Biological Forum – An International Journal **15(10): 255-262(2023)**

ISSN No. (Print): 0975-1130
ISSN No. (Online): 2249-3239

A Review on A Computer Vision System for Automatic Crop-Weed Detection

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(Received: 20 July 2023; Revised: 18 August 2023; Accepted: 19 September 2023; Published: 15 October 2023)
(Published by Research Trend)

ABSTRACT: Weed control is a significant factor that could affect crop productivity. With the advancement in technology, computer vision becomes one of the meticulous methods for instantaneously detecting crop-weeds and providing vital data for spot-specific weed supervision. Computer vision is a technology that employs a computer and a camera, rather than relying on the sensory visuals of an individual, to distinguish, trace, and evaluate the target for a better picture through image processing. This review summarizes the advances and challenges in spot-specific crop-weed detection over the past four years using computer vision technology. The summary of this study discusses conventional methods in weed management, which aid in the development of automatic crop-weed detection for on-field real-time weed control. There are still major challenges for crop-weed classification, such as the overlapping of crop plant foliage and varying illumination levels, leading to the failure of detection algorithms. To achieve universal acceptance of the technology, it is necessary to establish a broader crop dataset. In the upcoming days, through thorough investigation, computer vision techniques will be better applied in autonomous crop-weed detection. With the advancements in computer vision technology, the efficacy and accuracy of crop-weed detection are further enhanced. It also focuses on providing better understanding to laymen for decision support, which aids in the rapid growth of agricultural automation.

Keywords: Image Processing, spot-specific weed supervision, Sensory Visuals, Overlapping, Decision Support.

INTRODUCTION

Day by day, agriculture is becoming a crucial factor in improving the economy of all countries. Due to the increase in population and urbanization, there will be a gradual demand for agricultural produce, but cultivable land remains the same. Because of these reasons, drastic improvements in agriculture are the need of the hour (Wang *et al.,* 2019). The total population of the world will reach upto 9 billion by 2050, to meet the requirements of such a large population, the productivity and production must be increased exponentially (Arakeri *et al.*, 2017; Bakhshipour *et al.*, 2017). As of now, farming is encountering significant challenges such as environmental change, fragmentation in cultivable areas, a shortfall of irrigation supplies, and a lack of machinery for crop and land management. Particularly, weeds are becoming major threats as they consume most of the agricultural inputs (Lee *et al.,* 2010). However, there is a great interest among scientists, researchers, and farmers to solve the problems created by weeds. Weeds are unwanted plants that grow alongside crops and compete for agricultural inputs like nutrients, water, and sunlight, which could affect crop yields (Wang *et al.*, 2019). Several observations have proven that there is a strong interconnection between losses in crop yield and weed population (Hamuda *et al.,* 2017). Soni *et al.,* (2023) stated that uncontrolled weeds reduce crop yield by an extent of 35-88%.

A comprehensive overview on 43 Agricultural Diagnostic Expert Systems to identify the existing areas of expert systems in the field of agriculture, identify the development tools and techniques used for building agricultural diagnostic expert systems, and also identify the gap of existing diagnostic expert systems i.e., certainty factor, local languages and mobile phone technology (Saleem *et al.*, 2021).

The demand for potent and safe weed management is growing (Liakos *et al.*, 2018; Patricio and Rieder 2018). Traditionally, various operations have been followed to control weeds, among which manual weeding has been practiced for centuries and is still used by small and marginal farmers (Madhusudan and Preetham 2020; Saber *et al.*, 2015). However, traditional weeding has many disadvantages, such as being labor-intensive, costly for operations, and ineffective. So, finding an alternative weeding method is a problem that still needs to be addressed.

The latest advancements in agricultural mechanization and automation demonstrate that modern weeding methods for row crops and orchards involve the tillage of soil with mechanical tools or implements (Tillett *et*

al., 2008; Christensen *et al.,* 2009). Modern weeding practices, such as mechanical weeding, are more efficient and labor-saving compared to manual weeding. However, the drawbacks of these weeding interventions are that they can hardly eliminate intra-row weeds without a target identification support module, and they may cause crop damage (Norremark *et al.,* 2008; Hamuda *et al.,* 2017; Gai *et al.,* 2020). To achieve effective machinery for intra-row weeding, various supporting techniques, including the determination of crop standing height, peripheral thickness of the crop, leaf area, and real-time global positioning system navigation, have been used to detect the crops. However, this approach is unrealistic for densely sown crops as it assumes the same plant spacing between crops, leading to inefficient intra-row weeding (Lin, 2010; Norremark *et al.,* 2008; Tillett *et al.,* 2008; Cordill and Grift 2011).
Chemical weeding is one of the widely followed methods, practiced since the 1940s, and it has played a significant role in weed control (Hamuda *et al.,* 2017; Parra *et al.,* 2019). This advancement has led growers to rely heavily on chemical weeding since it is less time-consuming than conventional weeding practices (hand weeding and mechanical weeding). Usually, inorganic compounds are applied to crops uniformly, irrespective of the existence of weeds, leading to high operational costs. Additionally, the over-application of chemicals in farming has resulted in disastrous ecological contamination (Rodrigo *et al.,* 2014). Under such circumstances, spot-specific weed supervision (SSWM) is the most viable option. SSWM is a technique that efficiently applies herbicides with respect to weed composition. Hamuda *et al.* (2017) observed that using SSWM can save 30-75% of herbicides.

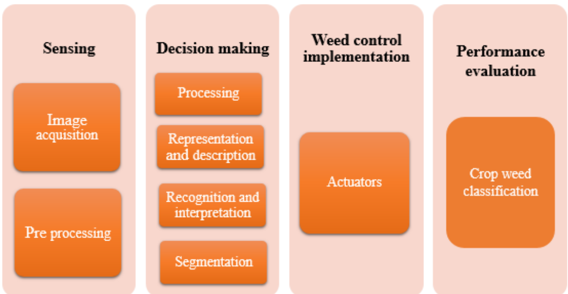

Fig. 1. Representation of SSWM system.

Four main steps are involved in SSWM. They are: (i) weed sensing, identifying, and measuring crop and weed parameters. (ii) Weed management model (decision-making algorithms) using the measured information. (iii) Weed control implementation. (iv) Performance evaluation (Christensen *et al.,* 2009). Every sub-step in each step is clearly represented in the figure above.
Out of all these elements, sensing plays a crucial role. This helps in providing the necessary data for making informed decisions and implementation. Specific crop-weed differentiation is a key element in the SSWM process; incorrectly detected or identified information may lead to system failure and greater crop loss (Quintanilla *et al.,* 2017; Rehman *et al.,* 2019). In recent times, computer vision technology has become an important tool in the crop-weed sensing system (Gomes and Leta 2012). This system enables computers/machines to perceive and differentiate between crops and weeds based on digital image content, such as photographs and videos (Astrand and Baerveldt, 2005). Once the target image/video (crop and weed flora) is captured, weed identification by computer vision is achieved by analyzing changes in color, location, texture, and size of weeds and crops. The utilization of these characteristics depends on the digital content of the sensed information.
The aerial remote sensing and ground-based sensing methods are two important sensing methods that have been explored in computer vision (Wojtowicz *et al.,* 2016; Hassanein and Sheimy 2018). Airborne remote sensing is primarily achieved through the use of piloted aircraft and Unmanned Aerial Vehicles (UAVs), which are remotely piloted aircraft. This system employs sensors, digital cameras, and satellites for data acquisition. The acquired photographs are later analyzed offline to produce weed maps for further use in SSWM.
This technique is beneficial for large-scale weed mapping, and UAVs have the advantage of vertical takeoff and landing. However, due to limited battery power, they have a short flight range and do not operate in real-time, resulting in lower spatial data resolution compared to ground-based sensing methods (Huang *et al.,* 2016).
On the other hand, the ground-based sensing technique offers portability, flexibility, and control over airborne remote sensing (Huang *et al.,* 2016). This technique collects and analyzes data in real-time, enabling real-time SSWM operations (Lopez-Granados, 2011; Peteinatos *et al.,* 2014; Hameed and Amin 2018).
Images and videos taken under field conditions are challenging to analyze using computer vision due to the low spectral resolution of captured data. This is because of the high variability and inconsistent illumination conditions (Vibhute and Bodhe 2012; Guerrero *et al.,* 2017). Apart from adverse lighting conditions, other environmental and soil factors, such as shadows, soil or gravel, and crops infected with weed flora, must be considered. Proper image preprocessing techniques are needed to address these adverse environmental conditions. Some of these issues can be mitigated by using camera filters and different cameras, such as NIR (Near-Infrared) filters and grayscale cameras (Astrand and Baerveldt 2005; Lameski *et al.,* 2017). Additionally, an artificial lighting system is employed to mitigate adverse lighting conditions.
The most commonly used ground-based real-time sensors are spectrometric, optoelectronic, and RGB-NIR imaging sensors. Spectrometric sensors measure the reflected intensity of multiple wavelengths and provide sufficient data to differentiate greenery from the soil. However, they may struggle to differentiate between various species, especially at advanced growth stages when crops and weeds have similar reflectance

properties (Lopez-Granados, 2011; Peteinatos *et al.*, 2014; Bakhshipour and Jafari 2018; Barrero and Perdomo 2018). Optoelectronic sensors measure reflection intensities within a few spectral bands, typically one or two, in the red/near-infrared (R/NIR) region. They are fast, efficient, and cost-effective for distinguishing foliage from the background (soil) and have been commercialized (Bakhshipour and Jafari 2018; Wang *et al.*, 2019).

Digital image processing is a common procedure for precise crop-weed discrimination, in which crop-weed flora is captured, and weeds are segmented from the acquired images. The success of this technique mainly depends on weed density, the characteristics of weed distribution, lighting conditions, crop-weed overlapping, etc. (Lin, 2010; Lopez-Granados, 2011).

The acute methods for precise weed identification in digital image processing involve the classification and extraction of weeds from the captured images. The effectiveness of image processing is significantly influenced by weed population, weed distribution characteristics, varying lighting conditions in the area, obstruction or overlap of plant and weed leaves, and differences in the growth stages of plants, among other factors (Lin, 2010; Lopez-Granados, 2011; Romeo *et al.*, 2013; Shaner and Beckie 2014; Chang and Lin 2018). Over the past few decades, researchers have made considerable progress in addressing these factors and improving the efficacy and robustness of weed identification.

Therefore, this paper focuses on the systematic review and the findings from the last four years (2017-2020) in the field of automatic weed detection. Section 2 provides a brief overview of the advancements and the application of computer vision technology in the area of automatic weed detection. Section 3 examines the challenges encountered when applying computer vision technology in weed detection. Section 4 concludes this work.

THE POSITION OF COMPUTER VISION TECHNOLOGY IN AUTOMATIC WEED DETECTION

This section provides a brief overview of the improvements and utilization of computer vision technology in the field of automatic weed detection over the past four years. The automatic detection of weeds is a crucial step in increasing crop productivity and achieving high yields. By fully utilizing computer vision technology for rapid and precise detection and differentiation of weeds from crops in the field, it is possible to automatically and accurately estimate weed density and control or remove weeds, reducing yield losses (Rehman *et al.*, 2019). Traditional manual and mechanical weed control methods suffer from issues such as high labor intensity, poor accuracy, long work timelines, and relative laboriousness (Raveendra *et al.*, 2019). Achieving high productivity in traditional weed control methods is challenging, but with the assistance of computer vision technology, a more effective solution for robust weed control is possible (Wang *et al.*, 2019).

Detecting and differentiating weeds in a crop field is a necessary condition for site-specific weed management (SSWM). Currently, many farmers still rely on non-site-specific weed control methods, which are time-consuming and labor-intensive. Computer vision technology offers a way to eliminate these constraints. Over the past few decades, researchers have put in significant effort to improve the accuracy of weed detection using computer vision technology.

Arakeri *et al.* (2017) integrated image processing, machine learning, and the Internet of Things (IoT) to develop a site-specific weed detection system for onion crops. The machine can identify weeds and onion crops with 96.8% accuracy in the field. This machine is both cost-effective and reliable for real-time weed detection and can be controlled remotely through a web interface. The accuracy of the system can be further improved by incorporating advanced machine learning programs. Burgos-Artizzu *et al*. (2017) created a computer vision-based site-specific weed detection system. This system consists of two autonomous subsystems: one for quick image processing, delivering fast real-time results (Fast Image Processing, FIP), and the other for more gentle and precise processing (Robust Crop Row Detection, RCRD), which corrects errors from the FIP subsystem. The system successfully identifies an average of 95% of weeds and 80% of crops under varying lighting, soil, and weed/crop growth conditions. There is significant potential for commercialization in the future. Guerrero *et al*. (2017) proposed an image processing algorithm that effectively detects crop rows in real-time. The developed algorithm demonstrates acceptable accuracy in estimating the position of a tractor with respect to crop rows and weed density.

Hamuda *et al.* (2017) developed a novel algorithm for a robust weed detection system based on color features and morphological erosion. This method classifies cauliflower crop areas in the image from weeds and soil under normal lighting conditions. The proposed algorithm uses the HSV color space for crop-weed discrimination. The algorithm exhibited high classification performance, recognizing 98.1% of cauliflower plants. Despite its high accuracy, the proposed algorithm relies on color. If the color of cauliflower leaves varies due to disease or very bright conditions, the misclassification rate may increase.

Rani *et al.* (2017) developed an automatic weed identification system based on image processing with the help of the MATLAB platform. They used the SIFT (Scale-Invariant Feature Transform) descriptor for weed detection. The developed algorithm achieved an accuracy of 95% and has been successfully implemented in mobile robotic weeders. Chang and Lin (2018) combined image processing and machine learning to create a miniature weeder capable of automatic weeding. This weeder segregates weeds and plants in real-time with an accuracy of 90%. This method holds great promise for automatic weeding. The rapidly deployable weed identification system is based on vision data and enables automatic removal of weeds without making prior assumptions about the existing weeds in the field (Hall *et al.*, 2018). The system has a three-channel structure consisting of primary field reconnaissance, offline processing, data classification, and meticulous weeding. This technology achieves 97% weed classification accuracy. However, despite its high accuracy, these assumptions are not always valid and have certain limitations for using this system for weed segregation.

Sabzi and Gilandeh (2018) combined image processing and machine learning to develop a system for crop-weed discrimination. The system has two main subsystems: (1) a video processing subsystem for crop detection and (2) a machine learning subsystem to segregate weeds and crop plants. They used a hybrid method comprising an Artificial Neural Network (ANN) and Partial Swarm Optimization algorithm (PSO) for segregation. The experimental results show that the ANN-PSO system achieves a classification accuracy of 97%. These results indicate that the proposed approach can be used for precise site-specific spraying.

Utstumo *et al.* (2018) developed a drop-on-demand (DoD) robotic herbicide applicator. They combined image processing with a support vector machine for crop-weed classification. The system efficiently controls all weeds in the field with a tenfold reduction in herbicide use. Field experiments show that DoD is a viable alternative to conventional spraying. Wu *et al.* (2020) combined novel computer vision and machine learning to develop autonomous robotic weeding system. They utilized a non-overlapping dual-camera to compensate for unspecified delays in crop-weed classification introduced by a Convolutional Neural Network (CNN)-based detection algorithm. They also developed a 3D tracking algorithm using Extended Kalman Filter (EKF) to provide high-accuracy tracing results across collected visual data. The developed machine demonstrates acceptable performance accuracy in different terrain conditions. In the same year, to perform herbicide application tasks with precision, Zhai *et al.* (2018) proposed a Precision Farming System (PFS) as a Multi-Agent System (MAS).

Table 1: Summary of work done on computer vision based weed detection.

Author and year	**Focus of work**	**Methodology**	**Software and hardware**	**Outcome**
Arakeri *et al.* (2017)	Instantaneous on spot weed control	Based on a combination of digital image processing, Artificial intelligence (AI) and internet of things (IoT)	Raspberry Pi, Ultrasonic sensor	The weed detection accuracy of 96.83% is achieved
Burgos-Artizzu *et al.* (2017)	Detection and discrimination of crop rows and weed patches	Image processing	Sony DCR PC110Eand JVC GR-DV700E	The developed prototype effectively detects an average of 95% of weds and 80% of crops
Guerrero *et al.* (2017)	Detection of crop row and weed density	Computer vision technology (image processing)	SVS-VISTEK color camera, Basler (SCA 1400-17Fc camera, Crio 9082	Position and orientation of tractor with respect to crop row is achieved, weed density is estimated
Hamuda *et al.* (2017)	Discrimination of crop, weed and soil for automatic weeding	HSV color space, PASCAL Visual object classes	GoPro Hero 4 Silver camera, OpenCV 2.4.10 software	Crop region and morphologies were accurately detected
Rani *et al.* (2017)	Segregation of carrot and curry leaf plants with weed identification	Image processing	SIFT descriptor	The developed algorithm is implemented in mobile robots for patch spraying of herbicides
Chang and Lin (2018)	Automatic crop weed classification and variable irrigation	Machine vision	Logitech digital camera	Crop-weed classification rate of 90% and chemical application rate of 90% is achieved
Hall *et al.* (2018)	Portable crop-weed detection system for spot-specific weeding	Computer vision technology	IDS UI-1240SE 1.3MP global shutter camera, AgBot II agricultural robotics platform	On spot crop-weed detection without prior knowledge about weed species is achieved
Sabzi and Gilandeh (2018)	To locate and identify potato plants and different types of weeds	Based on computer vision, Artificial Neural Network (ANN) and particle swarm optimization algorithm (PSO)	Samsung WB151F camera,	Classification accuracy of 98.1% was achieved
Sabzi *et al.* (2018)	Detection of three	Computer vision	DFK 23GM021	Detection accuracy of

	different weeds in potato plants	expert system based on nural network		98.38% and average computer response time of less than 0.8 s is achieved
Utstumo *et al.* (2018)	Detection and separation of seeded vegetable crops from weed	Image processing	Omnivision 4682 4MP sensor, DoD robot	Acceptable classification accuracy
Wu *et al.* (2020)	Automatic in-row weeding	Based on computer vision and deep learning	4-channnels JAI AD-130 GE camera, SRF235 ultrasonic sensors	Accurate and reliable in row weed detection
Zhai *et al.* (2018)	Site-specific application of herbicides	Genetic algorithm and particle swarm optimization algorithm (PSO)	Six unmanned Ariel vehicles	Accurate and reliable in precise spraying
Raveendra *et al.* (2019)	Weed detection and positioning for spraying	Computer vision-LabVIEW	NI smart camera, NI IMAQ	Discrimination of crop and weeds, positioning of weeds for herbicide application is achieved
Rehman *et al.* (2019)	Detection of goldenrod weed spot-specifically	Machine vision-quadratic classifier (DM-HIS model)	μeye camera, visual studio 2010 environment	Detection accuracy of 94.8 % was achieved
Ashraf and Khan (2020)	Weed density classification in rice	Image processing, GLCM texture features and moments features set	Mobile camera, LibSVM, MatLab 2014	Acceptable classification accuracy
Dadashzadeh *et al.* (2020)	Development of stereo vision system for segmentation between rice plants and weed	Based on artificial neural networks (ANNs) and two metaheuristic algorithms	Fujifilm FinePix Real 3D-W3 digital camera, MatLab 2018	The proposed stereo vision technology is promising
Raja *et al.* (2020)	Real-time weed-crop classification	Topical marker-based crop signalling technique	LED sensor (MINI-BEAM SM31RL), IR Sensor, cRIO-9004	The proposed system effectively detect 99.75% of crops and 98.11% of sprayable weeds
Sethia *et al.* (2020)	Real-time automatic weed detection	Image processing	Raspberry Pi camera	The weed detection accuracy of 99.5% is achieved

This system works efficiently and can strategize weed control tasks effectively. It performs well and can effectively plan chores and allocate limited resources. Applying herbicides only in the specific areas of weed presence significantly reduces the risk of contaminating plants, humans, animals, and irrigation sources. The application of machine vision using LabVIEW in automatic weeding can reduce human intervention in farming (Raveendra *et al.*, 2019). The proposed system can process digital images captured through the camera, and the acquired weed leaves are matched with a presumed database for classification. Decisions, such as herbicide application, are made based on the position calculation of the crop-weed scenario. Arduino takes control from LabVIEW and activates the applicators. Rehman *et al.* (2019) developed an integrated computer vision-based goldenrod weed identification system for spot-specific herbicide application. They used color co-occurrence matrices and statistical classifiers for goldenrod weed detection. The potential and real chemical savings ranged between 46.71% and 74.83% and 30.12% and 60.58%, depending on the weed and the applied area, respectively. These results indicate that the proposed method has the potential for spot-specific weed detection.

Ashraf and Khan (2020) proposed two weed segregation methods to differentiate images based on their weed population. The primary method uses textural characteristics obtained from the Grayscale Co-Occurrence Matrix (GLCM) and achieves a classification precision of 73%. An alternative method uses characteristics that are invariant to measure and revolution to segregate crop populations. The secondary method outperforms the initial one with an accuracy of 86% using the Random Forest Classifier. The proposed techniques are implemented in MATLAB software.

The proposed ANN-BA classifier provides accuracies of 88.74% and 87.96% for the right and left channels, respectively, over the test set. Crop-weed classification in a composite situation, when crop plant vegetation is overlapping and blocked by weeds, is very challenging. Raja *et al.* (2020) proposed a novel crop signaling technique where a signaling element is sprayed on the crop leaf area during initial growth stages. This applied signaling element is machine-readable and aids in differentiating crops from weeds. The system utilizes machine vision techniques and a crop-weed mapping algorithm for classification. Experimental outcomes show that the crop identification accuracy is 99.75%, with 98.11% sprayable weeds detected. In the same year, Sethia *et al.* (2020) developed an automatic machine vision-based weed detection and removal bot. The proposed system can identify and segregate crop-weeds in real-time based on their location coordinates. Field evaluation results show that crop-weed detection accuracy is 99.5%.

Based on the above research, computer vision techniques have been widely applied in weed detection and control, offering high precision, high efficiency, and cost-effectiveness. However, many of the investigations are still in the experimental phase and are greatly influenced by more complex factors such as illumination variations, crop overlapping, color fluctuations, and plant population.

THE CHALLENGES WITH COMPUTER VISION TECHNOLOGY IN THE AREA OF WEED DETECTION

For ideal image acquisition situations and specific crop features, current computer vision technology provides very promising detection results. However, in actual field applications, the task becomes extremely challenging. In late growth stages, plant leaves and weeds often overlap each other. Sometimes, unwanted materials, including soil and dead leaves, can become lodged on plant leaves, resulting in changes in the morphological and spectral features of the leaves. Crop-weed classification in composite situations, where crop plant vegetation overlaps and is blocked by weeds, is extremely challenging, leading to decreases in classification accuracy (Raja *et al.,* 2020). Plants undergo changes in the morphological, textural, and spectral features of leaves at different growth stages, which can reduce the performance of detection and classification models (Hassanein *et al.,* 2018; Sabzi *et al.*, 2020).

Varying lighting conditions in an outdoor environment pose another challenge. Fluctuating illumination levels lead to differences in colors, shadows, noise levels, saturation, reflections, and illumination of the same scene, resulting in the failure of detection and segmentation algorithms. To enhance the effectiveness of algorithms under varying illumination conditions, various color space models have been utilized (Tang *et al.,* 2016; Gai *et al.,* 2020). Even though these algorithms achieve high accuracy, they are dependent on specific color spaces. If the color of plant leaves changes due to infection or extremely sunny conditions, the misclassification rate may increase (Hamuda *et al.,* 2016).

With the rapid advancement of computer vision technology, it is increasingly used in the field of crop-weed detection. However, the technology still cannot overcome every constraint in crop-weed detection, and its application in this field is still in the early stages of development.

Currently, there is no large-scale public database available in the agriculture sector (Tian *et al.,* 2020), and current research findings often rely on information gathered by the researchers themselves during investigation and development stages, which may not be general and equivalent. The existing systems are insufficient for detecting a large number of weed species on a large scale. Therefore, it is essential to establish a comprehensive agricultural database. Additionally, the application of this technology needs to be extended to different crops and weeds, while improving operations such as slow image acquisition and slow response to diverse environmental conditions.

CONCLUSIONS

The review provides an overview of the application of computer vision technology in the field of automatic crop-weed detection. Specifically, the paper focuses on summarizing studies that highlight both the advances and challenges in crop-weed segregation for spot-specific weed supervision over the past four years. From the review, it can be concluded that previous work has significantly contributed to the advancement of automatic crop-weed detection, offering the benefits of affordability, high accuracy, and efficiency. However, considering the current scenario, we must also acknowledge the challenges that computer vision technology will encounter in crop-weed detection. Firstly, the task of crop-weed classification in complex scenarios, where crop plant vegetation overlaps and is obstructed by weeds, poses an extremely challenging problem that needs to be addressed promptly. Secondly, variations in illumination levels lead to differences in colors, shadows, noise levels, saturation, reflection, and glare in the same scene, causing detection and segmentation algorithms to fail. Therefore, the need for different color space models to adapt to varying illumination levels is essential. Lastly, in order to achieve universal acceptance of this technology, it is crucial to establish large-scale datasets.

In light of the above discussion, it can be inferred that computer vision technology will find more effective applications in autonomous crop-weed detection in the future. With the availability of large-scale datasets, computer vision technology is likely to gain universal acceptance in the field of crop-weed detection. In the upcoming days, as computer vision technology continues to advance, it will enhance the efficacy and accuracy of crop-weed detection, providing valuable insights to agriculturalists for decision support and contributing to the rapid growth of agricultural automation.

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How to cite this article: Madhusudan B.S., Ramineni Harsha Nag, Prajwal R., Aruna T.N. and Adarsha Gopala Krishna Bhat (2023). A Review on A Computer Vision System for Automatic Crop-Weed Detection. *Biological Forum – An International Journal, 15*(10): 255-262.