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REVIEW PAPER

Cultivating change: A review of progressive technologies in weed detection and management

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Abstract

Weed infestation poses a critical challenge to sustainable agriculture, leading to significant crop yield losses and escalating the use of chemical herbicides, which contribute to environmental degradation and health risks. One of the most pressing issues in weed management is the declining effectiveness of traditional weed control methods, which struggle to keep pace with the growing global food demands and the challenges posed by an anticipated population of 10 billion by 2050. The focus is on Precision Weed Management (PWM), emphasizing cutting-edge technologies such as computer vision, Unmanned Aerial Vehicles (UAVs), GPS-controlled patch spraying, laser treatments, and autonomous weeding robots. Computer vision, employing image processing and deep learning, emerges as a key player in automated weed detection, challenging traditional herbicide methods. UAVs equipped with advanced sensors facilitate high-resolution weed mapping, allowing for timely interventions. Laser and thermal treatments showcase targeted and efficient weed control, while autonomous weeding robots exemplify a hands-free, precise approach. The integration of these technologies not only promises enhanced productivity but also signifies a sustainable and environmentally conscious shift in global agriculture. The article highlights the limitations of traditional weed control methods and underscores the potential of emerging technologies to revolutionize weed management, offering precise, cost-effective, and environmentally friendly solutions.

Keywords

Automation, Intervention, Precision, Resilience

Introduction

In the quest for a sustainable outlook in crop production, the integration of advanced technologies in weed management is gradually turning out to be a significant innovation for addressing the pressing challenge of feeding a global population projected to reach nearly ten billion by 2050 (Worldometers 2023). The sheer quantity of food produced currently is insufficient to nourish the growing global population and it may be extremely difficult for humanity to meet this demand (Westwood et al. 2018). Crop cultivation faces constraints imposed by various biotic factors, alongside socioeconomic and issues associated with crop management (Ghersa 2013). In countries, whether developed or developing, unwanted plants represent the foremost biotic hurdles to agricultural output (Chauhan 2020). Approximately 1/3rd of total losses brought on by agricultural pests are attributable to weeds (DWSR-VISION-2050, 2015). Weeds cause significant losses in crop productivity by competing with plants for nutrients, water and sunlight (Monteiro and Santos 2022). They increase production costs while also reducing crop yield and degrading product quality. Weeds not only deplete crop yields and nutrients but also act as alternate hosts for a number of insect pests and diseases, which can lower the value of the land (Rao et al. 2020). In modern agriculture, weed infestations and weed behaviours are subject to frequent changes as a result of intensive management practices, ecological shifts, and climate change (Chauhan and Gill 2014). Mechanical methods and targeted cultivation practices can be employed for weed management using herbicides (Christensen et al. 2009). Intensive mechanization promotes soil erosion (Guccione and Schifani 2001) which degrades soil fertility. Herbicides can pollute the air, food, soil and water, posing human and animal health risks (Ribas and Matsumura 2009), as well as creating herbicide-resistant weed populations and ecosystem unbalance. The precision required to control weeds safely, effectively and without adverse consequences is lacking in the current weed control methods. For many farmers, controlling weeds is the biggest expense associated with production. Herbicide resistance and herbicide-applied off-target movement have left many growers with limited alternatives in conventional systems. Biotech crops face significant long-term biosafety questions, posing a major barrier to their further advancement, even if adopted (Rao 2018). As a result, new technologies in agriculture are rapidly advancing, significantly contributing to environmentally and economically sustainable weed management (Christensen et al. 2009). Precision weed management reduces inputs while maintaining weed control effectiveness (Young and Pierce 2014). Several Precision Weed Management (PWM) methods are being developed to scout and detect weeds in order to apply control measures where and when they are needed (Rao 2021).

Detection of weeds

Traditional methods of weed identification involve closely observing growth habits, emergence times, growth rates, and flowering periods throughout the growing season. Farmers utilize physical characteristics like leaf shape, colour, and texture for identification, often passing down this knowledge orally. Additionally, tactile identification, feeling and touching plants, aids in distinguishing between similar species, enhancing weed management strategies. Since this method become labour-intensive and less efficient in weed identification & control. Technologies like spectral reference image capturing, Machine learning module programming and deep learning have been developed. There are two methods for detecting weeds utilizing technology based on computer vision. They are conventional image-processing techniques (Weis et al. 2008) and deep-learning algorithms (Madala and Simha 2021).

Detecting through image processing methods

Traditional image-processing algorithms extract crucial features from weeds and plants through one or multiple methods after which a classifier is applied to those features to determine the particular type of plant or weed (Fig. 1). The most frequently extracted features from the images of crops and weeds are texture, shape, colour and spectral characteristics (Wu et al. 2021). Traditional techniques in image processing encompass shape extraction, spectral feature extraction, texture extraction and colour feature extraction. The merits and demerits of the above given methods are presented in Table 1.

Shape descriptor analysis

Shape descriptors like area, perimeter, diameter, eccentricity, circularity, rectangularity, etc. can be used to study the shape information in images. These descriptors are broadly categorized into two types: region-based and contour-based (Aktas 2012). Another way to characterize shape information would be to use statistical characteristics like moments (Wu et al. 2021). Ferreira et al. (2017) grouped pixels according to comparable colour and spatial closeness using simple linear iterative clustering (SLIC) superpixel segmentation. Using this technique, the images were divided into sections that featured multiple soy and target weed leaves. Convolutional Neural Networks (CNNs) were then used for classification, yielding a higher classification accuracy (99.5%) than more conventional machine learning (ML) classifiers like support vector machines (SVM). With an accuracy of less than 86%, Herrera et al. (2014) categorized weeds into monocots and dicots by utilizing six geometric shape descriptors viz., minor and major axis length, circumference, area, eccentricity, and diameter and seven Hu moments (Hu moments are seven shape-invariant measures used for image recognition, independent of translation, rotation, or scaling),

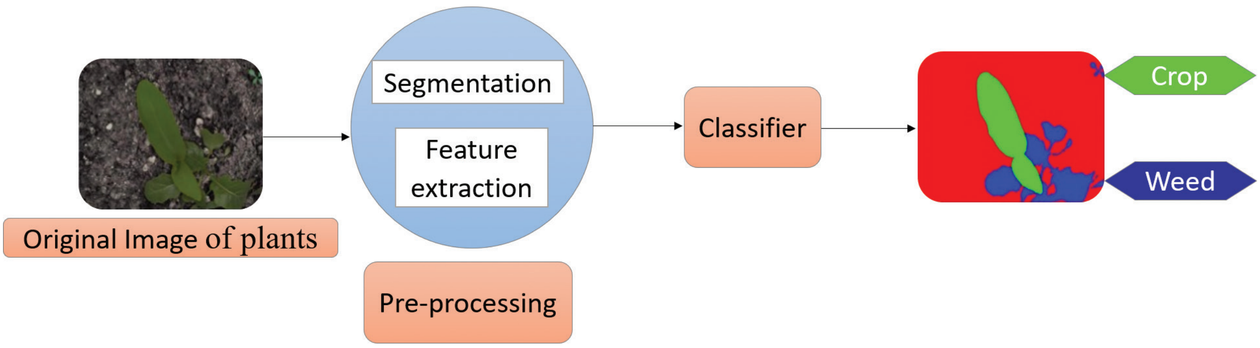

Figure 1. Outline of weed detection based on image processing; source: Rai et al. (2023).

followed by applying four decision-making techniques based on fuzzy logic - a method that handles uncertainty by allowing variables to have degrees of truth rather than just being completely true or false.

Colour descriptor analysis

Accuracy of detection based on colour relies significantly on the specific plant under examination and its colour distinctions. Colour, unaffected by changes in scale, size, or position, is a prevalent approach to differentiate plants from their surroundings, providing information about unusable objects (Vijayakumar et al. 2023b). Rasmussen et al. (2019) used a colour analysis-based detection procedure to distinguish green vegetation from mature ones in RGB images captured by UAVs. Under varying environmental conditions, they successfully identified 92–97% of weed patches in fields of barley and wheat. In a study conducted by Burks et al. in 2000, the researchers employed the hue, saturation and intensity (HSI) aspects of colour to discern between 6 distinct varieties of soil and weeds. Models based on the colour co-occurrence matrix (CCM) approach were developed, identifying optimal feature combinations through discriminant analysis for the highest classification accuracy. Discriminant classifiers trained with these models showed that combining saturation and hue yielded the most effective classification accuracy (93.3%), whereas using intensity as the sole feature performed the worst.

Spectral descriptor analysis

Spectral features are used to differentiate plants having different coloured leaves. Certain researchers have utilized visible light and near-infrared spectra (Vis–NIR) (Shapira et al. 2013), multispectral/hyperspectral imaging (Huang et al. 2016) and fluorescence (Longchamps et al. 2010) for identifying various plant species. Louargant et al. (2017) assessed how image resolution influences the ability to differentiate small weeds from plants using multispectral images that were captured and spectral mixing applied to the pixels. Slaughter et al. (2004) aimed to distinguish tomato plants and nightshade weeds using both a broadband colour classifier and a narrowband (10 nm bandwidth) hyper-spectral classifier in the visible region. Digitalized data from the 8-bit/band revealed that the broadband colour classification rate was 76% and the narrowband colour classification rate was 87% in controlled spectrophotometer measurements of about 400 leaf samples. Although the precision of the broad-spectrum colour classifier remained unchanged when the data was digitalized at 12-bits/band, the performance of the narrowband classifier rose to 95%. Borregaard et al. (2000) stated an 89–94% precision in differentiating between crops and weeds using narrowband reflectance at 694 and 970-nanometer wavelengths when assessing the capability of ground-based hyperspectral machine vision systems, considering alternative wavelengths. Pignatti et al. (2019) differentiated weeds and corn crops by analyzing carotenoid and chlorophyll content through spectral indices or by inversely applying PROSAIL (PROSPECT and SAIL radiative transfer models).

Texture descriptor analysis

Texture features, representing the spatial arrangement of pixels, are commonly employed in image classification (Wooten et al. 2011). There are four main categories in which texture feature methods can be placed: statistical method, model-based method, structural method and transform-based method (Bharati et al. 2004). Statistical techniques encompass approaches like histogram properties, local binary descriptors and co-occurrence matrix methods with the Gray Level Co-occurrence Matrix being the most prevalent. Examples of model-based techniques include fractal and autoregressive models; examples of structural techniques include identifying texture granularity by analyzing variations in energy and edge features; examples of transform-based techniques include wavelet and curvelet transforms. Crop and weed leaves contain a lot of texture information, which is useful for tasks involving recognition and classification (Dryden et al. 2003). Ishak et al. (2009) created a novel feature vector set for weed species classification by combining Gabor wavelet (GW) and gradient field distribution (GFD) to extract directional texture features. Bakhshipour et al. (2017) extracted four feature-rich sub-images using the Haar

Table 1. Merits and demerits of feature extraction methods.

Feature extraction methods	Features
Shape (Ferreira et al. 2017)	**Advantages:** User-friendly, robust to lighting and capture variations, and resilient to noise and translation
	Constraints: Efficiency is hampered by occlusion, and challenges arise from similar leaf shapes and deformations due to disease and insects. Typically, used alongside other methods to enhance performance
Texture (Bakhshipour et al. 2017)	**Advantages:** Gray level insensitivity, easy GLCM implementation, and HOG's rotational invariance with low computational complexity
	Constraints: GLCM demands extensive processing due to its substantial dimensionality, resulting in a high memory consumption
Spectral (Jinglei et al. 2017)	**Advantages:** Offer adequate details to differentiate crops from soil. Effective in scenarios involving partial occlusion
	Constraints: Struggles in early stages with similar crop and weed reflectance, influenced by capture time, and demands expensive spectral cameras
Colour (Rasmussen et al. 2019)	**Advantages:** Easily extractable when there is a noticeable color difference and remain unaffected by Variations in scale, size, and positioning
	Constraints: Influenced by variations in lighting, leaf diseases, and crops and weeds with similar colours

wavelet transform. Wavelet transformation was employed to derive 52 texture features for the analysis of weed patch textures. Among sugar beet crops, a 96% detection rate for weeds was recorded. Relying solely on textural features for detection may be effective only when there is significant differentiation between weeds and plants. Challenges, such as sensitivity to noise, resolution, rotation, and computational complexity, are inherent in texture-based methods (Vijayakumar et al. 2023b).

Detection through deep learning algorithms

Earlier methods for weed and crop differentiation involved extracting features using image processing and employing an ML classifier for pixel classification. The limited improvement in ML accuracy stems from the requirement for prior knowledge in manually designing features. In contrast, neural networks, empowered by increased processing capabilities and abundant training data, autonomously learn features and optimize weights across layers, significantly enhancing DL performance (Zhang et al. 2022). DL is a subset of ML with a unique learning approach, involving the quantity and data type each algorithm utilizes. It has found uses in various fields that involve computer vision. It is applied in industrial robots, autonomous cars, UAVs and robots for object detection. DL has seen widespread application in agriculture, encompassing fruit detection (Koirala et al. 2019), crop disease detection (Khamparia et al. 2020), yield prediction and mapping (Vijayakumar et al. 2023a), crop classification (Camargo et al. 2021) and weed detection (Garibaldi-Márquez et al. 2022). DL techniques eliminate the need for feature extraction and can improve weed identification and crop differentiation by utilizing differences in semantic and spatial features (Wu et al. 2021). This part will explore CNN-based DL techniques and non-CNN approaches employed for weed identification, where the non-CNN methods involve fully convolutional networks (FCNs), as well as unsupervised and semi-supervised feature learning (Table 2).

CNNs for detection of weeds

DL refers to neural networks characterized by deep layers or intricate structures, gaining prominence since 2006 due to remarkable advancements, particularly in speech recognition. CNNs stand out as the prevalent form of deep learning (Zhao et al. 2019). CNNs are complex neural networks with multiple layers, including convolutional layers, pooling layers, dropout layers, rectified linear unit layers (ReLU) and fully connected layers (Fig. 2). The convolution layer plays a role in extracting image features. Introducing the ReLU further disrupts linearity, compensating for any linearity introduced during convolution. Pooling layers are employed to reduce the size of feature maps, decreasing the parameters and overall processing in the network. This crucial layer conducts down-sampling on the feature maps from the preceding layer, yielding new feature maps with reduced resolution and substantially diminishing the spatial dimension of the input. The flattened output of the last Pooling or Convolutional Layer serves as input for the fully connected layer. In neural network architectures that forecast a multinomial probability distribution, the activation function in the output layer employs the SoftMax function, as noted by Tharun et al. (2022).

Types of CNNs

The utilization of CNNs for weed detection and classification has notably increased in the last decade. In their study, Potena et al. (2017) employed two distinct CNNs, referred to as sNet and cNet, for the rapid and precise categorization of weeds and crops based on NIR and RGB images. Vegetable segmentation was made easier with the lightweight sNet's one convolutional layer, ReLU activation function, and max pooling layer. In contrast, pixel-wise crop and weed classification was done using the deeper cNet. Beeharry and Bassoo (2020) conducted a study examining the effectiveness of AlexNet and artificial neural networks (ANNs) in classifying soybean, grass, broadleaf weeds and soil using UAV-based images. The AlexNet algorithm demonstrated an impressive accuracy of 99.8%

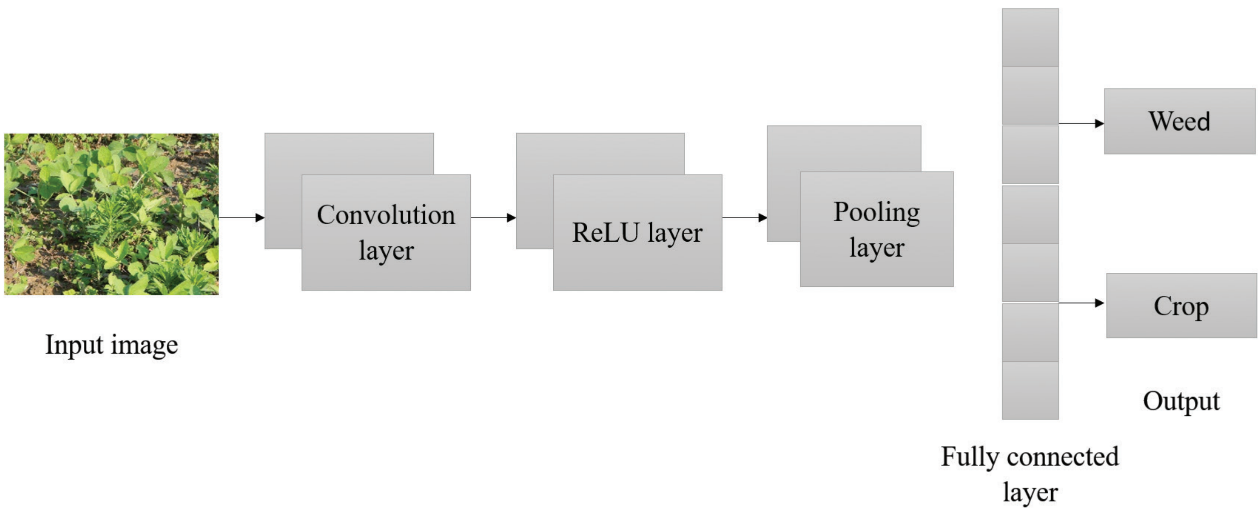

Figure 2. Architecture of weed detection.

Table 2. Techniques involved in supervised and semi-supervised learning.

Learning method	Technique	Features
Supervised learning	Improved Semantic Segmentation Network (You et al. 2020)	**Advantages:** Enlarges receptive field; learns robust features **Limitations:** Large labeled datasets needed; very time-consuming
	Fully Convolutional Network (FCN) with 3D Convolutions (Lottes et al. 2018)	**Advantages:** Preserves spatial relationships; good for structured environments **Limitations:** May have a problem in solving problems in complex and unstructured domains; high computational complexity
	VGGNet for weed detection (Yu et al. 2019)	**Advantages:** It is very efficient in detecting several broadleaf weed species; high accuracy **Limitations:** Heavy computation power needed; not very suitable for large-scale applications
Semi-supervised learning	Pseudo-labeling with synthetic image dataset (Zou et al. 2021)	**Advantages:** Saves time on manual labeling; can be applied in the case of scarce labeled data **Limitations:** Success depends on the quality produced; may not reflect the variability of the actual data
	Semi-supervised Generative Adversarial Network (SGAN) (Khan et al. 2021)	**Advantages:** High accuracy with a high percentage of the data being unlabelled data; suitable for organisations that are still growing **Limitations:** May need to adjust the architecture of GAN; depends on the quality of the initial labeled data

in classification, surpassing the ANN algorithm (50%). Graph Convolution Networks (GCNs) represent a modified version of CNNs designed to operate on data structured as graphs (Kipf and Welling 2016). Jiang et al. (2020) employed a combination of GCN and a feature extractor based on ResNet-101 to enhance weed detection, particularly when dealing with limited datasets. Using semi-supervised learning, they combined characteristics from a weed CNN with their corresponding Euclidean metrics to generate a GCN graph. The method demonstrated significant accuracy, ranging from 96% to 99% across four weed types, outperforming cutting-edge approaches like VGG16, ResNet-101 and AlexNet. Bah and colleagues (2018) employed an unsupervised training dataset and CNN to detect weeds in fields of spinach and beans. The results closely aligned with supervised data labelling, showing a 6% difference in the area under the curve (AUC) for the bean field and 1.5% for the spinach field.

Weed detection using non-CNNs

Although CNN is prominent in weed and object detection, there is significant potential for other approaches such supervised and semi-supervised feature learning, FCNs, ANNs, and Region Proposal Networks (RPN). Bakhshipour and Jafari (2018) explored the implementation of two widely used algorithms, Support Vector Machines (SVM) and ANNs for automated weed detection in a field of sugar beet. The findings indicated that ANN outperformed SVM in crop-weed discrimination. Ma and colleagues (2019) introduced a resilient image segmentation approach utilizing SegNet, a fully Convolutional Neural Network, for semantically segmenting weeds and rice seedlings in paddy fields. When compared to traditional semantic segmentation techniques like U-Net and FCN models, the SegNet-based approach produced a high precision of 92.7%, while the latter techniques produced accuracy rates of 89.5% and 70.8% respectively. Hu et al. (2020) presented Graph Weeds Net, a novel semi-supervised deep framework. The network showed an amazing 98.1% accuracy on the Deep Weeds dataset, efficiently extracting weed patterns from various graphs and evaluating the connections between graph vertices. Dyrmann and colleagues employed a Fully Convolutional Network (FCN) that underwent training on datasets containing over seventeen thousand annotations to identify weeds in colour images, particularly those characterized by significant occlusion (Dyrmann et al. 2017).

Accurate weed detection forms the foundation for successful weed management. Once detected, advanced management strategies can be implemented to reduce their impact and enhance the crop productivity.

Weed management methods

Robotics

In recent times, the emergence of robotic technology has provided an alternative approach to SSWM. This advancement in precision agriculture, encompassing weed management, resembles manual hoeing or knapsack spot spraying but eliminates the need for human presence (Rao 2021). An agricultural weeding robot comprises both hardware and software components, featuring an unmanned, self-steered platform equipped with various weed detection units. Currently, a diverse range of robotic machines and systems has been developed globally, such as Hortibot, EcoRobot, Ladybird, Robocrop, Robovator Hoeing Robot, Thermal Hoeing Robot, Bonirob, AgBot, Swarmbots, IC-Cultivator, RIPPA, and more (Rao 2018) (Fig. 3).

A prototype robotic system with a mechanical device to remove weeds within the crop rows was designed by Astrand and Baerveldt (2002). The robot employs a system based on colour vision for recognizing weeds and a vision system utilizing gray-level for guiding within the rows. The Intelligent Autonomous Weeder (IAW) is a robot platform designed for automated weed control in maize fields, utilizing mechanical drivers (Bakker et al. 2010). It autonomously weeded 18 parallel tramlines, each 40 meters in length at a speed of 0.5 meters per second. Raja and colleagues (2020) created an instantaneous, completely automated system to manage weed knives, aiming to remove weeds within rows near to tomato and lettuce plants. The system

Figure 3. Different weeding robots. **a.** Hortibot; **b.** Ecorobot; **c.** Ladybird; **d.** Robocrop. Source: Hill P (2018), New Scientist (2012), Willsie (2024).

demonstrated an accuracy level of 83%. Bonirob (Sellmann et al. 2014) employs a mechanical ramming rod to crush weeds in carrot cultivation experiments using decision tree learning to differentiate between plants and weeds based on parameters like leaf colour, shape and leaf size. This mechanism claims 90% effectiveness in weed elimination. Carbon Robotics, a company based in Seattle, engineered a laser weeder characterized by sub-millimeter precision, capable of covering 2 acres per hour at a speed of 1.6 kilometer per hour (Carbon Robotics 2023). While commercial weeding machines are entering the market, their limited applicability to specific crops and high costs hinder widespread adoption. Research is currently focused on developing versatile and cost-effective robotic systems capable of adapting to various scenarios and environments efficiently.

UAV-based remote sensing technique

Imaging sensors mounted on the ground and satellites have proven valuable in weed control applications (Castro et al. 2012). An overview of remote sensing systems on airplanes, satellites, ground-based platforms and UAVs utilized in weed control is provided in Table 3.

UAVs offer a unique platform for gathering data (remote sensing), surveillance (weed presence) and implementing management measures (herbicide applications) (Huang et al. 2018). UAVs play a significant role in precision agriculture, particularly in the mapping of weeds. Equipped with advanced cameras and sensors, UAVs can swiftly cover extensive hectares, providing photographic material for identifying weed patches in just a few minutes (Krishna 2018). Image processing techniques, including deep neural networks, CNNs and object-based image analysis (Tsouros et al. 2019) are employed to process these images. UAVs have undergone thorough testing on primary crops like *Hordeum vulgare* and *Triticum* spp., (Rasmussen et al. 2019) identifying various dicotyledonous weeds like *Chenopodium album*, *Amaranthus palmeri* and *Cirsium arvense* (Huang et al. 2018) as well as monocotyledonous weeds such as *Avena* spp., *Lolium* spp., and *Phalaris* spp. (López-Granados et al. 2006) Precise weed detection for generating herbicide prescription maps, especially in wide-spaced crops like maize, depends on accurately locating vegetation elements within the crop rows. Studies by Mink et al. (2018) demonstrated the potential of UAV imagery for site-specific herbicide applications, detecting the presence or absence of weeds in row crops. Remote sensing, in general, has been widely employed for detecting and mapping weeds in agriculture. Shaw (2005) emphasizes the appeal of remote sensing in identifying nuanced alterations in plant features, making it a valuable tool for identifying weed infestations, estimating weed patch sizes and locations in agricultural production. Hence, combining image-processing technologies with UAVs shows potential for efficiently managing diverse weeds that impact crops, offering significant environmental advantages (Hunter et al. 2020).

GPS controlled spraying

The categorization of spraying systems can be delineated as detecting "Green on Brown" or "Green on Green". Green on Brown (GoB), distinguishes between green vegetation and soil as well as crop residues by analyzing spectral data within the Vis-NIR ranges. Green on Green (GoG) employs advanced imaging algorithms to distinguish between verdant crops and green weeds (McCarthy et al. 2010). Patch spraying predominantly occurred through the utilization of georeferenced weed maps (Allmendinger et al. 2022). Application maps were generated using interpolated weed distribution maps and economic thresholds for weed management (Weis et al. 2008). Herbicides were applied in regions where weed growth exceeded the economic threshold, while the boom sections were deactivated in areas with minimal weed infestations. Longchamps et al. (2014) pioneered the creation of a novel real-time patch spraying mechanism utilizing weed coverage information extracted from digital imagery,

Table 3. Exploring the description and practical applications of remote sensing systems in weed control. Source: Huang et al. (2018).

Remote sensing systems	Characteristics	Coverage width	Elevation	Spatial resolution
Satellite	Large scale regional studies	10 to 2800 km	600 to 800 km	1.25 to 1000 m/pixel
Manned aircraft	Site and time specific	1200 to 7150 m	500 to 3000 m	20 to 150 cm/pixel
UAV	Highly site and time specific with continuous 3D analysis	20 to 400 m	10 to 200 m	1 to 30 cm/pixel
Ground-based	Site-specific and time-dependent, constrained by ground conditions	<5 m	<5 m	0.1 to 1 cm/pixel

specifically in maize cultivation. Jensen and Lund (2006) utilized patch-spraying algorithms to safeguard vulnerable and scarce weed species. In 2006, Gerhards & Oebel introduced a sprayer system with three tanks, which was controlled by GPS technology (Kverneland Cerberus) utilizing georeferenced spray maps for each tank. Bi-spectral cameras have been utilized to capture imagery aimed at weed categorization, relying on an analysis of shapes. The sprayer, utilized for controlling different weed types, achieved an average herbicide saving of 50% in various crops through patch-spraying. In 2016, Gonzalez-de-Soto et al. created a robotic patch sprayer with 12 high-speed solenoid valves based on GoG technology. Weed detection can be done offline or onboard, with detection accuracy reaching approximately 99%. Amazone's AmaSelectSpot with DroneLink is a commercial sensor-guided patch-sprayer utilizing an offline approach. It scans the field with an RGB camera before application, creating an overview map through integrated software. It potentially reduces herbicide usage by up to 80% depending on weed density (KG A-WHDS & C 2022).

Laser treatment

A laser denotes a tool that releases light via optical amplification, employing the stimulated release of electromagnetic radiation. It showcases properties such as uniformity, single-colour emission, focused direction, and significant strength when applied to various substances (Ferraz et al. 2007). It can eliminate weeds by directing a high-energy laser beam to cut, burn, or hinder their growth. A laser weed remover features a sophisticated setup where precision depends on factors like the detection system, laser guidance, and speed of operation. If the recognition system accurately distinguishes crops from other plants, real-time precision can be achieved, reaching up to 93% (Rakhmatulin et al. 2021).

Various laser variants, such as CO_2 lasers (Heisel et al. 2002), diode lasers (Wöltjen et al. 2008), and fibre lasers (Coleman et al. 2021), have been tested in weed control studies. Shah and Lee (2015) employed a robot cart with 16 lasers, activated by detecting green hues against a soil backdrop using HSV transformation. The laser system exhibited 63.6% accuracy in weed elimination. Xiong et al. (2017) evaluated a weeding technique employing two class-1 laser pointers with a 5 V power supply and achieved a high accuracy rate of 97% in indoor environments. However, this approach may falter in complex scenarios where colour segmentation and morphological operations are insufficient for weed detection.

Thermal weed control

Thermal management methods can be categorized into two primary groups based on their mode of operation: (a) direct heat applications, which include flame treatment, infrared treatment, heated water, steam application, and warm airflow and (b) indirect heat applications, such as electrocution, microwave exposure, laser treatment, and UV light exposure. Moreover, freezing is recognized as a separate and opposing stressor for plants (Rask et al. 2007).

The Waipuna technique, created in Auckland, New Zealand, effectively removes weeds by mixing foam (coconut oil and maize oil) with hot water (95 °C) (Kristoffersen et al. 2008). A weed steam device with both fast (53 L/h) and slow (15 L/h) flow rates was investigated by Abdulridha et al. (2019). Within three days of application, they found that the high flow rate caused a 93–97% weed mortality rate. In just 2–4 seconds of exposure, superheated steam can completely destroy a variety of weeds due to its greater coverage and penetration relative to heated water (Upadhyaya and Blackshaw 2007). Studies led by Sartorato et al. (2006) revealed that microwave exposure effectively regulated various weed types, albeit with considerable energy requirements ranging from 1000 to 3400 kg diesel per hectare. They suggested optimizing efficiency through a flux setup. Fergedal and Fergedal (1994) studied liquid nitrogen and carbon dioxide snow for weed management.

Status in India

Various weed detection software and technologies are being employed in India to enhance agricultural practices. Examples include WeedRemeed, a cloud-based system utilizing drones and AI/ML for effective weed management (2pisoftware 2024); an automated weed detection system utilizing image processing and machine learning deployed on field robots; a weed recognition system employing image processing techniques for targeted interventions (Bhongale and Gore 2017); and the integration of drone and sensor technology for site-specific weed management, all aimed at reducing herbicide use, improving crop yields, and promoting sustainable agriculture (Esposito et al. 2021). Weed and crop identification employed the Random Forest classifier, trained offline with a proprietary dataset and then tested in the field. Agrochemical spraying utilized a PWM-based fluid flow control system guided by vision-based feedback for precise application (Alam et al. 2020).

Conclusion

To conclude, the technologies discussed represent a significant breakthrough in weed management. They offer both accuracy and speed, supporting essential practices for the future of agriculture. As we work to feed the growing global population, these innovations promise to enhance yield rates and promote sustainable farming methods. Continuing to advance and implement these technologies is crucial for developing agriculture into a field focused on precision and sustainability.

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