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Advancements in precision control in intra-row weeding: A comprehensive review

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Abstract
Sensor-based weed detection is a significant breakthrough in precise weed management that reduces the need for manual work and herbicides. GPS systems have shown promising results, with a single pass covering 30-49% of the intra-row area. Additionally, using an RGB sensor and a laser sensor together can identify the center of a plant, regardless of lighting conditions. Robots have demonstrated the ability to distinguish 99.7% of crop plants in dense outdoor areas with high weed density. These advancements offer opportunities for more effective and environmentally-friendly weed management in different farming systems.

Keywords: Precision weed management, intra row weeding, GPS systems, RGB sensor, laser sensor, eco-friendly weeding

Introduction
Weeds are a significant problem in agriculture, as they compete with cultivated plants for vital resources such as sunlight, water, and nutrients. This competition can lead to poor crop growth, lower yields, and increased expenses for farmers. Proper weed management is therefore crucial to ensure that crops grow properly and produce healthy, high-quality yields. Weed management involves essentially controlling weeds in two distinctive crop zones namely intra-row and intra-row space. Inter-row weeding involves removing weeds growing between rows of crops, often carried out with mechanical weeding machinery and is easier and less time-consuming. Whereas, weed control in the intra row spaces in the crop rows is more challenging because the crop fall in line of the weeds. Moreover, the weeds grow in close proximity to the main crop plant, which makes intra-row weeding more intricate and challenging task by available mechanical weeders. Traditional manual tools, such as khurpi, grubber, spade, wheel hoe, and push-pull weeders, remain common for intra-row weed removal. Technological advancements have introduced automated systems that have made possible the mechanization in intra row weed management. These systems, equipped with specialized machinery, can eliminate weeds within the same row as the crop by distinguishing between crops and weeds (Kumar *et al*., 2022) [138]. Various sensor technologies are under development for in-field use in weed management. These sensors play a crucial role in weed management and are capable of directly detecting weeds in the field or indirectly assessing factors such as total plant coverage, leaf area, photosynthetic activity, and plant height. The primary focus is on ground-based sensor technologies designed to distinguish between weeds and crops or indirectly measure weed infestation. This integration has significantly improved sensor capabilities in weeding operations, contributing to enhanced reliability and the generation of more extensive datasets (Kumar *et al*., 2019) [139]. Mechatronic systems have been developed, incorporating machine vision, controls, and mechanical actuation to selectively remove weeds within a crop row (Berkmortel *et al*., 2021) [11]. Thermal weeding techniques such as soil steaming and flame weeding are also discussed as intra-row weed management methods (Kumar *et al*., 2022) [138]. Sensor-based technologies have been adapted for managing intra-row weeds in crops with wider rows (Kumar *et al*., 2022) [138]. Cutting-edge technologies, including image segmentation, plant height measurement, machine vision systems, and sensor-based methods, show promising potential in accurately distinguishing crops from weeds (Al-Badri *et al*., 2022; Hasan *et al*., 2021 and Teja *et al*., 2022) [5, 40, 110].

The integration of sensors, microcontrollers, and computing technologies has provided the way for autonomous guidance systems in agriculture (Pallottino *et al*., 2019) [140]. The use of advanced sensor technologies in weed management has the potential to transmute the agricultural industry, helping farmers for weed management efficiently and cost-effectively while maintaining high yields and quality crops. The development of more sophisticated and accurate sensor systems will continue to play a significant role in shaping the future of agriculture and weed management. Recent technological progress, particularly the integration of sensor-based technologies, machine vision, and control systems in agriculture for intra-row weeding, is comprehensively explored in this review.

Overview of different advanced intra row weeding techniques vision based weed control techniques

In precision agriculture, an innovative approach called vision-based intra-row weeding control is being developed to effectively manage weeds while minimizing harm to crops. This method combines advanced sensor technologies and selective weeding tools within crop rows, advancing sustainable and efficient farming practices. Various types of vision-based intra-row weeding systems have emerged in agricultural technology. The autonomous vision-based navigation and control for intra-row weeding system employs a plant classification algorithm with easy-to-extract features, enabling autonomous navigation without GPS reliance. The computer vision-based intra-row weeding system compensates for classification delays through a non-overlapping multi-camera system, allowing for more advanced detection algorithms. Vision Systems identify weeds in the crop and use tools to remove them, while electro-mechanical systems automate intra-row weeding by combining machine vision and control. These diverse systems showcase innovative approaches to address the challenge of intra-row weeding, contributing to the advancement of efficient and accurate weed control in agriculture. Researches support the potential of this method, demonstrating the effectiveness of image segmentation, plant height identification, machine vision systems, and sensor-based approaches in distinguishing between crops and weeds (Wu *et al*. in 2019) [129]. This enabled the way for further exploration of advanced technologies, image processing methods, and robotics to enhance the accuracy and efficiency of weed control within crop rows.

Laser and 3D LiDAR based weed detection and control

Laser vision-based intra-row weeding is a technology that uses sensors for precise weed detection and control various types of lasers, including CO2 lasers, diode lasers, and fiber lasers, have been employed for weed control experiments. With the right detection, localization, and laser targeting hardware and software, this technology has the potential to remove not only the inter-row weeds but also the intra-row weeds, making it a promising solution for precision agriculture. The light energy from CO2 and fiber lasers is absorbed strongly by plants, leading to weed detection (Gates *et al*., 1965) [151]. The combination of plant species recognition tools with laser-equipped small autonomous vehicles presents a sustainable alternative to widespread herbicide use. Laser-based weed detection and control represents a significant progress in precision agriculture. In past, Hilton *et al*. (2000) [42], developed a laser system that used varying wavelengths, to achieve accuracy with a range of 1-10 centimeters. It was effective both during the day and at night. The latter utilized laser beams for maize stalk detection, employing a lateral quasi- sinusoidal motion to avoid stalks, resulting in high weed removal rates and reduced herbicide use. This environmentally sustainable approach demonstrated effectiveness in various crops, particularly with a 94.5% weed removal rate and only 0.8% crop damage in a Chinese cabbage test area (Cordill and Grift, 2011) [23]. Light detection and ranging (LiDAR) sensors demonstrated promise for weed detection and discrimination, offering advantages like higher sampling resolution and faster scanning rates. LiDAR is a device that emits light through optical amplification based on the stimulated emission of electromagnetic radiation. Emission wavelengths of lasers are typically in the visible and the near infrared light spectrum. Ground-based LiDAR sensors initially designed for characterizing tree and vine canopies, have been adapted to create a system for detecting and differentiating weed species within the intra-row areas of maize fields (Rosell *et al*. 2009 and Rosell & Sanz 2011) [142-143]. The hypothesis driving this innovation is centered on the estimation of weed height using LiDAR sensor, with the aim of utilizing height differences as a means to effectively discriminate between various weed species. LiDAR, a remote-sensing technique for distance measurement, was tested for weed characterization in the intra-row area of a maize field (Andjur *et al*., 2013) [6]. The study aimed to discriminate weed species based on their heights using LiDAR. Mounted on an all-terrain vehicle, the LiDAR sensor scanned downwards, capturing the vegetation profile. The results, correlated with manually determined height values, showed a high correlation (r^2 = 0.88) and significant discrimination capabilities, especially for tall weeds like Sorghum halepense. Grass weed species tend to exhibit higher height profiles compared to broad- leaved weed species. This distinct height difference provides a reliable basis for discriminating between these two categories of weeds. In the context of maize fields, the general height of weeds is notably lower than that of the maize crop. This disparity in height serves as a key factor in effectively distinguishing between the weeds and the crop in maize fields. Examining the potential of Light Detection and Ranging (LiDAR) sensors for weed detection, the research emphasizes key parameters such as target size and orientation, elucidated through trials with artificial targets (Shahbazi *et al*., 2021) [97]. The findings underscore the direct influence of target size and orientation on detectability at varying scanning distances. In a field trial within a wheat plot, the stationary LiDAR impressively achieved a 100% weed detection rate based on height disparities with the crop canopy. While LiDAR sensors have shown promising results in weed detection, further research efforts are warranted to enhance their efficacy for this purpose. Continued investigation and refinement of LiDAR technology can contribute to optimizing its capabilities and improving the accuracy and reliability of weed detection systems.

Image processing and species discrimination

In addition to advancements in inter-row weed management, significant progress has been made in intra-row weed control using image processing techniques. The ability to automatically identify and remove weeds within crop rows has become a crucial aspect of modern agriculture, contributing to increased farming efficiency and crop yields. Reflectance measurements at different wavelengths have proven to be a valuable tool in intra-row weed discrimination. Vrindts *et al*. (2002) [121] demonstrated impressive results with 97% accuracy in distinguishing between crop and weed species in laboratory conditions using this approach. This method involves capturing the reflectance characteristics of plants at various wavelengths, allowing for the differentiation between desirable crops and unwanted weeds. Furthermore, Joao (2004) [15] introduced a novel approach for classifying and mapping weed species in minimum-tillage systems. The algorithm presented in this work focuses on individual leaf extraction, achieving a 75% success rate for accurate leaf extraction. This signifies progress in developing precise methods for characterizing and managing intra-row weed populations. Otsu's method, combined with modified excess green features, has been utilized for automatic thresholding in weed image segmentation (Mansheng and Dongjian, 2007) [64]. This technique helps in effectively separating weed objects from the crop background, facilitating accurate identification and subsequent removal.

Morphological operations and shape-based classification have shown success in achieving accurate differentiation between corn and weed objects within crop rows (Agrawal *et al*. 2012) [1]. Recent studies have also explored real-time discrimination between weed patches and crop rows. These methods focus on the structure, texture and shape of the plants, enabling precise discrimination in real-world agricultural scenarios. Despite these advancements, there is ongoing research to further improve intra-row weed management. Burgos-Artizzu *et al*. (2011) [14] proposed a computer vision system that combines fast image processing (FIP) and a robust crop row detection (RCRD) system. This innovative approach achieved an average weed detection rate of 95% and a crop detection rate of 80%, with minimal false negatives, showcasing the potential for real-time and accurate intra-row weed management. Elstone *et al*. (2020) [26] emphasized the need for testing at high weed densities and enhancements in plant identification and system calibration to ensure robust performance under varying conditions. These innovations hold promise for further improvements in weed discrimination within crop rows, ultimately enhancing overall agricultural productivity.

Hyperspectral and spectral imaging

Hyperspectral imaging, a fusion of imaging and spectroscopy, collects full-wavelength spectral information for each image pixel. When combined with VIS/IR spectroscopy, it creates a 3-D image with one spectral and two spatial dimensions, providing both spectral and image features of plants. It helps us understand the characteristics of objects without harming them. The specific frequencies of vibrations in the visible or infrared spectrum can be analyzed and quickly learn about the properties of materials without any special preparation of the samples. Hyperspectral and spectral imaging play pivotal roles in intra-row weeding, enabling precise discrimination of crop plants and weeds based on their distinct spectral signatures. These advanced imaging technologies provide valuable data for developing targeted and efficient weeding strategies, contributing to improved agricultural practices. The initial RGB color image is formed by combining the captured broad-spectrum data that includes red (R), green (G), and blue (B) lights. Broad band data, while less sensitive than full-wavelength spectra, can still distinguish crops from weeds (Slaugher *et al*. 2008) [102]. Zhang *et al*. (2012) [144] successfully combined a hyperspectral imaging system with a precise pulsed-jet micro-dosing setup for targeted delivery of heated organic oil to control intra-row weeds in early- stage tomatoes. The multispectral Bayesian classifier achieved a 95.9% average discrimination rate for tomato, *Solanum nigrum*, and *Amaranthus retroflexus* based on canopy reflectance. The application of heated oil, at a rate of 0.85 mg/cm² in 10-ms pulses, demonstrated effective weed control (95.8% for S. nigrum and 93.8% for *A. retroflexus*) with minimal damage to tomato plants (2.4%). There are three methods to acquire full-wavelength hyperspectral images: line scanning, area scanning, and point scanning. Selected feature variables from the full-wavelength region can simplify a multispectral system to highlight specific object characteristics. With its lightweight hardware and faster calculation speed, multispectral imaging is becoming the successor to hyperspectral technology (Kamruzzaman *et al*. 2016) [145]. Other useful features for plant detection include visual textures, biological morphology, and spatial contexts. Texture features describe the arrangement of image pixel gray levels, providing measures like coarseness and regularity. Biological morphology refers to plant shape and structure. Spatial context, or location information, can improve discrimination accuracy in crop fields (Su *et al*. 2018) [158]. The latest spectral sensing aims to identify a few key spectra from continuous narrow-band data for plant classification. Using principal component analysis (PCA), feature wavelengths from 350 to 2500 nm were selected. This enabled effective weed classification, including barnyard grass and green foxtail, from two seedling cabbages using Bayesian discriminant analysis (Deng *et al*. 2016) [146].

Gao *et al*. (2018) [31] introduced a hyperspectral snapshot mosaic camera for precise weed and maize classification, relying on 185 spectral features and employing an optimal random forest model to achieve high accuracy. These authors have significantly advanced the application of hyperspectral imaging in intra-row weeding, and their work is complemented by a range of other studies that have harnessed this technology for diverse challenges specific to intra-row weeding. Notably, vegetation indices, particularly those proximate to the red edge, emerged as significant contributors to the classification. Hyperspectral remote sensing (HRS) technology is employed for a competitive experiment combines comprehensive competition indices (CCI) and deep learning. Notably, the study establishes a robust relationship between various weed competitive pressures and structural/physiological changes in maize, offering precise quantification through accumulative/transient competition indices (CCI-A and CCI-T). The approach, outperforming traditional methods like relative competitive intensity (RCI), demonstrates superior dispersion capabilities (Lou *et al*. 2022) [147].

Robotic systems with camera integration

Automated selection of assessment areas for crops and weeds relies on precise knowledge of crop row locations within the image. To ensure optimal results, it is crucial to position weed assessment areas strategically, avoiding any overlap with crop leaves. Tian *et al*. (1997) [112] developed a machine vision system for detecting tomato seedlings and weed plants in agricultural fields. The system successfully identified 65% to 78% of target crop plants and had an error rate of less than 5% in identifying weeds as crop plants. Utilizing a vegetative index invariant to natural daylight variations, the transformed image was segmented into soil and vegetative components. Hague *et al*. (2006) [39] proposed an automated method for evaluating crop and weed areas in tractor-mounted camera images of widely spaced cereal crops. The algorithm robustly located crop rows, automatically positioned assessment zones for crop and weed growth, and demonstrated consistent results compared to manual assessments, providing an accurate mapping of crop and weed areas in the images. Limited scientific evaluations exist for the weeding performance of new robotic weeders. For instance, a study on Robocrop in transplanted cabbage demonstrated low crop damage levels under typical commercial growing conditions, achieving weed reductions between 62% and 87%

within a 240 mm radius zone around crop plants (Tillett *et al*., 2008) [113]. Machine-guided technologies for precise, automated intra- row weed control have rapidly advanced, leading to the commercialization of at least three automated intra-row cultivators. Two of these employ machine vision based on cameras, while the third detects crop plants by interrupting a light beam over the crop row. These systems, however, require easily distinguishable crops and weeds, limiting their applicability to transplanted crops where weeds are not a predominant part of the vegetation (Rasmussen *et al*. 2012) [148]. Langsenkamp *et al*. (2014) [54] showcased the effectiveness of the "tube stamp" tool, achieving a remarkable 93.86% reduction in intra-row weeds in field conditions. Part of the Remote Farming project, this autonomous field robot tool, assisted by a human worker, uses cameras, a manipulator arm, and the tube stamp for precise individual plant weed control. With a narrow impact zone of 11 mm, it minimizes soil disturbance, proving successful in dense row crops without affecting the surrounding soil. In addition to academic research, several startups are pioneering automatic weed control technologies, utilizing advancements in robotics to enhance efficiency and sustainability in agriculture (Steketee, 2017, Farm Machinery Ltd, 2019) [149]. Developing a reliable, intelligent robotic system for real-time weed control in intra row crops is essential to boost crop productivity and address labor shortages. The study compared an intelligent mechanical weeding machine with non-intelligent tools in transplanted onion and white cabbage. While intelligent weeding did not outperform simpler tools in onions, it provided comparable weed control in cabbage, eliminating the need for subsequent manual weeding near the plants (Malender *et al*., 2015) [68]. Zheng *et al*. (2017) [136] introduced an automated maize and weed detection method utilizing color features and post-processing algorithms. This approach achieved remarkable overall accuracy rates of 90.19%, 92.36%, and 93.87% over three years. In the field of weed detection using robotic systems with camera integration. An autonomous mobile manipulation system utilizes high-speed image processing and visual servoing for fast plant detection and precise treatment (Michaels *et al*. 2015) [69]. Designed to counter the challenges of declining field worker availability and the laborious nature of manual weeding, the system demonstrates competitive performance by treating single plants in less than 1 second during experiments in field-like conditions. Ahmad (2018) [2] designed a mechanical weeding actuation system that incorporated a machine vision system for pinpointing crop plant locations. This innovation facilitated precise mechanical weeding operations without harming the crops. Raja *et al*. (2019) [89] presented a novel computer vision algorithm for automated weed control in leafy vegetables. Leveraging the crop signaling technique, this approach marks crop plants with a machine-readable compound, enabling high-accuracy detection and classification of in-row weed-crops throughout the season. Tailored for lettuce fields, the algorithm achieves 99% crop detection accuracy, identifying 98.11% of weeds within 1.2 seconds per pair of images, showcasing its reliability and robustness compared to other sensor-based methods in situations with high weed densities and visual occlusion.

Navigation and localization techniques

Robotic weeding, as demonstrated by Nørremark and Griepentrog (2004) [74], is crucial for efficient and precise weed control in agriculture. Their findings underscore that 26.4% of sugar beet plants at the 4-6 leaf stage cover weed main shoots, emphasizing the need for robotic tools to address these challenges. Bossu *et al*. (2009) [13] introduced a comprehensive approach for crop/weed discrimination utilizing image processing based on wavelet transforms, comparing it with Gabor filtering. This study demonstrated that the wavelet-based method, specifically using Daubechies 25 and Meyer wavelets, outperformed Gabor filtering in weed-to-intra-row (WIR) measurement for both synthetic and real agronomic images. Among various wavelet basis functions tested, Daubechies 25 wavelet proved to be the most efficient, striking a balance between processing time and accuracy, making it a favorable choice for real-time crop/weed discrimination applications. Kelly *et al*. (2012) [46] introduced an object-based image analysis (OBIA) procedure using color-infrared images from quadrotor UAVs for site-specific weed management in maize fields. The procedure effectively identified and classified crop rows, achieving 100% accuracy in row identification and 90% accuracy in defining longitudinal row borders when compared to ground-based measurements of weed emergence. Peña *et al*. (2013) [81] presented an approach by utilizing unmanned aerial vehicles (UAVs) and object-based image analysis (OBIA) to create detailed weed maps in early post-emergence of weed management. The method involves a three-phase process, including crop row classification, discrimination of crops and weeds based on their positions relative to rows, and the generation of weed infestation maps. The results demonstrated a high potential for reducing herbicide application and weed management costs with an 86% overall accuracy in categorizing weed coverage. Yano *et al*. (2016) [130] presents a UAV-based system for weed surveying in sugarcane fields, offering close-up species recognition and addressing the limitations of traditional sampling methods. The weed detection system achieved an overall accuracy of 82% and a kappa coefficient of 0.73 in initial tests. Zhang *et al*. (2017) [132] proposed a navigation method for robotic weed control based on SUSAN corners and an improved sequential clustering algorithm, enabling the extraction of guidance lines for navigation in complex paddy fields. Guerrero *et al*. (2012) [37] introduced an automatic image segmentation strategy for maize fields using Support Vector Machines, achieving a 93.1% success rate in identifying plants with masked and unmasked green spectral components. These navigation and image processing techniques play a crucial role in the intelligent paddy field weeding robot in South China, where environmental complexities and similarities between weed and rice seedlings pose significant challenges. Several studies have yielded noteworthy research results in the realm of intra-row weeding. Tannouche *et al*. (2016) [109] successfully implemented real-time weed detection through computer vision and designed robotic control strategies, leading to enhanced weed removal precision and reduced herbicide usage. In summary, various innovative technologies and techniques are being employed to advance weed detection and control in precision agriculture. Researchers are making significant progress in enhancing crop productivity while minimizing the impact of weeds through the use of advanced imaging technologies, robotic systems, navigation and localization techniques, and performance comparison studies. Some of vision-based techniques are presented in Table 1.

Table 1: Some vision-based techniques

Type of classifier/technique	Datasets	Purpose	Plant	Features	References
ANN, CNN, and Deep learning	Kernel and kernel size	A vision-based classification system to separate value crops from weeds	Sugar beet	Tensorflow by Google	Milioto *et al.* (2018) [70]
	Shape, color and texture feature	Identification of weeds in relation to soybean and soil and classification of them	Soyabean	Superpixel segmentation algorithm, Support Vector Machines, AdaBoost and Random Forests	dos Santos Ferreira *et al.* (2017) [24]
NDVI, NIR and Infra-red index	Shape features	A vision-based classification system for mobile robots to separate value crops from weeds	Sugar beet	Hue-saturation lightness (HSL), Random Forest Classification, Computed coordinate differences	Lottes *et al.* (2017) [61]
	Color and shapes feature	Detection and localization accurately against different weed species at different growth stages	Lettuce, broccoli, tomato, pepper, green beans	color (RGB), IR (Infrared) and depth information, semiconductor based PMD (photon mixer devices) sensor	Gai (2016) [30]
	Features extracted from a large overlapping neighborhood	Plant classification without segmentation process: Feature extraction and classification	Carrot	Random Forest classifier	Haug *et al.* (2014) [41]
	Geometric Features	Vision-based classification system for RGB combined with near infra-red (NIR) imagery	Sugarbeet	multi-class Random Forest classification, Unmanned ground vehicle (UAV)	Lottes *et al.* (2017) [62]
	Spectral, Shape and Textural Features	Characterize shape, textural and spectral features to differentiate between corn and a number of weeds and optimize the combined key features	Corn	Segmented principal component analysis (SPCA)	Lin *et al.* (2017) [58]
Vision sensor	Recognition based on crop size and location in an image	Sarl Radis machine to detect the location of an approaching crop and monitor the location of a crop relative to the weeding tool	Corn	Integrated weed management (IWM) strategies	Berkmortel *et al.* (2021) [11]
	Kernel function	Robustness of the computer vision against illumination variability	Maize	Bayesian framework	Tellaeche *et al.* (2007) [111]
	Textures segmentation	Segmentation from processed contain textures of three main Types: green plants, soil and sky	Barley and corn	Supervised fuzzy clustering	Guijarro *et al.* (2010) [38]
	Detectable pattern marks or signals	To differentiate between crops and weeds to enable targeted weed removal and reduce hand-weeding time	Lettuce and tomato plants	Lab VIEW software algorithms, two methods of plant signaling: physical plant labels and topical markers	Kennedy *et al.* (2019) [47]
Object-based image analysis (OBIA)	Three features (statistical, texture-based, geometrical and spatial)	Uses of histograms as opposed to the idea of using statistical 115 metrics to simplify the objects	Sunflower	Unmanned Aerial Vehicles (UAVs)	Pé rez-Ortiz, *et al.* (2015) [83]

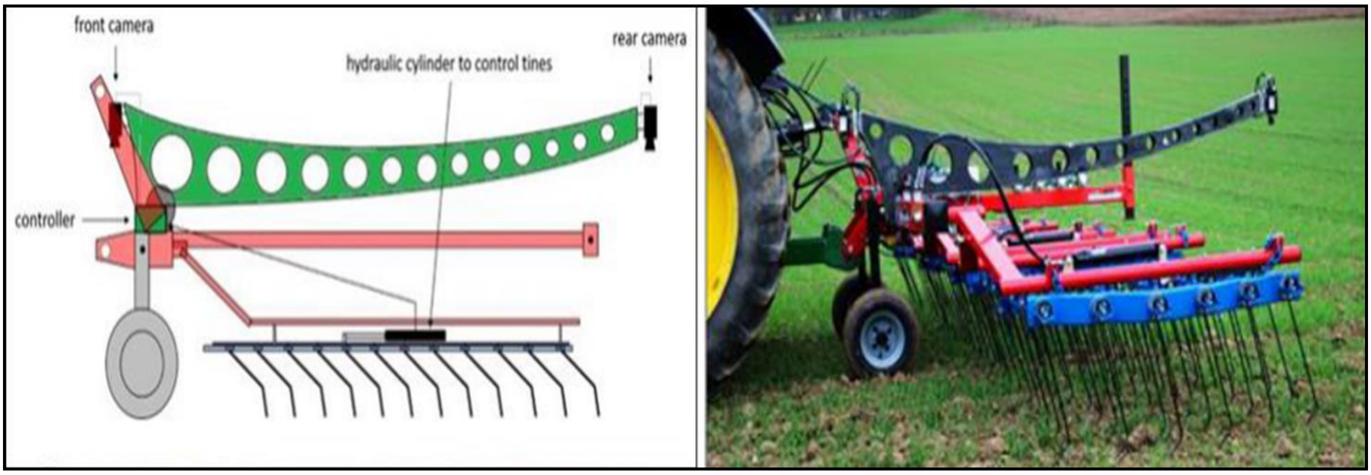

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Fig 1: The harrow containing automatic adjustment of tine angle (Gerhards *et al.*, 2021)

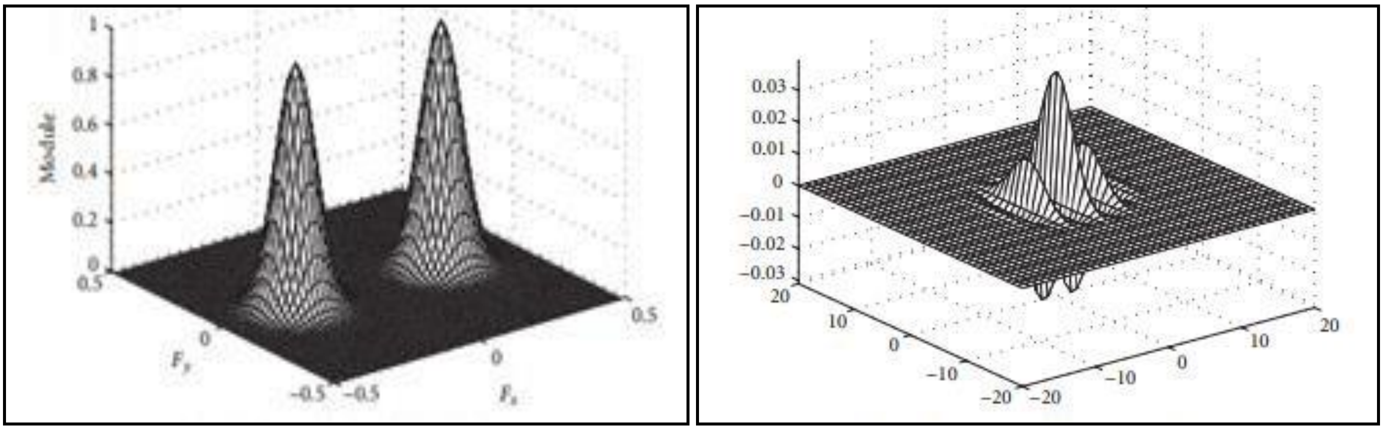

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Fig 2: (a) Spatial representation of Gabor filter, (b) Fourier transform of Gabor filter (Vioix *et al*. 2002)

In this review paper on vision-based intra-row weeding control, it becomes apparent that the adoptions of these technologies and methods holds significant promise for achieving more sustainable and efficient weed management in agriculture. The upcoming sections will provide an in-depth exploration of these contributions, shedding light on the advancements in this swiftly evolving field**.**

GPS-Based Positioning Systems

Stafford *et al*. (1996) [103] discuss the Silsoe Patch Spraying System, which relies on weed patch field maps. These maps are built using diverse methods, including farmer input, aerial imagery, and handheld GPS devices. The system includes user-friendly software and ensures compatibility with the patch spraying technology. The system of comprised side-shifting frame attached with vertically directed tine-rotor (cycloid hoe) with sigmoid shaped. The system navigated with reference to pre-defined waypoints for tillage parallel to crop rows and around individual crop plants. The system evaluation was based on quantification of treated areas for uprooting and burial and the corresponding prediction of weed control efficiencies. A single and double pass of an 80 mm wide row band provided tillage of 30-49% and 31-58% of the intra-row area, with highest coverage at a speed of 0.32 ms-1 with even plant spacing (Nørremark *et al*. 2012) [150].

Precision intra-row weed control with gps-guided tools

Precision intra-row weed control with GPS-guided tools has been a topic of extensive research, garnering attention from various authors in the field. In their study, Griepentrog and Dedousis (2010) [36] explored the utilization of a GPS-based system for accurate lateral control of hoes in agriculture. The system effectively minimized lateral deviations and achieved cross-track errors ranging from 0.009 m to 0.028 m, highlighting the crucial role of GPS technology in enhancing weeding efficiency. Nørremark *et al*. (2007) [75, 78] conducted research to create geo-spatial maps of individual crop plants using precision seeding equipment retrofitted with optical sensors and real-time kinematic global positioning systems (RTK-GPS). They achieved a high level of accuracy, with 95% of sugar beet seedlings emerging within 37.3 mm of the recorded seed drop positions in the geo-spatial seed map. Ruiz *et al*. (2012) developed a fully automatic, intra-row weed knife control system utilizing RTK-GPS, achieving a mean error of 0.8 cm in centering the close-to-crop zone. Van Evert *et al*. (2010) introduced a pioneering robot for organic farming, leveraging centimeter-precision GPS for autonomous navigation in pastures. The system achieved a remarkable 93% success rate in detecting broad-leaved dock weeds during on-farm field tests, and 73% of weed removals were within
0.1 meters of the taproot, thanks to GPS-guided precision. Mattivi *et al*. (2021) [66] employ low-cost UASs and open-source software to map weed distribution, significantly reducing herbicide treatments to just 3.47% of the field. This approach offers a cost-effective, sustainable solution for weed management in small to medium-sized farms within the framework of Agriculture 4.0. Samseemoung *et al*. (2012) [94] utilized low altitude remote sensing (LARS) images from crane-mounted and helicopter-mounted platforms to monitor crop growth and weed infestation in a soybean field. Crane-mounted platforms provided better image quality at altitudes below 10 meters, making them cost- effective for low altitude applications. They found that NDVI values at 28 days after germination (DAG) had a strong correlation with image capture altitudes, with R-squared values of 0.75 for crane-mounted and 0.79 for helicopter- mounted systems. Additionally, the study showed high R-squared values (>0.75) when correlating chlorophyll content with indices from these images at different stages of crop growth. Sun *et al*. (2010) [107] achieved impressive numerical results, with a mean error of just 2 cm between predicted and surveyed plant locations, and 95% of predictions within 5.1 cm of actual locations. This underscores the significance of GPS technology in accurately mapping transplanted row crops, facilitating precision tasks like intra-row weed control and enhancing agricultural efficiency.

Automated intra-row weed control with gps and machine vision

Bak and Jakobsen (2004) [7] introduced an autonomous vehicle with improved field maneuverability based on four-wheel steering (4WS) and a distributed control system. The 4WS concept enhanced path tracking, maintaining a fixed orientation relative to the path, with a standard deviation of 1.0 for moderate turns at low speeds. However, the error increased to 7.9-10.7 in sharp turns at higher speeds. Nørremark *et al*. (2008) [76-77] developed an autonomous intra-row weed control system using RTK-GPS navigation. Their field tests demonstrated effective weed control without collisions, even at speeds of up to 0.52 m/s. The system maintained transverse position accuracy within ±16 mm at 0.31 m/s and ±22 mm at 0.52 m/s, with minimal tine intrusion into the uncultivated zone (max. 9 mm out of 1224 observations). Ahmed *et al*. (2011) [3] introduced an automated machine vision system using local binary pattern (LBP) for distinguishing between broadleaf and grass weeds in digital images. Their method, utilizing template matching and support vector machine classification, achieved high accuracy when classifying 200 field images, with 100 samples from each category. Ahmed *et al*. (2014) [4] introduced a texture-based weed classification method with LBP, LTP, and LDP operators. In experiments with 400 field images, the approach outperformed existing methods, providing efficient classification of broadleaf and grass weeds. Lease *et al*. (2020) [56] developed a high-precision weed classification model for autonomous field robots, achieving a classification accuracy of 87.9%. This innovative approach, based on rotation-invariant uniform local binary pattern (LBP) features and ensemble optimization with CMA-ES, enhances weed management in early crop growth stages, increasing agricultural efficiency and reducing resource competition.

In the study by Berge *et al*. (2012) [10], the authors highlight the potential for herbicide savings through patch spraying (PS) in arable fields. They introduced Weedcer, a machine vision algorithm, to estimate relative weed cover (RWC) and relative may weed cover (RMC) based on high-resolution images. Field trials demonstrated that mean RWC and RMC per management unit (12.0 × 12.5-m) were generally adequate. Bengochea-Guevara *et al*. (2016) [9] focused on developing a small autonomous field inspection vehicle for precision agriculture. The system integrated a camera with a GPS receiver to enable efficient and low-impact scouting of crop fields. The GPS played a crucial role in route planning, ensuring the robot could cover the entire field without damaging crops. Kanagasingham *et al*. (2019) [45] aimed to create an autonomous weeding robot for rice fields, integrating GNSS, compass, and machine vision. Their system achieved an average deviation from the ideal path of 45.9 mm, with heading compensation accuracy of less than 2.5°. Wang *et al*. (2019) [122] employed GPS and machine vision for weed recognition, achieving precise weed removal and improved grapevine health. Lopez *et al*. (2020) [151] applied GPS and machine vision to target weeds, leading to a remarkable increase in crop yield and quality. Chang *et al*. (2012) [18] developed three algorithms for spot- specific agrochemical application in wild blueberry fields using co-occurrence matrix-based textural features. Forty- four features were extracted from NTSC luminance (L), hue, saturation, and intensity (HSI) images. The DF_ALL model achieved 98.1% overall classification accuracy in 83 ms. For practicality, the DF_HSISD, DF_SISD, and HSILD algorithms are preferred, with overall accuracies of 94.9%, 92.7%, and 91.4%, and processing times of 55, 27, and 29 ms, respectively. Zhou *et al*. (2021) [137] developed a visual navigation system for outdoor orchards, achieving high accuracy with path extraction accuracy between 90.36% and 96.81%. The program executed within 0.55 seconds under various sunlight conditions, offering real-time capabilities. Their method outperformed traditional Hough transforms, offering an effective approach for UGV navigation in orchards with minimal lateral errors (maximum 0.118 meters). Nikolić *et al*. (2021b) [73] integrated site-specific and time-specific weed control strategies using a weed emergence prediction model. They employed a UAV for weed detection with an orthophoto resolution of 3 cm and used artificial neural network (ANN) and the visible atmospherically resistant index (VARI) for classification. Results showed high overall accuracy (98.6% for ANN and 98.1% for VARI) with significant reductions in the area to be sprayed, ranging from 65.29% to 93.35% for VARI and 42.43% to 87.82% for ANN.

Non-image sensor systems

Intra-row weed control utilizes various methods and mechanisms, including weeding harrows, torsion weeders, rotary hoes, finger weeders, and vertical brush hoes (Mohler, 2001; Bond and Grundy, 2001; Upadhyaya and Blackshaw, 2007; van der Weide *et al*., 2008) [67, 152-154]. While these mechanical approaches are commonly employed, only a limited number of studies have explored the development of selective mechanical methods. Non-image sensor systems have become essential tools in the field of intra-row weeding, providing innovative solutions for precise and efficient weed management. These systems utilize various technologies, including UV-induced fluorescence, laser- based optical sensors, phototransistors, ultrasonic plant detection, and mechatronic mechanisms. Notably, Huzaifah *et al*. (2021) [155] employed UV-induced fluorescence alongside unmanned aerial vehicles (UAVs) for large-scale weed monitoring in maize fields. Their work signifies a significant advancement in precision agriculture. In a different context, Korresa *et al*. (2019) [156] explored a shift in weed science towards integrated management strategies, including "many little hammers" and technology-driven solutions, to combat herbicide resistance and enhance weed control in modern agriculture. For organic farming practices, Monteiro and Santos (2022) [71] introduced phototransistor-equipped weeding machinery, offering selective weed control without chemical herbicides. In variable terrains, Khan *et al*. (2020) [157] introduced the CED-Net, a compact cascaded encoder-decoder network for precise weed and crop detection in farmland via semantic segmentation. CED-Net's efficiency with fewer parameters results in shorter training and inference times, and it outperforms or matches other state-of-the-art networks across multiple evaluation metrics, while requiring only 1/3 to 1/5 fewer parameters than comparable models like U-Net and SegNet. Lastly, Coleman *et al*. (2022) [22] integrated mechatronic systems with AI-driven algorithms, leading to more effective and environmentally friendly herbicide applications in maize fields. These developments collectively underscore the dynamic and evolving landscape of non-image sensor systems for intra-row weeding.

UV-induced fluorescence for corn-weed discrimination

Keränen *et al*. (2003) [48] further extended the UV-induced fluorescence technique, achieving a classification accuracy of 93% in distinguishing between crop plants and various weed species, significantly reducing manual weeding efforts. Longchamps *et al*. (2010) [60] explored UV-induced fluorescence for discriminating between corn and various weed species. Their method, involving principal component analysis and linear discriminant analysis, achieved a success rate of 91.8%, demonstrating effective weed discrimination. Tyystjärvi *et al*. (2010) [115] explored the use of chlorophyll fluorescence fingerprinting for identifying maize and barley amidst six weed species in outdoor pot-grown plants. Their measurements, taken under variable natural conditions, showed promising results. A neural network classifier, utilizing 17 features from each fluorescence induction curve, correctly classified 86.7% to 96.1% of the curves as either crop (maize or barley) or weed. For individual species classification, success rates ranged from 50.2% to 80.8%.

Laser-based optical sensor for precision depth measurement

Van der Linden *et al*. (2008) introduced a laser-based optical sensor known for its remarkable precision in depth measurements. This sensor is now poised to revolutionize weed management, offering depth measurements accurate to at least 1 mm and an average measurement speed of 35 ms. Marx *et al.* (2012) [65] explored environmentally and energetically sustainable weed control methods, focusing on CO2 laser technology.

They assessed the impact of laser radiation (10,600 nm) with varying spot diameters, positions, and intensities on two weed species at different growth stages. The study resulted in the development and validation of weed-specific laser damage models, pinpointing the probabilities of successful laser application (psuccess = 0.95). Paap (2014) [80] have further improved this technology by enhancing real-time data processing capabilities, reducing measurement error to just 0.5 mm. Li *et al.* (2017) [57] addressed the issue of imprecise weed control practices due to a lack of weed identification and positioning equipment. They presented a spectral sensor designed for accurate weed identification, utilizing characteristic wavelengths (595, 710, 755, and 950 nm) selected based on weed investigations in winter rape fields. The sensor, featuring active LED light sources and a well-structured optical system, was successfully calibrated and verified, achieving determination coefficients ranging from 0.799 to 0.892. In actual weed identification experiments, the sensor demonstrated a notable average recognition rate of 90.7%.

Phototransistor-based maize crop weed control

Shearer *et al.* (1991) [99] created and tested a selective applicator for post-emergence herbicides in row crops. Using NIR light and a phototransistor receiver to sense weed competition, their system activated a solenoid valve at the spray nozzle. Initial findings showed a promising herbicide savings of 15% with no detrimental impact on weed control. Wang *et al.* (2000) [123] implemented phototransistor-based weed control in soybean cultivation, enhancing precision and achieving an 87% reduction in herbicide application. Cordill and Grift (2011) [23] introduced an innovative approach for weed control in maize crops, utilizing phototransistors to measure stalk diameters and selectively target weeds based on size relative to maize stalks. The laser beams for maize stalk detection, employing a lateral quasi- sinusoidal motion to avoid stalks, resulting in high weed removal rates and reduced herbicide use. This environmentally sustainable approach demonstrated effectiveness in various crops, particularly with a 94.5% weed removal rate and only 0.8% crop damage in a Chinese cabbage test area.

Co-robot system for intra-row weed control

Pe ŕ ez-Rui ź *et al.* (2016) introduced a co-robot system for intra-row weed control in row crops, significantly reducing manual labor requirements for weeding compared to traditional methods. The co-robot uses a single odometry sensor for cost minimization and has been evaluated in an experimental trial, demonstrating its effectiveness. Ge *et al.* (2013) [34] introduced a mechanical arm design for a laser weeding robot aimed at replacing chemical weeding. The design incorporates a mechanical arm, a laser generator, and a control center with impressive precision, effectively dividing the laser's working area into a 10×10 grid. The analysis demonstrated the arm's small error in targeting the laser beam toward the weeds, along with an optimized execution area sequence resulting in a shorter arm moving path. Mechanical inter-row weed treatment offers several viable options, but the choices become more constrained for intra-row treatment. Particularly, for densely planted row crops like carrots, there is currently no method available for individual plant weed control, primarily due to the heightened risk of causing damage to the cultivated plants.

Automated intra-row weed control with ultrasonic plant detection

Saber *et al.* (2015) [92] introduced an automated intra-row weed control system with an ultrasonic plant detection system. This system demonstrated a strong correlation (R2 = 0.94) between sensor-estimated and manual height measurements of crop plants, achieving varying weed control efficacy for different species. Reiser *et al.* (2017) [90] investigated the use of a low-cost sonar sensor for autonomous selective spraying of individual plants, aiming to reduce costs, resource consumption, and environmental impact in agriculture. Their autonomous robot accurately detected plant positions with 2.7 cm precision, reducing liquid usage by 72% compared to conventional spraying methods, thus showing potential for efficient and sustainable weed control. Jakasania *et al.* (2019) [44] evaluated an automated intra-row weeder equipped with an ultrasonic sensor, finding that a minimum plant-to-plant distance of 35 cm allowed operation without damaging crops, with the most effective forward speed identified as 1.0 km/h. W. Zhang *et al.* (2022) [133] have implemented an automated weeder with improved ultrasonic sensors in cotton fields, achieving more precise weed removal and a 70% reduction in manual labor requirements.

Mechatronic system for precise electronic weed control

Kurstjens and Perdok (2000) [52] investigated the effectiveness of intra-row mechanical weed control using soil cover. They examine how a plant's resistance to soil cover relates to its height, flexibility, and leaf shape. The research highlights the importance of soil conditions and implement settings in the relationship between weed control and crop covering, with limited burial depth primarily causing growth reduction rather than complete weed elimination. Pötsch and Griesebner (2007) [86] emphasized the importance of visualizing and addressing broad-leaved dock issues on a farm level. They introduced the Mini-WUZI, an Austrian innovation for mechanical dock control, capable of removing up to 400 dock plants per hour. Sujaritha *et al.* (2017) [105] developed a weed-detecting robotic model for sugarcane fields, achieving a 92.9% accuracy in detecting different weed species. Their approach, based on fuzzy real-time classification of leaf textures, holds promise for enhancing the efficiency and cost-effectiveness of weed management in Indian sugarcane cultivation. Kumar *et al.* (2020) [50] introduced a mechatronic system incorporating a four-bar linkage mechanism and inductive sensing, guided by a fuzzy logic algorithm for precise electronic weed control. Preliminary field evaluations demonstrated effective weed control with minimal crop damage.

Integration of machine learning

The integration of machine learning for intra-row weeding represents a transformative development in modern agriculture, providing intelligent solutions for the precise identification and removal of weeds. By harnessing the power of advanced algorithms and sensor technologies, these systems offer the potential to greatly enhance the efficiency and effectiveness of weed control practices in farming.

Advancements in Machine Learning for Weed Detection

The integration of machine learning into intra-row weeding systems marks a significant shift in precision agriculture, offering advanced tools for precise weed identification and removal. Leveraging sophisticated algorithms and sensor technologies, these systems hold the potential to greatly improve weed control efficiency. Cho *et al.* (2002) [21] developed a machine vision system that achieved a high recognition rate for radish and weeds. Bosilj *et al.* (2020) [12], further utilized the knowledge transfer in deep learning for crop-weed classification reduced retraining time by up to 80%, demonstrating its efficiency. Even with imperfectly annotated data, their approach achieved classification performance within 2% of networks trained with pixel-precision data, emphasizing its potential for cost-effective and precise agriculture. Sánchez and Gallandt (2020) [95] examined Franklin Robotics' Tertill, an autonomous weeding robot designed for home gardeners, and found it to be highly effective in controlling both broadleaf and grass weeds. The study emphasized the significance of its simple yet efficient design, which could provide insights for developing larger-scale farm weeding robots, highlighting key design criteria such as weed density, emergence patterns, working rate, and weeding mechanisms, regardless of the technology used for plant detection.

With innovative machine learning s for weed detection, Tang *et al.* (2017) [108] applied feature engineering along with a Naïve Bayes classifier to recognize seedlings, resulting in an approach with a 90% accuracy in seedling detection. Liu and Bruch (2020) [59} utilized deep learning methods for seedling detection, achieving a high accuracy rate of 96% for precise weeding operations. Chen *et al.* (2021) [20] employed multi-feature fusion with K-means clustering and Support Vector Machine (SVM) to extract images and identify seedling positions, allowing for accurate weeding. Fawakherji *et al.* (2021) [28] further advanced this field by using a conditional Generative Adversarial Network (cGAN) for crop/weed segmentation, creating a multi-spectral dataset with Near-Infrared (NIR) information.

Torres-Sospedra and Nebot (2014) [114] advanced the machine learning method by appling a noisy learning procedure to weed detection. This approach addressed challenges associated with varying weather and light conditions. The system demonstrated a significant improvement, with an average Precision Error Rate (PER) increase of approximately 5% compared to traditional training and other noisy ensembles. The most effective classifier with traditional training had an average PER of 32.4%, while the top-performing noisy classifier, trained with CVCv3Conserboost, achieved an average PER of 37.9%. In field tests involving 130 images from orange groves, the CVCv3Conserboost trained with noisy learning yielded an average performance of 95.0% in the first stage and 92.28% in the second stage. These results underscore the efficacy of this approach for weed detection and reducing chemical inputs. Furthermore, an improved Convolutional Neural Network (CNN) model for weed identification was proposed to address issues with the traditional Alex Net model (Sun *et al.* 2018) [106]. This enhanced model integrates dilated convolution, multi-scale fusion, and global pooling to optimize training time and achieve high precision. Through extensive parameter exploration, the optimal model demonstrated over 90% recognition accuracy after just four training epochs, with a memory requirement significantly lower than traditional models. The improved model's recognition capability, enhanced by a wider network structure and global pooling, achieves an average test accuracy of 98.80%. This makes it a promising tool for intelligent weed and seedling identification devices.

Su (2020) [104] discusses the importance of early weed control in crop production, highlighting the use of smart agriculture and advanced sensing technology like spectroscopy, color imaging, and hyperspectral imaging combined with machine learning algorithms (CNN, ANN, SVM) to accurately differentiate between crops and weeds. Olsen (2019) [79] addressed the need for robotic weed control in rangelands, introducing the DeepWeeds dataset of 17,509 labeled images from Australian rangelands. Using Inception-v3 and ResNet-50 models, they achieved high average classification accuracies of 95.1% and 95.7%, respectively, demonstrating the potential for real-time robotic weed control implementation in the complex rangeland environment. Additionally, Shirzadifar (2018) [100] investigated visible and near-infrared spectroscopy's potential in discriminating three weed species in a greenhouse experiment. Using the Soft independent modeling of class analogy (SIMCA) method with second derivative preprocessing on NIR spectra, they achieved a remarkable 100% accuracy in classifying water-hemp, kochia, and lamb's-quarters with 63 test samples. Specific wavelengths, like 640, 676, 730 nm in the red region, and 1078, 1435, 1490, and 1615 nm in the NIR region, were identified as most effective for weed discrimination. Quan *et al.* (2022b) [87] highlighted the significance of mechanical weed control in organic agriculture. They developed an intelligent intra-row robotic weeding system based on deep learning, consisting of a mobile robot platform and weeding units. Through field trials, they identified the most effective weeding knife for different field conditions, achieving an impressive 85.91% weed removal rate and a minimal 1.17% crop injury rate. Zhang *et al.* (2023) [131, 134] introduce an improved Swin-Unet model for precise weed recognition in maize fields, achieving remarkable results with a mean intersection over union of 92.75% and a mean pixel accuracy of 95.57%. The model's high inference speed of 15.1 FPS further enhances its significance for real-time, accurate crop and weed segmentation, aiding the development of intelligent agricultural equipment. More recently, Visentin *et al.* (2023) [120] combined remote human-controlled rover motion with a pre-trained Deep Neural Network (DNN) for autonomous weed identification and removal. These advancements contribute to the development of intra-row weeders, enhancing their precision and efficiency, and paving the way for more sustainable weed management strategies in agriculture.

Multi-Sensor Fusion: The Future of Weed Detection

In the progress of comprehensive weed detection, Wang *et al.* (2019) [122] integrated multi-sensor data, including LiDAR and RGB images, with machine learning algorithms. Their system achieved a 96% accuracy in identifying weeds, highlighting the potential of multi-sensor fusion for precise and comprehensive weed management in diverse environmental conditions.

Challenges And Future Prospects

In agriculture, sensor-based systems that detect weeds have the potential to revolutionize farming practices. However, these systems face significant challenges. They must be able to distinguish between weeds and crops, navigate complex and unpredictable field environments, and integrate data from multiple sensors. To fully realize the potential of these techniques, the system needs to improve the accuracy and speed of detection algorithms using advanced machine learning techniques such as deep learning and reinforcement learning. We also need extensive and diverse datasets that include various weed and crop species, growth stages, and environmental conditions to develop the discrimination capabilities required to solve the weed-crop identification problem.

In agriculture, sensor systems that detect weeds need to be adaptable and resilient. By combining data from cameras, LIDAR, hyperspectral sensors, and more, we can create a comprehensive vision to identify weeds among crops. This will help farmers manage weeds precisely and in a timely manner. It is also important to process sensor data in real-time to enable quick analysis of high-resolution data. This will help optimize agricultural efficiency while conserving resources. In the future, we need to integrate sensor-based technologies with automated weeding systems to create autonomous robots that can accurately map and identify weed infestations. These robots will reduce reliance on human intervention and harmful herbicides, leading to a sustainable future where humanity and nature thrive together.

Conclusion
Sensor-based weed detection systems are emerging as cutting-edge solutions in intra-row weeding practices. These systems leverage the prowess of vision-based cameras, the precision of GPS-based positioning, and the versatility of non-image sensors to open new avenues for accurate and targeted weed control. The seamless integration of machine learning algorithms empowers these sensor-driven solutions with data-driven insights, elevating weed detection capabilities to unprecedented levels of sophistication and precision. Despite the challenges, the search for a sustainable and resource-efficient agricultural future is fueled by confronting complexities related to robust weed- crop discrimination, mastering navigation through intricate field environments, and optimizing the fusion of multi- sensor data. The convergence of advanced technology and agricultural practices sets the stage for an empowered agricultural landscape, where each stride towards optimized weed management reverberates with the cadence of progress. Sowing the seeds of change in sensor-based weed detection systems holds the promise of a harvest teaming with prosperity - a future where precision agriculture and environmental sustainability unite in harmony.

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Conflicts of Interest
The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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