of farmland, which while effective to some extent, may also harm biodiversity in the region and cause environmental pollution in the process of weed removal. Steps thus need to be taken to ensure that only the unwanted weeds are removed from the main crop population, with minimal detrimental effects on the environment.

Advances in research and the fusion of technology and agriculture have resulted in precision agriculture, which is a boon to farmers worldwide. Precision agriculture consists of agricultural methods that utilize advanced sensors, software, and cameras for data collection and analysis, with the goal of higher yields, higher profits, and more sustainable land use [2]. Computer vision, which seeks to imitate the human eye's act of perceiving and understanding the world, features several implementations for the task of precision agriculture [3] These include; the use of computer vision and deep learning to locally detect pockets of weeds and subsequent removal through chemical, mechanical or electrical systems [1]; the use of robotics and computer vision to automatically wipe out the weeds with minimal human intervention [2]; ground-level mapping and subsequent navigational techniques of farms for monitoring crop health and identification of weeds through computer vision [4]; and even the use of a "farm-copter", that is, a quad-copter with cameras that flies over farmland and captures images of crops, which are then analyzed and relevant data provided to

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the farmer, allowing them to take actions to combat against weeds and pests [5].

The aforementioned techniques are all excellent applications of computer vision in conjunction with precision agriculture to the problem of weed control. However, there still exists a gap in research, particularly in how disparate the various methods that are currently being employed are. This paper sought to identify and catalog the relevant studies, critically analyze them and thus provide a detailed review of past research on the topic. This will enable future researchers and farmers to identify what techniques already exist, their different levels of success and feasibility, and which techniques work best for their particular unique situations. To meet this objective, the following research questions were asked;

1-What are the different computer vision techniques currently being used for weed control?

2-In which situations do computer vision techniques give the most accurate results?

3-What is the efficacy of the different techniques being used?

2. MATERIAL AND METHOD

The study implemented a systematic literature review (SLR) to identify and select relevant articles while minimizing the chance of possible bias during the review process [6].

2.1. Search Strategy

The systematic literature review began with a search for the selected keywords that were relevant to the subject matter of the study. The keywords employed were “Computer Vision” AND “Precision Agriculture” AND “Weed Control” coupled with the synonyms listed in the following table. These keywords were then used to search through high-quality databases, namely Scopus, IEEE, and ScienceDirect, between a period of eleven years, from 2011 to 2022. These three journals were selected as they covered the fields of Agricultural and Biological Sciences and Computer Science, making them ideal sources of journals for this particular literature review.

Table 1. *Keywords search query*

	Keyword	**Synonyms**
MAIN	“Computer Vision”	“Machine Vision” OR “Vision”
AND	“Precision Agriculture”	“Precision Farming” OR “Smart Farming”
AND	“Weed Control”	“Weed Management”

2.2. Inclusion and Exclusion Criteria

The study used inclusion and exclusion criteria as part of the selection process to obtain articles that were relevant to the researchers’ aims. The inclusion criteria stipulated that only research articles published in the English language and that were fully accessible in the aforementioned databases, were to be chosen. The records that did not meet these conditions were excluded from the review.

Table 2. *Inclusion and Exclusion Criteria*

Inclusion Criteria	Exclusion Criteria
Research articles published in the English language	Papers that were not written in the English language
Documents published within the last eleven years from 2011 to 2022	Duplicated papers
Full text papers that are accessible and downloadable	Full text of the document is not accessible on the internet
Available within the selected databases	The study aim is not clearly defined
Studies that focused on Computer Vision, Precision Agriculture, and Weed Control	Relevant studies, but either Computer Vision, Precision Agriculture, or Weed Control are not the main objects of impact
Studies that considered Computer Vision, Precision Agriculture, and Weed Control as the main objects of impact	Conference Papers, editorial materials, and literature reviews

2.3. Selection Criteria

The PRISMA diagram was used to screen records for the primary study selection process that fall into the aforementioned parameters. The acronym PRISMA stands for, "Preferred Reporting Items for Systematic Review and Meta-Analyses" [6]. It allowed the researchers to exclude papers duplicated between the databases. It also allowed the researchers to exclude studies without clearly defined aims, studies that are not relevant to the research questions, and studies that only focused on one keyword as opposed to all of them, i.e., computer vision, precision agriculture, and weed control.

A total of one thousand and thirty (n=1030) articles were retrieved from a preliminary search of the three databases, with the individual databases contributing records as follows: Scopus (n=398), IEEE (n=101), and ScienceDirect (n=531). Out of these results, records whose full text was not accessible on the Internet totaled four hundred and fifty (n=450). Papers other than research articles were also removed, and these totaled four hundred and twenty-four (n=424) Papers not in the English language totaled nine (n=9), and these were removed in the process as well.

Up next was a check for duplicates, which identified five (n=5) sets of duplicates among the articles. Upon merging them, the new total number of articles came down to 142 research articles. Thus, a hundred and forty-two articles (n=142) were left to be assessed for eligibility. The remaining articles were then examined against the research questions to ensure that they could provide some insight into them and subsequently the theme of the paper. After applying the aforementioned criteria, a total of thirty-five (n=35) articles remained as primary studies for review. These excluded articles whose study aim was not clearly defined and articles that were relevant but did not focus on computer vision, precision agriculture, and weed control.

2.4. Data Extraction

Data extraction was carried out on the remaining articles that met the selection criteria. This was conducted following the parameters shown in the table below.

Table 3. *Data Extraction Form*

Data Item	Description
Author, Citations, Location, Year	Give the author names, citation count, publication location, and year of publication
Theory considered	Which theory/area of expertise was considered in the study
Purpose of the study	The main aim of the study
Research design	What research design was utilized
Key findings	Show the main results from the articles
Challenges	What limitations were faced in the research process

2.5. Data Analysis

After the data was collected and extracted from the articles, it was synthesized through the construction of a summary table and subsequently evaluated along methodological and theoretical aspects based on the utilization of computer vision in precision agriculture for weed control. This was carried out to answer the established research questions.

3. RESULTS

3.1. Computer Vision Techniques for Weed Control

Several computer vision techniques were utilized in the studies with the aim of weed control. Studies primarily focused on accurately distinguishing between crops and weeds from image analysis through semantic segmentation, which then allowed the farmers to combat the infestation with precision as opposed to conventional blanket herbicide applications [7, 8, 9, 10, 11]. A few studies focused on real-time detection technology of weeds, with some employing sensor technology coupled with computer vision to detect weeds, analyze soil fertility, and alert on fires in the field [12, 13, 14, 15]. Some studies also focused on holistic systems for weed control, providing the mechanisms for weed detection and subsequent targeting via herbicides all in one solution e.g., through a smart sprayer or automated mechanical weed remover solutions [13, 16, 17]. Some studies also utilized 3D approaches and geometric analysis in their machine vision experiments in an attempt to produce better detection algorithms [18, 19, 20, 21].

A large number of studies implemented machine vision techniques in conjunction with some machine learning technologies. These included deep neural networks, convolutional neural networks, supervised and semi-supervised learning, Support Vector Machines, Radom Forest classification, and K-nearest neighbors' classification. Of note is a study that used fuzzy logic and children's guesses as a starting point in building their system as opposed to training neural networks [22]. This method yielded insightfully positive results, outperforming more conventionally trained, neural-network-backed computer vision techniques.

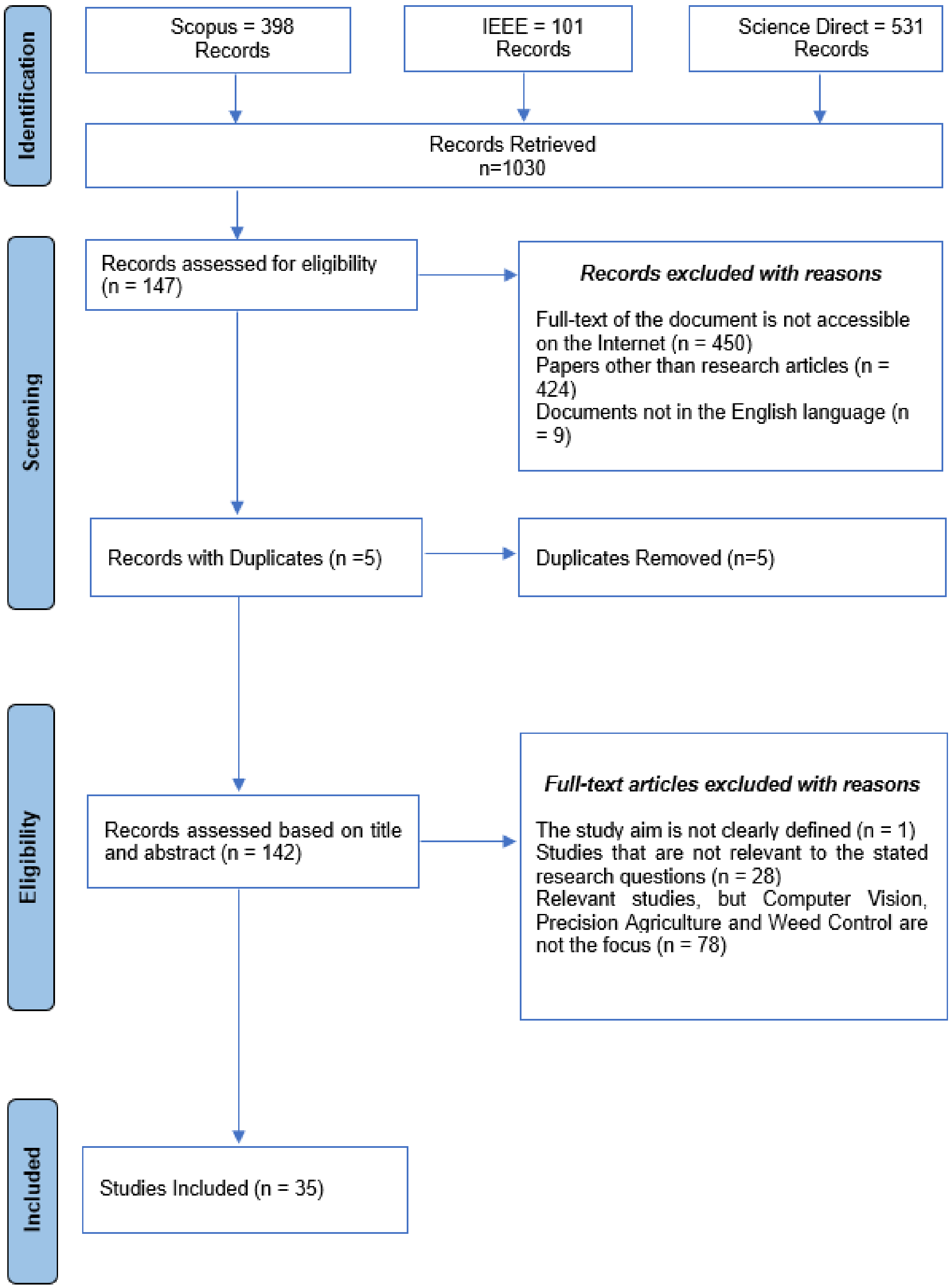

Figure 1. *PRISMA Flow Diagram for the selection process*

3.2. Computer Vision Techniques and the Conditions They are Most Successful

The aforementioned methods were all found to be high in efficacy, except for end-to-end or fully autonomous solutions. The rest of the methods required relatively little capital to implement and were accessible to most farmers in the know of their existence. However, the autonomous and vehicular solutions needed an infusion of capital to implement and this may be out of the reach of farmers who are not too well off, such as smallholders and those in third-world countries [13, 23, 24, 25].

As for the knowledge backing needed, implementation of computer vision with the aim of weed control primarily required some background knowledge of what machine vision architecture one was going to implement and the machine learning method to be used.

3.3. Efficacy Rates of the Different Computer Vision Techniques Being Used for Weed Control

All the methods showed exceptional results in aspects such as accuracy and sensitivity. A convolutional neural network implementation within computer vision was the most prevalent iteration of a robust precision agriculture system, and coincidentally also made up the most accurate system, with an accuracy rate of 99.19% when it came to crop and weed detection. Most models were able to achieve accuracy rates of 90% and upwards, with the lowest-scoring one coming in at 59.8% [15, 24].

4. DISCUSSION

The review worked to analyze the various computer vision techniques utilized in precision agriculture for weed control. Most of these implemented a facet of machine learning, be it Support Vector Machines, Back Propagation, or Convolutional Neural Networks. These AI tools were then used in the machine vision systems to create models that accurately detected weeds, pests, and diseases in crops.

The results show that generally, computer vision is primarily employed in image analysis as opposed to the less common application within real-time autonomous weed detection and control systems. Farmers and researchers alike use computer vision as a first step in mitigating weed population, then once they can get a working model and identify the problem areas, additional weed control efforts are sought. Prevention and early detection are preferred to fighting full-blown infestations, and as such, the farmers' and researchers' methodologies have merit in that regard.

Another point of note is that autonomous systems are relatively expensive to build and utilize. Retrofitting tractors with expensive cameras, building smart sprayers and use of autonomous vehicles represent significant investments that are not to be taken lightly and thus may be out of the range of quite a few researchers and farmers.

New techniques are being explored in research in addition to machine learning implementations, and these involve Masks' Law, Clifford Algebra, 3D techniques, and even the use of children's minds in conjunction with fuzzy logic. These methods are arguably faster to implement, as all the aforementioned machine learning models need to undergo some aspect of training. They are also more cost-effective as they typically do not require as much computing power as machine learning systems to conduct vision analysis.

While techniques deployed singularly on their own are adept at weed control, it is the synergy brought about by the combination of two or more techniques that brings the greatest payoff to researchers and farmers alike in precision agriculture. The confluence of fluorescent imaging, crop signaling, and 3D localization algorithms yielded significant payoffs while offering a unique method of weed detection and control to researchers in one case. In another case, wireless sensor networks together with machine learning implementations of Support Vector Machines and Random Forest were able to accurately monitor for pest and weeds and was also affordable to set up. Simple systems involving Convolutional Neural Networks and smartphones were used to detect corn leaf disease in real time, functioning even when the software was not connected to the internet. In these cases, synergistic approaches to precision agriculture represented attainable end-to-end real-world applications of computer vision in the task of weed control.

Table 4. *General Description of The Studies*

Ref #	Author/Number of Citation(s) (C)/Location (L)	GfE/Theory considered	Purpose of the study	Research design	Key finding (s)	Challenges
4.	(Zhao et al., 2021) C=5 L=USA	Transfer learning, deep learning	Create a pipeline to improve object detection using deep learning, with applications in precision agriculture.	Experimental study	The new object detection method resulted in a smaller need for manual-labeling tasks, saving time and effort. It also showed improvements in object detection after training from augmented datasets, can scale to other crops, and work as an effective weed combating measure.	The study should have employed more real images from which to build synthetic images for the training of the pipeline.
7.	(You et al., 2020) C=8 L=South Korea	Deep Neural Network (DNN) Based segmentation model for crop/weed recognition, coupled with a convolutional layer (CNN) and DropBlock	Improve on semantic segmentation (pixel-wise classification) networks for weed/crop identification	Experimental study	While previous studies only used DNN alone for segmentation, the introduction of a CNN and DropBlock improves the model's performance by 4.65% and 1% respectively.	The model having to contend with various lighting conditions and image capture angles from the camera, which was overcome by the use of a CNN.

8.	(Asad & Bais, 2020) C=20 L=Canada	Deep learning, semantic segmentation, Maximum Likelihood Classification (MLC)	Propose a two-step approach for manually labeling weeds in agricultural images and use of semantic segmentation for the detection and mapping of weeds. These are coupled with iterations over different feature extractors and meta-architectures.	Quantitative study	The two-step approach for manually labeling images saves time, reduces errors, and increases labeling efficiency. Semantic segmentation was promising for weed detection, with a Mean Intersection Over Union (MIOU) value of 0.8288 and Frequency Weighted Intersection Over Union value of 0.9869. SegNet was found to be the better meta-architecture and ResNet-50 feature extractor was found to have better performance over VGG16.	The study did not include soil samples which would have shed even more light between soil characteristics and weed densities.
9	(Sodjinou et al., 2022) C=5 L=Benin	Semantic segmentation, K-means algorithms	Segment between crops and weeds in images where a complex presence of weeds exists through semantic segmentation and K-means algorithm.	Experimental study	Accurate segmentation of crops and weeds was achieved where images had a complex presence of weeds and attained a maximum accuracy of 99.19% with their method.	Image quality decreased once semantic segmentation was implemented to detect weeds. This may be dealt with in the future through quality enhancement.
10.	(Wang et al., 2020) C=12 L=China	Semantic segmentation, deep learning	Carry out pixel-wise semantic segmentation via an encoder-decoder deep learning network.	Experimental study	The deep learning network applied did not require a lot of training data. Near Infrared Information (NIR) improved segmentation accuracy of the process, compensating for poor illumination conditions in the system.	The model is bulky as is, and cannot be deployed to more portable systems such as mobile devices without first subjecting it to compression.

11.	(Zhang et al., 2022) C=3 L=USA	Support Vector Machines (SVM), Visual Group Geometry 16 (VGG16)	Identify and classify crops and weeds through RGB image texture features and contrast between ML and DL methods	Experimental study	Deep Learning performed better than machine learning efforts to detect weeds and crops, with VGG16 classifiers beating out SVM classifiers with scores of over 93%.	The study was limited to only a few species of weeds and crops found in the midwestern region of USA.
12.	(Bhanu et al., 2019) C=11 L=India	Multi-agent-based context-aware information gathering, Wireless Multimedia Sensor Networks (WMSN).	Develop a system of sensor networks coupled with context-aware systems and agent technology for monitoring agriculture i.e., to detect weeds, fire, diseases, and soil fertility.	Simulation	The proposed system performed better than the previous Context Aware Wireless Irrigation Systems (CAWIS) in terms of context detection time, energy consumption, delay, and fusion time.	The increase in the number of nodes caused communication delays, increases in energy use, context detection time, and fusion time. The introduction of more sink nodes is recommended for future research.
13.	(Partel et al., 2019) C=91 L=USA	Neural Networks to aid in target detection and classification, deep learning, transfer learning, Convolutional Neural Networks.	To build a low-cost, smart sprayer that allows for the precision targeting and management of pests and weeds.	Experimental study	A low-cost system ($1500) was built for precision targeting and spraying of weeds which when coupled with AI, was able to achieve a precision rate of 71% and a recall rate of 78% on real plants.	Price of Graphics Processing Units; the more expensive ones yielded better results. The sprayer performed slightly worse in shadow-less areas and experienced a majority of misses on its right side for inconclusive reasons.
14.	(Kamath et al., 2019) C=23 L=India	Wireless sensor network applications, Raspberry Pi, Random Forest, Support Vector Machines	Develop a wireless sensor network system using Raspberry Pis to monitor paddy crops for weeds and carry out their targeted elimination.	Experimental study	A wireless sensor network was successfully developed and implemented. It was low-cost and was able to watch the crops for pests and weeds.	The sensor network could be expanded with more functionality, such as soil analysis, humidity sensing, and illumination analysis.
15.	(Cubero et al., 2020) C=8 L=Spain	Robotics, remote sensing	Create a remote-controlled field robot for detecting maladies and pests in crops via remote sensing techniques.	Experimental study	A remote-controlled robot that can detect maladies and pests with accuracies of up to 67.3% in the lab and 59.8% in the field was developed.	The system relies on remote piloting, which may be labor-intensive, as opposed to a completely autonomous system.

16.	(Dimililer & Kiani, 2017) C=11 L=North Cyprus	Back propagation neural network (BPNN), robotics	Create a framework from neural network algorithms that enables farmers to conduct real-time maize plant detection and simplify their in-row weeding efforts.	Experimental approach	The BPNN implemented was accurate 88% of the time. The entire system was flexible, fast, and robust, with the BPNN able to finalize its training after 2213 iterations within 82 seconds.	The image datasets used for the training and testing of the BPNN could have been more expansive, as the study only used 30 images for the training set and 50 images for the generalization set.
17.	(Albanese et al., 2021) C=1 L=Italy	Artificial intelligence, machine learning (ML), smart cameras, deep neural networks (DNN)	Present a smart trap that autonomously identifies and captures pests and alerts the farmer of their location for pesticide application	Quantitative study	The system used ML algorithms to identify pests captured in the traps and provide an early warning system for farmers. ML analysis occurs on board the smart trap, thus bandwidth costs for wireless transmission of images are reduced. An energy harvester for the trap was also implemented.	The limited energy of the smart traps, which the researchers attempted to mitigate via an energy harvesting mechanism installed alongside the trap.
18.	(Smith et al., 2018) C=11 L=UK	3D crop analysis, photometric stereo	Develop a 3D approach to computer vision that overcomes the current 2D approach's limitations i.e., perspective, occlusion, changes in background light, and parallax.	Experimental approach	The 3D system was able to accurately determine plant textures with high resolutions even under direct sunlight. It also measured the size of produce in the field to an accuracy of within 10% under a range of environmental conditions.	Real-world conditions for testing the 3D imaging system were hampered as the tractor which held the system had issues related to power supply.
19.	(Khan et al., 2019) C=14 L=China	Clifford geometric algebra, unmanned aerial vehicles (UAVs)	Implement Clifford geometric algebra in tandem with the use of UAVs to get authentic color space image processing and better carry out precision agriculture.	Experimental study	The use of Clifford algebra (CA) yields genuine color space image processing over the typical RGB segmentation approaches. Edge detection may be carried out using CA and it can be used to detect and measure plant variability and soil changes.	More studies implementing Clifford Analysis in segmentation need to be carried out concerning precision agriculture.

20.	(Del-Campo-Sanchez et al., 2019) C=12 L=Spain	Artificial neural networks, geometry	To determine the impact that the *Jacobiasca lybica* pest has on vineyards through artificial neural network techniques and geometric techniques.	Experimental study	The use of machine vision and geometric techniques was able to improve results during pest detection.	Soil and affected vegetation in a 2D space suffer from similar radiometric responses, which can be a source of error.
21.	(Su et al., 2022) C=2 L=China	Fluorescent imaging, crop signaling, 3D localization algorithm	Develop a method of distinguishing between soybean crops and weeds through crop signaling and computer vision algorithms	Experimental study	Soybean plants were identified from weeds through crop signaling, through seeds being treated with an Rh-B marker, and 3D imaging as the marker gave off unique optical characteristics.	The study may have benefitted from coupling the 3D imaging system with actual weed removal mechanisms and tested it as such.
22.	(Kiani et al., 2017) C=1 L=North Cyprus	Children, Early-age child recognition, Fuzzy logic.	Build an automated system for mechanically pulling out weeds, starting first by using actual human children to make guesses as to what plant is a weed and later honing this systematic analysis with fuzzy logic	Quantitative study	An Application Programming Interface (API) that emulated the human brain and did not rely upon neural networks was built. The API is implemented on low-cost platforms and its use resulted in a 95% accuracy rate which slightly outperforms typical neural network-based classifiers.	The experiment was only carried out under extreme July sun lighting conditions and does therefore not account for overcast weather.
23.	(Shorewala et al., 2021) C=2 L=India	Deep Learning-based Semi-Supervised Approach for robust approximation of weed density from images captured by autonomous robots. Convolutional Neural Networks (CNN) also used.	Develop an economically feasible way for analyzing farm images, and seek an alternative to the resource-intensive supervised ML approaches that need huge amounts of manually annotated images to train.	Quantitative study	Proposed approach detected weeds from the images provided with a maximum recall of 0.99 and an accuracy of 82.13%. The study reduced reliance on manually annotated images as it employed semi-supervised learning.	Several iterations are necessary to come up with vegetative masks for the model, which is time-consuming.

24.	(Dankhara et al., 2019) C=5 L=India	Autonomous robots, IoT, Supervised Learning.	To propose an architecture for the use of IoT in smartweed detection and precision agriculture.	Exploratory research	An IoT-based intelligent robot built from a Raspberry Pi, Sprayer, Pi Camera, and software components may increase the accuracy and precision of weed removal from the field. Reduction of herbicides present in the field would occur, reducing health problems arising from their use.	A shortage of good quality pixel-wise images reduces the accuracy of results.
25.	(Li et al., 2022) C=0 L=UK	Robotics, Lane Detection, Novel Image Processing Pipeline	Develop a new image processing pipeline to detect and follow narrow cereal crop rows with high fidelity. It is intended to be integrated with robotic applications.	Experimental study	Initial machine vision efforts were prioritized over later ML manipulations. The new method can pick out rows despite cases of significant occlusion, work on low-cost hardware, in real-time, and on high/low-resolution images.	The robotics aspect of the study may not hold up to drastic terrain shifts as it has only been tested on straight rows.
26.	(Patayon & Crisostomo, 2021) C=1 L=Philippines	Deep learning, neural networks.	Propose a system implemented through computer vision and artificial intelligence to detect abaca bunchy top disease.	Experimental study	For precision under the DSLR, performance of the model is better when images of leaves and petioles are used for training while performance of the model is better when images of petioles are used under mobile device image capture.	The study was limited by its dataset of training images and did not explore other architectures such as ResNet, AutoML, or GoogleNet.
27.	(Liu & Chahl, 2021) C=0 L=Australia	Deep Neural Networks (DNN), Convolutional Neural Networks (CNN)	Create a machine vision system capable of detecting invertebrates on crops in the field for precision application of pesticides.	Quantitative study	The system aided early detection of invertebrates on the crops. A novel virtual ML model training database was also created. The study found that ResNet performed better than AlexNet and VGG for pest classification.	Limited training data for the CNN which the researchers mitigated through the use of a virtual database.

28.	(Partel et al., 2021) C=0 L=USA	Machine vision, artificial intelligence, sensor systems, Convolutional Neural Networks (CNN)	Develop a real-time smart sprayer sensing system capable of classifying tree leaf health, and tree leaf density, can adapt to environmental changes, and can also pick out trees from other objects.	Experimental study	The system cost $2000 to develop and was able to estimate tree height with low average error of 6%. It also classified trees based on whether they were young, mature, old, dead, or if they were not trees with a success rate of 84%. It also better-targeted weeds for spraying, reducing spraying volume by 28% in contrast to conventional spraying (where the nozzle is always open).	The cameras on the smart sprayer system are susceptible to dust, sunlight, and water. The smaller field of view may also be a limitation for the cameras.
29.	(Hu et al., 2021) C=2 L=USA	Convolutional Neural Networks (CNN)	Determine effects of illumination consistency and picture quality on the performance of convolutional neural networks.	Simulation study	Using more variability in image illumination for training purposes may mitigate the dip in performance of the CNN brought about by real-world illumination variability, but it does not match up to the benefit that is brought to the CNN's performance by using images from similar lighting conditions.	The simulation of image degradation contained images that still possessed some level of blur and noise and thus the best convolutional neural network performance that is feasible remains unknown.
30.	(Kamath et al., 2020) C=7 L=India	Laws' Masks based texture classification, Random Forest Classification.	Propose a different approach to weed identification from images by use of Laws' masks, which is primarily utilized in healthcare but may be adapted for agricultural purposes.	Experimental study	Laws' masks classification was able to extract a total of 70 features from the images, and subsequently use these to train the Random Forest Classifier to detect weeds with an accuracy of 94%	Low number of publicly-available crop and weed benchmark datasets for researchers to use.

31.	(Le et al., 2020) C=7 L=Australia	Local binary patterns, contour masks, feature extraction, Support Vector Machines (SVM)	Develop a way of combining features extracted from local binary pattern operators and contour masks to increase the discrimination rate between broadleaf plants.	Quantitative study	The system reduced noise, improved plant classification accuracy, and exhibited peak performance at 98.63% in identifying morphologically similar plants. The system allowed for real-time detection and classification of plants.	The system may have further-reaching applications, not just those of identifying morphologically similar crops and weeds and other avenues should be explored.
32.	(Mishra et al., 2020) C=18 L=India	Deep learning, Convolutional Neural Network (CNN)	Develop a way through machine learning algorithms to recognize corn leaf disease in real-time.	Experimental approach	A deep CNN was designed and deployed that identified corn diseases in real-time with accuracies of up to 98.40% without the need for the Internet. The algorithm also identified corn diseases from images captured on smartphones with an accuracy of 88.66%.	The dataset was limited in terms of the number of maize diseases it included.
33.	(Varalakshmi & Aravindkumar, 2019) C=0 L=India	Support vector machines (SVM), Sobel detection, active contour	Develop an automated system for the detection and analysis of diseased leaves for the targeted application of pesticides.	Experimental study	The SVM approach was found to offer higher accuracy over other methods, having better sensitivity among the selected classifiers and overall performing better than them.	The method may be expanded to also give recommendations as to exactly what treatment is needed to tackle the plant disease, enriching the precision farming experience.
34.	(Singh et al., 2019) C=74 L=India	Multilayer Convolutional Neural Network (MCNN)	Create a way of effectively diagnosing mango leaves suffering from Anthracnose fungal disease through integrating deep learning and machine vision.	Experimental study	The model performed well, being able to detect anthracnose disease 97.13% of the time. The model developed was also simple and efficient in terms of computational power used.	Working with real-time data sets caused the study to encounter some inconsistencies in its experiments.

35.	(Pallottino et al., 2018) C=12 L=Switzerland	k-Nearest Neighbour (k-NN), shape analysis, machine vision.	Develop a system fitted onto tractors to allow real-time field operations and control tillage, aiding in precision agriculture, particularly weed control.	Experimental study	k-NN algorithm performed well under conditions of poor ambient lighting, which contrasted with the poor performance of the initial unsupervised algorithms.	At times, the tractor adversely cast two distinct lighting conditions on the crop rows, muddling the efficacy of the k-NN and machine vision system. The system was also not currently feasible at speeds greater than 1km/h^{-1}.
36.	(Bosilj et al., 2018) C=12 L=UK	Attribute morphology, segmentation, classification, Support Vector Machines	Develop a new method for image processing that relies on attribute morphology for segmentation and classification, as opposed to commonly used thresholding techniques.	Experimental study	The proposed approach can be used to segment the finer details of crop areas locally, can identify discriminating features, and classify plants as either weeds or crops at competitive rates.	The pipeline was not optimized to yield maximum speed, which is a limitation that can be tackled in later iterations.
37.	(Kiani & Mamedov, 2017) C=17 L=North Cyprus	Fuzzy analysis	Develop a method to identify plant disease through machine vision based on fuzzy logic and human brain approximations, without the need for neural networks or lengthy training of the system.	Experimental study	The study was able to develop a system free of neural networks that was accurate for detection and segmentation of crop maladies 97% of the time and took 1.2 seconds to compute the results.	Strong outdoor sun illumination hampered the identification of disease in some cases.
38.	(Montalvo, et al., 2012) C=127 L=Spain	Vision system atop an autonomous mobile agricultural vehicle, image segmentation, and double thresholding for crop row detection.	Develop an automatic method for crop row detection in maize fields with high weed pressure for precision targeting with herbicides.	Quantitative study	Initial thresholding recovers both weeds and crops, but upon the second thresholding, only crops are positively identified, even in areas with high weed pressure. This indicates that the addition of a second thresholding step is beneficial in areas with high weed densities.	Weeds and crops have similar Red. Green and Blue (RGB) spectral values and the vibrations from the vision system mounted on the vehicle impede image capture.

39.	(Burgos-Artizzu et al., 2011) C=194 L=Spain	Fast Image Processing (FIP) and Robust Crop Row Detection (RCRD)	Develop an accurate computer vision system comprising FIP and RCRD that is capable of functioning in the field in real-time and under uncontrolled lighting conditions for weed discrimination.	Quantitative study	The combination of the FIP and RCRD results in 85% detection of weeds and 69% of crops with videos subjected to blurriness/lighting changes and 95% detection of weeds and 80% of crops in fair videos.	The system was only tested on videos; thus, it remains to be seen if the accuracy statistics will hold up once tested in the field.
40.	(Tellaeche et al., 2011) C=102 L=Spain	Support Vector Machines (SVM), Machine Vision	Develop an automatic computer vision system capable of detecting *avena sterilis* which is a weed that grows among cereal crops.	Quantitative study	Since *avena sterilis* and cereal crops are similar in appearance, the new proposed approach is broken down into two stages, segmentation, which is first carried out using regular processing techniques, and decision-making, which is carried out by use of SVM.	The system may not be robust against lighting variability.

5. CONCLUSION

The field of precision agriculture is poised to be an abundant research area. This coupled with reducing costs of computer processors and cameras means that more researchers and independent practitioners will continue to experiment with various iterations of computer vision techniques with different implementations in precision agriculture for weed control. The interest of researchers in the last decade alone is promising, given the rising trend in publications on the subject matter. Machine learning plays a big part in computer vision techniques, with methods such as Convolutional Neural Networks, Support Vector Mechanisms, and k-nearest neighbour algorithms being utilized extensively. Unconventional methods such as the fusion of fuzzy logic and children’s guesses or crop signaling via fluorescent imaging must not be disregarded as they offer their own speed and efficiency contributions to the area. Synergistic applications whereby several techniques are used in tandem offer the best chance of effective weed control and are worth pursuing as they pool together several strengths from disparate methods. Research on weed control has come a long way and current studies promise to reduce the labor efforts of farmers significantly, all at relatively inexpensive costs, and also increase crop profits and aid the environment in its recovery.

The systematic literature review was limited by the time period within which it bound itself, i.e., 2011 to 2022. It was also bound by the selection criteria used and the databases employed in the review process. Further studies may incorporate more databases and also seek out articles on the subject matter in different languages, not just those written in the English language.

Declaration of Ethical Standards

The authors prepared the study in accordance with all ethical guidelines.

Credit Authorship Contribution Statement

D.K., J.K. and T.K.: Conceptualization; D. K.: Resources, Review, Supervision, and Project Administration. J. K: Methodology, Investigation, Formal Analysis, Original Draft. T. K.: Format Adjustment

Declaration of Competing Interest

There is no conflict of interest with any institution or person within the scope of the study.

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Data Availability

All data used in the study are available from the corresponding author upon reasonable request.

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