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Review

Applications of deep learning in precision weed management: A review

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ABSTRACT

Deep Learning (DL) has been described as one of the key subfields of Artificial Intelligence (AI) that is transforming weed detection for site-specific weed management (SSWM). In the last demi-decade, DL techniques have been integrated with ground as well as aerial-based technologies to identify weeds in still image context and real-time setting. After observing the current research trend in DL-based weed detection, techniques are advancing by assisting precision weeding technologies to make smart decisions. Therefore, the objective of this paper was to present a systematic review study that involves DL-based weed detection techniques and technologies available for SSWM. To accomplish this study, a comprehensive literature survey was performed that consists of 60 closest technical papers on DL-based weed detection. The key findings are summarized as follows, a) transfer learning approach is a widely adopted technique to address weed detection in majority of research work, b) less focus navigated towards custom designed neural networks for weed detection task, c) based on the pretrained models deployed on test dataset, no one specific model can be attributed to have achieved high accuracy on multiple field images pertaining to several research studies, d) inferencing DL models on resource-constrained edge devices with limited number of dataset is lagging, e) different versions of YOLO (mostly v3) is a widely adopted model for detecting weeds in real-time scenario, f) SegNet and U-Net models have been deployed to accomplish semantic segmentation task in multispectral aerial imagery, g) less number of open-source weed image dataset acquired using drones, h) lack of research in exploring optimization and generalization techniques for weed identification in aerial images, i) research in exploring ways to design models that consume less training hours, low-power consumption and less parameters during training or inferencing, and j) slow-moving advances in optimizing models based on domain adaptation approach. In conclusion, this review will help researchers, DL experts, weed scientists, farmers, and technology extension specialist to gain updates in the area of DL techniques and technologies available for SSWM.

1. Introduction

The rise of deep learning (DL), a subfield of machine learning (ML) and artificial intelligence (AI), is a giant leap towards revolutionizing automation in precision agriculture (Albanese et al., 2021; Yang and Xu, 2021; Jiang and Li, 2020). Years ago, no one would have imagined that one day unmanned ground robots and unmanned aerial systems (UASs) could be enabled to monitor crop plants and eliminate weeds, a task that was usually performed by humans. DL has contributed significantly in precision agriculture domains involving, disease detection (Chowdhury et al., 2021; Liu and Wang, 2021), crop plant detection and counting (David et al., 2021; Rai and Flores, 2021), crop row detection (Bah et al., 2019; Pang et al., 2020), crop stress detection (Gao et al., 2020b; Butte et al., 2021), fruit detection and freshness grading (Ismail and Malik, 2021; Sa et al., 2016), fruit harvesting (Onishi et al., 2019), and site-specific weed management (SSWM) (Fernández-Quintanilla et al., 2018; Liu et al., 2021).

SSWM is a procedure that requires varying weed management practices adjusted according to weed location, density, and population (Wiles, 2009). These practices are accomplished using variable rate technology (VRT) that sprays herbicide in real-time as decided by the central brain of the machine, the vision-based image processing algorithm. Currently, there are two types of VRT-based applications, 1) map-based, and 2) sensor-based. Map-based is a common approach in which

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the map of an area is generated based on the georeferenced samples of soil or plants. Since this process involves manual soil sample collection for further analysis, therefore it is an expensive and time-taking process (Lima and Mendes, 2020). However, sensor-based mapping is a faster process that involves data collection and processing on-the go. All the processing is accomplished in real-time by leveraging the application of ML or DL techniques during in-field motion of ground or aerial technologies.

Prior to 2015, traditional image processing and conventional ML algorithms were deployed on digital images acquired using ground robots (Ahmed et al., 2012; Guerrero et al., 2012; van Evert et al., 2011). Amongst traditional image processing techniques, analyzing and extracting morphological features and textural characteristics of weed species was a widely adopted approach in identifying weeds amongst crop plants. Morphological features were based on shape measurements and shape descriptors such as, area, diameter, perimeter, and convexity (Herrera et al., 2014; Mursalin and Mesbah-Ul-Awal, 2014). Whereas textural characteristics were defined as the arrangement of gray level pixels in a specified area of a digital image. These characteristics were estimated based on the statistical and structural features defined using regularity, roughness, closeness, uniformity, or entropy (Prema and Murugan, 2016). As the techniques advanced, researchers designed or modeled a classifier that was trained on the aforementioned features. These classifiers were called as ML-based classifiers. Prominent ML classifiers such as, Random Forest (RF), Support Vector Machine (SVM) and naïve Bayes, were trained on a small sample-size images to classify weeds from crop plants. Due to limited number of training images fed for training purpose, these classifiers were limited in achieving robustness and stability in a highly complex environment that included, shadows, occlusion, look-alike weeds, unknown objects, and image distortion due to motion blur. Additionally, only a small number of research studies could deploy ML-based classifiers for real-time weed management. This was mostly due to the incapability of these classifiers to localize the presence of weeds which was later addressed by DL algorithms, the bounding boxes.

Integrating DL techniques enhances the advanced algorithms to classify weeds from crop plants in real-time. This is a crucial step as in-field weeding machines decide their spraying pattern based on these algorithms. But, developing such algorithms is a challenging task when it comes to classifying similar weed species that share similar color or shape properties as a crop plants in early growth stages. Furthermore, weed classification becomes more challenging in an extensive and complex background with a wide field of view (Olsen et al., 2019). Although several researchers have tackled this problem (Huang et al., 2018; Yu et al., 2019a; Olsen et al., 2019), fine-tuning these algorithms for scalability and generalization in multiple field scenarios needs tremendous research efforts. Further, any levels of success made in DL-based algorithms will enable SSWM technologies to efficiently classify multiple weed species followed by proper weed control actions.

The term "deep" in deep learning refers to the presence of hundreds of successive layers of representations of the input data. These representations (also called data encoding) are defined as the description that captures the underlying information of an image. In a deep neural network, this information is transformed and made more specific in a hierarchy (LeCun et al., 1989). The neural networks (NNs) in DL transforms the digital image into hierarchical levels of representations with each hierarchy carrying more specific information about the image than the previous ones. This is what typically makes DL special and better than conventional ML techniques. ML (or shallow learning), on the other hand, tends to use only one or two layers of representations of the input data that is manually engineered, called, feature engineering. Additionally, to select the best features, domain expertise is required to transform raw images into a suitable feature vector for a classifier to classify images. DL or layered representation learning uses a very complex network structure that automates the process of learning all the features from an input image. Unlike ML, DL automatically extracts local as well as global features from these layers of representations jointly rather than in succession (Chollet, 2017).

DL has paved its way for public attention and industrial research for SSWM in precision agriculture. The key reason why industries and university researchers are adopting this approach is because DL has the ability to sift through unstructured and large-scale data. This data is usually in the form of audios, videos and images where the DL algorithm tends to perform classification and detection tasks on similar distribution (Serre, 2019). Plethora of open-source application programming interfaces, such as, Keras (Chollet et al., 2015), TensorFlow (Abadi et al., 2016), and PyTorch (Paszke et al., 2019), could be credited to train a DL model in few hours depending on the size of the data with adequate computational power. Additionally, the computational bearing of palm-sized microprocessors have also increased multiple times dividing the processing tasks parallelly across powerful graphical processing units (GPUs), tensor processing units (TPUs), and existing central processing units (Jeon et al., 2021).

Apart from highlighting DL-based advancements for SSWM, this review also highlights a trend by describing a paradigm shift from ground-based to aerial-based technologies for SSWM. Therefore, to enumerate better, the outline of this paper is described in the figure (Fig. 1). The rest of the paper is organized as follows: section 2 outlines the materials and methods that explains the process behind performing a systematic literature review; section 3 provides the results and discussions of the analysis done during the literature survey. Within this section, the broad topic of SSWM is divided into two sections, proximal and remote sensing-based weed detection. Section 3.2, proximal sensing, is subdivided into two categories, application of DL techniques to classify weeds in still image context and unmanned weeding robots (UWRs) for in-field weed detection. Similarly, section 3.3 highlights remote sensing-based weed identification and is sub-categorized into orthomosaic imagery processing and spray drones for spot spraying applications. Section 4 presents the future directions for deploying novel techniques for weed detection using DL. Finally, section 5 concludes the paper with key findings, research gaps, and contributions. Collectively, the objectives of this review study are to:

a. Provide a brief survey of precision weeding technologies (including sensors/cameras) that uses DL to classify weeds in still image as well as real-time setting;
b. Report DL models and current techniques that are employed for weed detection;
c. Illuminate the ongoing research trend in aerial-based weed detection;
d. Present limitations of DL pertaining to each sensing categories; and,
e. Navigate future directions to implement novel techniques for weed identification using DL.

2. Materials and methods

2.1. Systematic search for technical papers on weed detection using DL techniques

An organized literature search was performed by selecting three academic databases, namely, Science Direct, Web of Science, and Agricola (Table 1). Specific keywords within the advanced search section of the database repositories were used that would result in the number of retrieved articles. The search keywords used were; [("Weed detection") AND ("Deep learning")], using the Boolean operator, AND. To extract relevant articles from the retrieved ones, the abstract of all the retrieved articles was read so that the subject matter was in coherence with the title of this paper. Additionally, screening criteria, such as, duplicate papers, and non-English papers were applied to the selected database for a confined and high-quality paper selection. Finally, a graph was plotted (Fig. 2) that describes the number of published technical articles on DL for weed detection in the last decade (2011–2021).

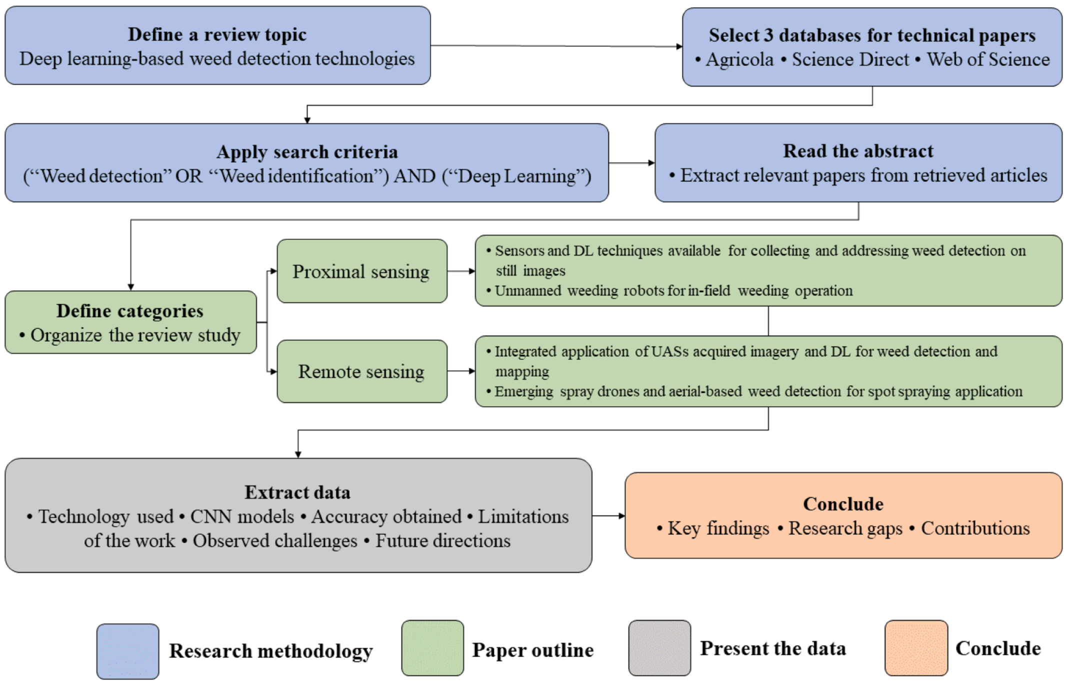


Fig. 1. Review paper layout flowchart.

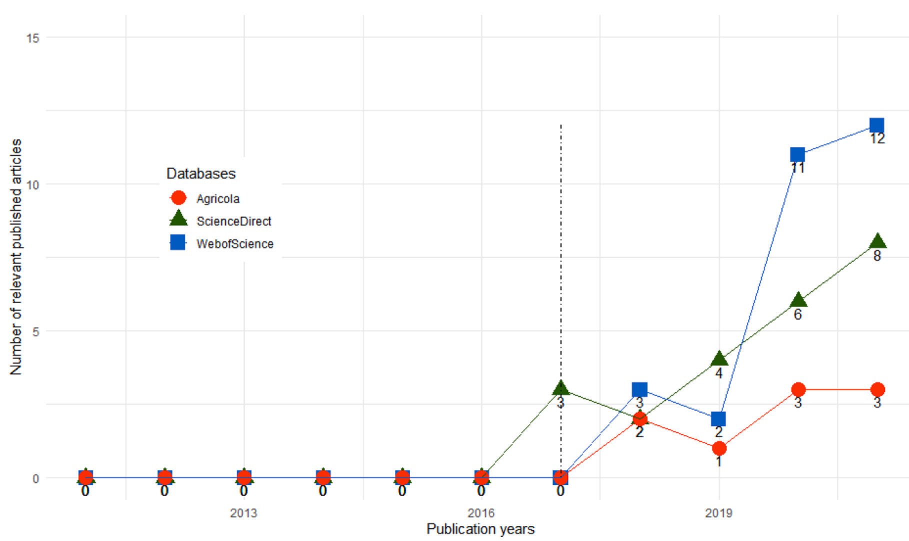


Fig. 2. The trend in published technical articles on weed detection using DL (2011 – 2021).

Main motivation to write this review article was to provide a detail answer to the question; how is deep learning enabling precision weeding technologies to address site-specific weed management in the 21st century? To address this question, 60 articles were reviewed (Table 2) that can be sub-categorized as follows:

a. Sensors and DL techniques available for collecting and addressing weed detection on still images.
b. DL-based UWRs for in-field (real-time) weeding operations.
c. Integrated application of UASs acquired imagery and DL for weed mapping or weed detection.
d. Emerging spray drones and research on aerial-based weed detection for spot spraying application.

3. Results and discussion

3.1. Analyzing the trend of published technical papers on weed detection

As mentioned in the previous section 2.1., a graph was plotted to visualize a trend in published technical articles for weed detection

Table 1
Academic databases to extract relevant articles on weed detection using DL.

S. No	Database	Retrieved articles*	Relevant articles¥
	Science Direct	98	23
	Web of Science	71	28
	Agricola	72	9

Note: *Search year = 2021 – 2011; ¥Relevant articles extracted from the retrieved ones after applying the screening criterion.

(Fig. 2). According to Table 1, out of 98 retrieved articles in Science Direct, 71 in Web of Science, and 72 in Agricola databases, the number of relevant articles were 23, 25, and 6, respectively. During the search analysis, 12 papers within the Web of Science database was found to be in common with the Science Direct database, therefore, it was removed as per the duplicate paper criteria. Furthermore, the number of papers reported in Agricola were less because most of the papers were found duplicate within the two other database. Based on the graph (Fig. 1), highest number of publications is reported in Web of Science in 2021 (12 papers, Fig. 1). Similar observation can be seen in Science Direct database as well. The trend (vertical black dot-dash) signifies that a greater number of technical articles on weed detection using DL techniques were published after 2017. Therefore, this indicates that it was only after 2017 that the potential of DL was realized in identifying weeds amongst crop plants.

3.2. Proximal sensing-based weed detection

The word "proximal" originates from a Latin term Proximus, meaning, nearest or next. Proximal sensing refers to the use of sensors that are employed close to an object. These sensors generally take time for image acquisition as they are scanned through an object delivering information in multiple bands. After image acquisition step, the output is processed for human interpretation either on high-end computers or edge platforms using DL techniques. This section discusses about different image acquisition technologies as well as DL techniques used for weed detection either on still images or real-time in-field conditions.

3.2.1. Proximal sensors for weed image acquisition

In the past years, forefront cameras and/or sensors for weed image acquisition have been, (1) RGB (Jiang et al., 2020; Hung et al., 2014), (2) multispectral for weed mapping (Louargant et al., 2017; Pantazi et al., 2017), and (3) hyperspectral for spectral-based analysis (Li et al., 2021). Out of all the three categories of sensors, the application of multispectral and hyperspectral sensor has been explored mostly in remote sensing and proximal sensing, respectively. On the other hand, RGB sensors have been used in proximal and remote sensing due to economic reasons. Various ground-based technologies have been equipped with RGB sensor to acquire field images of weeds and crop plants (Laursen et al., 2017; Kounalakis et al., 2018; Rasti et al., 2019). Whereas, in other research work, hand-held cameras (Ahmad et al., 2021; Pathak, 2021; Tang et al., 2017), mobile phone (Pearlstein et al., 2016), light detection and ranging sensor (LiDAR) (Shahbazi et al., 2021), depth camera (Andújar et al., 2016), and ultrasonic sensor (Andújar et al., 2012) have also been used to acquire images of weeds and crop plants. Different types of image acquisition technologies are shown in the figure (Fig. 3). Acquired images from these sensors are processed on high-end computers to perform weed-to-crop classification.

3.2.1.1. DL techniques to identify weeds in still image context

3.2.1.1.1. RGB images. Typically, the application of DL techniques for weed detection varies according to the sensor type. Initially, DL algorithms were developed to be implemented on RGB images (Mahony et al., 2019). But, to spread its application across a variety of sensing technologies, these algorithms were further tuned to classify weeds in images with depth (RGB-D), hyperspectral (section 3.2.1.1.2), and multispectral sensors (3.3.1.2) as well. For example, Faster R-CNN and VGG-16 architectures were used as a backbone model to train RGB-D images for weed identification in a wheat field (Xu et al., 2021a).

Wide use of DL techniques has been adopted on RGB images because DL has the ability to sift through enormous amounts of unstructured data resulting in a fast automated feature extraction ability (LeCun et al., 2015; Young et al., 2018; Parico and Ahamed, 2021). According to the current research trend in weed detection, an approach in DL, called transfer learning (TL) is widely adopted to train pre-trained CNN models on custom dataset (Fig. 4) (Subeesh et al. 2022; Chen et al. 2021). TL aims at transferring the knowledge from the source domain to the target application by improving its learning performance (Zhuang et al., 2021). In real life this can be understood as someone who knows how to ride a bicycle can simply learn to ride a motorbike since the domain is similar, riding. In a similar fashion, a CNN model, AlexNet, was trained on ImageNet dataset (Krizhevsky et al., 2012) can now be generalized through TL in the agricultural domain to recognize weeds from crop plants (Yan et al., 2020). The basic structure of a CNN model consists of three vital layers, convolutional layer, pooling layer, and a fully connected layer. The convolutional layer is used to extract features (using filter operations) on the given input image (Fig. 4a). These features can be edges or corners that results in creating a final feature map which is fed as an input to the next pooling layer. Pooling layer performs downsampling by decreasing the dimension of the feature map so as to ease computational costs. Finally, the downsampled image is fed to a fully connected neural network layer (FCNN) (Fig. 4b) that consists an activation function used to recognize the final test image (Fig. 4c). Nowadays, the task of classifying weeds from crop plants is mostly based on the TL approach as it relaxes the need for large-scale image data collection, reduces model training hours, and eliminates the need to develop a new NN model (Tan et al., 2018).

In the agricultural domain, CNN is a widely adopted network used for training and identifying weeds amongst crop plants (Kamilaris and Prenafeta-Boldú, 2018). After the huge success of ImageNet Large Scale Visual Recognition Challenge (ILSVRC) (Russakovsky et al., 2015), different models within CNN, like, Residual Neural Network (He et al., 2015), Visual Geometry Group (VGG) (Simonyan and Zisserman, 2014), and You Look Only Once (YOLO) (Redmon et al., 2015) were designed to leverage image recognition or classification tasks. These models paved a way in less time for weed detection. The first reported literature addressed the use of CNN models by using VGG-16 to perform pixel-wise weeds to crop plants classification (Dyrmann et al., 2016a; Dyrmann et al., 2016b) (Fig. 5a). This literature study also explored the applicability of models in classifying weeds that were occluded by maize plants with over 94.4 % classification accuracy. Recently, Chen et al., (2021) performed a very thorough evaluation of 27 state-of-the-art CNN architectures to classify 15 different species of weeds in cotton production. The results show that ResNet-101 achieved the highest F1-score of 99.1 % in classifying weed species. In a similar fashion, a comparison benchmark of multiple CNN models, GoogleNet, VGGNet and DetectNet, was explored that identified weeds in turfgrass (Espejo-Garcia et al., 2020). The challenge of identifying multiple weed species in a single image has been addressed in the work by Ahmad et al. (2021). The authors have assessed the performance of 3 image classification model (VGG-16, ResNet-50, Inception-V3), and one object detection model (YOLOv3) to classify and locate the presence of weeds in soybean production (Fig. 5b). Results show that VGG-16 achieved 99.1 % accuracy in classifying weeds whereas YOLOv3 scored a mAP value of 54.3 % in classifying multiple weeds in single image.

The fusion of different CNN models has also resulted in significant success to classify weeds from crop plants. For example, five multiple CNN models were fused extract the best features for weed classification tasks (Hoang Trong et al., 2020). Their method estimated the priority scoring by calculating the Bayesian conditional probability and score vector based on each model' contribution when classifying weed species. The study was accomplished by concluding that fusing too many models might render the classification tasks redundant. Similarly, feature combination using two CNN architectures, i.e., batch normalization from AlexNet and depth filters from VGGNet, resulted in a hybrid network, called AgroAVNET (Chavan and Nandedkar, 2018). Results show that AgroAVNET achieved an accuracy of 98.2 % in identifying 12 weed species. The combination of conventional ML and DL techniques is also a very promising approach in classifying weeds from crop plants. For instance, Espejo-Garcia et al., (2020) extracted the best features

Table 2
In-depth summary of technology and DL models used for weed detection in the last decade.

S. No.	Reference	Dataset/Technology	Weed species	DL model	Accuracy
			Weed detection on still image context		
1	Dyrmann et al., (2016a)	Mobile phones	22 different crop plants and weed species	CNN-based model	86.20 %
2	Tang et al., (2017)	Canon EOS 70D	Cephalanoplos, digitaria, bindweed	k-means pre-training with CNN network	92.89 %
3	Chavan and Nandedkar, (2018)	Plant seedling dataset	Fat hen, chickweed, cleavers, charlock, blackgrass, loose-silky bent, scentless mayweed, cranesbill, shepherd’s purse	AgroAVNET – a hybrid of AlexNet and VGGNet	98.23 ± 0.51
4	Farooq et al., (2018)	JAI BM-141GE	Not mentioned (patch-based weed mapping)	MatConvNet	—
5	Teimouri et al., (2018)	Based on Public dataset	Field pansy, common chickweed, blackgrass, hemp-nettle, scentless mayweed, cereal, brassicaceae, maise, cranesbill, etc.	InceptionV3	Average accuracy obtained was 70 %
6	Adhikari et al., (2019)	Handheld camera (specific name not mentioned)	Wild millet	ESNet, Faster R-CNN, EDNet, DeepLabV3	Precision and F1-score of 84.56 % and 82.16 %, respectively
7	Bosilj et al., (2019)	Based on public dataset	Specific name not mentioned	SegNet-Basic	Multiple accuracies obtained based on the variability of the dataset used
8	Binguitcha-Fare and Sharma, (2019)	Dataset from Aarhus University Signal Processing group	Scentless Mayweed, common chickweed, shepherd’s purse, cleavers, redshank, fat hen, etc.	ResNet101	98.4 % on validation and 96 % on testing dataset
9	Farooq et al., (2019)	XIMEA	Lawn weeds (specific name not mentioned)	MatConvNet	95.7 %
10	Jiang, (2019)	Not mentioned (Public Dataset)	12 species from Plant Seedlings Dataset	VGG16	91 % on verification dataset
11	Yu et al., (2019a)	SONY Cyber-Shot Digital Camera	Dandelion, ground ivy, spotted spurge	VGGNet, GoogleNet, AlexNet, DetectNet	F1-scores of VGGNet and DetectNet was 92.7 % and 98.4 %
12	Yu et al., (2019b)	SONY Cyber-Shot Digital Camera	Dollar tree, old world diamond-flower, florida pusley	VGGNet, GoogLeNet, DetectNet	DetectNet performed best with an accuracy > 99 %
13	Asad and Bais, (2020)	Nikon D610	Specific name not mentioned	U-Net, SegNet	SegNet based on ResNet-50 with 99.4 %
14	Arun et al., (2020)	Crop/Weed Field Image Dataset (CWFID)	Specific names as mentioned within the dataset	Reduced U-Net	Testing accuracy of 95.3 %
15	Espejo-Garcia et al., (2020)	Nikon D700 Digital Camera	Black nightshade, velvetleaf	Xception, Inception-ResNet, VGNets, Mobilenet, DenseNet	DenseNet combined with support vector machine (SVM) achieved an F1-score of 99.3 %
16	Jiang et al., (2020)	Canon PowerShot SX600	Bluegrass, sedge, etc.	Graph Convolutional Network (GCN)	GCN-ResNet-101 achieved 97.8 %, 99.3 %, 98.9 % and 96.5 % accuracy on four different weed datasets
17	Khan et al. (2020)	Rice seeding and weed dataset, BoniRob dataset, carrot crop vs. weed dataset, and a paddy–millet dataset	Weeds as mentioned in these datasets	Cascaded encoder-decoder network (CED-Net)	F1-score of 83.08 %
18	Hoang Trong et al., (2020)	Not mentioned	12 species from Plant Seedling dataset and 21 species from CNU weeds dataset	VGG, Mobilenet, Inception-Resnet, Resnet, NASNet	Multiple accuracies obtained based on the models and dataset combinations
19	Gao et al., (2020a)	Nikon D7200	Hedge bindweed	YOLOv3-tiny	mAP of 76.10 %
20	Peteinatos et al., (2020)	Sony Alpha 7R Mark 4	9 weed species	VGG16, ResNet50, Xception	Average F1-scores of VGG-16, ResNet-50, and Xception were 82.00 %, 97.00 %, and 98.00 %, respectively
21	Hu et al., (2020)	DeepWeeds public dataset	8 weed species	Graph Weeds Net (GWN)	Top-1 accuracy of 98.10 %
22	You et al., (2020)	Bonn and Stuttgart datasets	Soil dicot weed and grass weed	Customized DNN sematic segmentation model	Model achieves mean pixel accuracy (mPA) of 93.44 %
23	Ahmad et al., (2021)	Sony WX350, Panasonic DMC-ZS50	Cocklebur, redroot pigweed, giant ragweed, foxtail	VGG16, ResNet50, InceptionV3, YOLOv3	VGG-16 with an accuracy of 98.90 % and YOLOv3 with a mAP of 54.30 %
24	Chen et al., (2021)	Mobile phones and handheld cameras	Over 15 weed species (Waterhemp, Nutsedge, Eclipta, Carpetweed, etc.)	27 DL models that includes, ResNets, VGGs, Inceptions, MobileNets, etc.)	ResNeXt101 achieved the best F1-score of 98.93 ± 0.34 %
25	Hussain et al., (2021)	Canon camera	Lamb’s quarter	GoogleNet, VGG-16, EfficientNet	EfficientNet with PyTorch framework showed an accuracy between 92 % – 97 %
26	Fawakherji et al. (2021)	BOSCH Bonirob	Publicly available dataset: Sugar beet, Sunflower, and	Bonnet, U-Net, and UNet-ResNet	UNet-ResNet with 97 % precision accuracy
27	Jin et al., (2021)	Digital camera	Brassica rapaspp. chinensis	CenterNet	Precision and F1-score of 95.60 % and 95.30 %, respectively
28	Junior and Ulson (2021)	No specific device mentioned	Azevém, Buva, Capim-Amargoso, Capim-Pé-deGalinha, and Caruru Palmeri	YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x	YOLOv5x achieved mean accuracy of 77 %
29	Xu et al. (2021a)	Intel RealSense RGB-D	Grass weeds and broadleaf weeds	Customized CNN based on Faster R-CNN and VGG16	Model achieved an overall precision score of 89.3 %

(*continued on next page*)

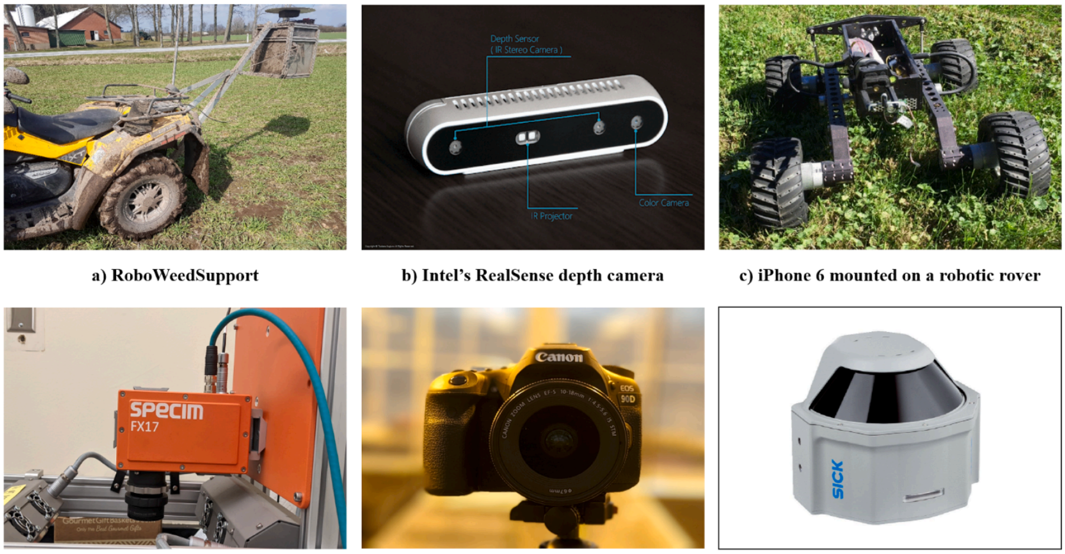
Table 2 (*continued*)

S. No.	Reference	Dataset/Technology	Weed species	DL model	Accuracy
30	Espejo-Garcia et al. (2021)	Early crop weed dataset	Black nightshade, tomato	DenseNet, Xception,	Xception network achieved 99 % accuracy on test set and 93.2 % on noisy dataset
31	Xu et al., (2021b)	Publicly available dataset	Black-grass, Charlock, and Cleavers	TX-XGBoost	Test accuracy of 99.6 %
			Real-time weed detection		
32	Jeon et al., (2011)	Machine vision system installed with a Canon SD110 Camera	Cocklebur, common lambsquarters, morning glory, velvetleaf	ANN (Artificial Neural Network)	Identification rate of corn plants (remaining weeds) were 72.6 %
33	Lottes et al., (2018)	Bonirob robotic platform	Specific name not mentioned	Fully Convolutional Network (FCN)	81.5 % precision accuracy on weed dataset
34	Milioto et al., (2018)	Bonirob robotic platform	Specific name not mentioned	Mask RCNN	Multiple accuracies achieved based on the type of dataset used
35	Kounalakis et al., (2019)	Monochrome camera (PointGrey GS3-U3-23S6M-C)	Broad-leaved dock	AlexNet, VGG-F, VGG-VD-16, Inception-V1, ResNet50, ResNet101	ResNet-50 with 96.1 % ± 0.1
36	Olsen et al., (2019)	AutoWeed	8 weed species	InceptionV3, ResNet50	Inception-v3 and ResNet-50 achieved classification accuracy of 95.1 % and 95.7 %, respectively
37	Partel et al., (2019)	Smart sprayer with Logitech Webcam installed	Portulaca weeds	YOLOv3-tiny, YOLOv3	YOLOv3 achieved 78 % accuracy for target spraying application
38	Champ et al. (2020)	Autonomous electrifier robot	*Brassica nigra* (L.) W. D. J. Koch, *Matricaria chamomilla* L., *Lolium perenne* L., *Chenopodium album* L., and natural weeds	MaskR-CNN	Multiple accuracies achieved as per weed classes
39	Hussain et al., (2020)	Smart variable rate sprayer (SVRS)	Lambsquarters	YOLOv3-tiny, YOLOv3	mAP score of YOLOv3 (93.2 0 %) was better than YOLOv3-tiny (78.20 %)
40	Rakhmatulin and Andreasen, (2020)	Laser-based weeding prototype	Cough grass	SqueezeNet coupled with Viola-Jones Algorithm	Up to 88 % detection accuracy
41	Ruigrok et al. (2020)	Robotic precision spraying system	Volunteer potato, sugar beets	YOLOv3	Precision score of 84.3 %
42	Liu et al., (2021)	Variable rate sprayer	Spotted spurge, shepherd's purse	AlexNet, VGG16, GoogleNet	VGG-16 achieved precision and F1-scores of 96 % and 94 %, respectively
			Weed detection involving UASs and DL models		
43	dos Santos Ferreira et al., (2017)	DJI Phantom 3 Pro	Broadleaf and grassweeds	ConvNets	Achieved > 98 % mean accuracy
44	Bullock et al., (2019)	Sony A600 mounted on a UAV	Foxtail, Yellow nutsedge	Edge-Stretch Context (ES-Context)	Accuracy and precision scores of 95.7 % and 75.5 %, respectively
45	Chechliński et al., (2019)	Weeding machine with a Raspberry Pi 3B + for vision-based tasks	Specific name not mentioned	Custom CNN model combining DenseNet, ResNet, U-Net, MobileNets	Models achieve satisfactory accuracy between 47 % – 67 %
46	Beeharry and Bassoo, (2020)	UAV (Specific name not mentioned)	Broadleaf	ANN, AlexNet	AlexNet achieves an accuracy of 99.80 % on the test dataset
47	Sivakumar et al., (2020)	DJI Matrice 600 with Zenmuse X5R	Waterhemp, Palmer Amaranthus, common lambsquarters, velvetleaf, foxtail	SSD, Faster RCNN	Precision and F1-score of Faster RCNN and SSD were, 65 % and 66 %, and 66 % and 67 %, respectively
48	Huang et al., (2020)	UAV	Scop, Barnyard grass	AlexNet, VGGNet, GoogLeNet, ResNet	VGGNet achieved the best accuracy of 77.20 %
49	Zhang et al., (2018)	DJI Phantom 3	5 types of weeds	YOLOv3-tiny, YOLOv3	Accuracy of YOLOv3 was 87.00 % as compared to YOLOv3-tiny (78 %)
50	Zou et al., (2021)	DJI Mavic 2 Pro	Green bristlegrass, milkweed, sedge	U-Net	Segmenting accuracy of 93.40 % weeding area
51	Khan et al., (2021a)	DJI Spark	Specific name not mentioned	YOLOv3	Average accuracy to identify weeds was 95.30 %
52	Khan et al., (2021b)	DJI Spark	Goosegrass	Semi-supervised Generative Adversarial Network (GAN)	Technique was able to achieve 90 % accuracy
53	Lam et al., (2021)	DJI Phantom 3 and 4	Broad-leaved dock	VGG16	VGG16 was able to achieve an accuracy and F1-score of 92.10 % and 78.70 %, respectively
54	Etienne et al., (2021)	DJI Matrice 600 Pro	Redroot pigweed, giant ragweed, velvetleaf, giant foxtail, etc.	YOLOv3	Average precision for monocot and dicot weeds were 91.4 % and 86.1 %, respectively
55	Milioto et al., (2017)	JAI Camera	Specific name not mentioned	CNN architecture with blob-wise classification	Multiple accuracies obtained based on the hardware platform and dataset used
56	Sa et al., (2018a)	DJI Mavic	Specific name not mentioned	SegNet	Model achieves an acceptable F1-score of 81 %
57	Sa et al., (2018b)	DJI Inspire 2 and Mavic	*Amaranthus retroflexus, Galinsoga spec., Polygonum spec*, etc.	Customized SegNet	Customized SegNet achieves an accuracy of 78.20 %
58	Osorio et al., (2020)	DJI Mavic Pro	Specific name not mentioned	YOLOv3 and Mask R-CNN	Weed detection accuracy achieved by both the models were 94 %
59	Ukaegbu et al., (2021)	DJI Phantom 3	Grassweed	ResNet-50	Validation accuracy was 98.40 %

(*continued on next page*)

Table 2 (*continued*)

S. No.	Reference	Dataset/Technology	Weed species	DL model	Accuracy
60	Khan et al., (2021c)	Quadcopter coupled with a Raspberry Pi 4	Specific name not mentioned	5 custom CNN models	Average score of 95.50 % was achieved in classifying weeds



a) RoboWeedSupport b) Intel's RealSense depth camera c) iPhone 6 mounted on a robotic rover

d) Hyperspectral sensor (FX17) e) Sony's DSLR f) LiDAR

Fig. 3. Sensors available for weed image acquisition.

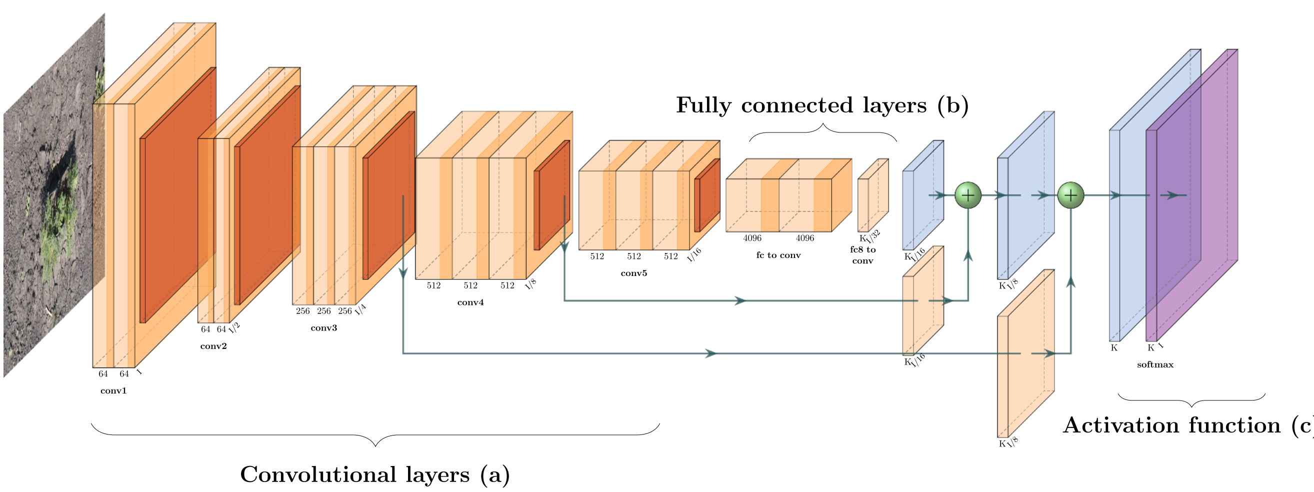


Fig. 4. Basic structure of a CNN-based model.

using multiple CNN models that were then fed to ML classifiers for training and testing purposes. Another work by Tang et al., (2017) combined an unsupervised K-means feature learning algorithm with a CNN model to classify weeds from soybean seedlings.

Based on the literature study, it is clear that CNNs are the most applied technique in the agricultural domain for weed detection. Most of the research studies have used self-built or publicly available dataset to train a pre-trained model using TL. However, based on the ongoing research trend on weed detection, researchers are working towards improving accuracies for weed species with limited number of training images (class imbalance). For example, increase in the classification accuracy of Spurred Anoda weed was reported (from 48 % to 90 %) by adopting weighted cross entropy loss function approach during the model training process (Chen et al., 2021). Similarly, Nasiri et al. (2022) combined the dice and focal losses as a custom linear loss function to tackle imbalanced dataset challenge. In most of the research work, DL model benchmarking and comparison is found to be a common pattern to decide the best neural network for weed detection. However, based on the technical publications, no one specific DL model cannot be used to identify weeds in multiple environments or a completely unseen location. For instance, in some study, AlexNet may have classified weeds with high accuracy while in some VGG-16 outperformed AlexNet. Therefore, it is hard to decide and stick to one DL model that would perform best with high accuracy in almost any field conditions. Future research direction should focus on improving the feature extraction capability of pre-trained models (Peng et al., 2022) or model customization technique (Razfar et al. 2022). Since, DL technique has an automated feature extraction ability, this step needs tremendous

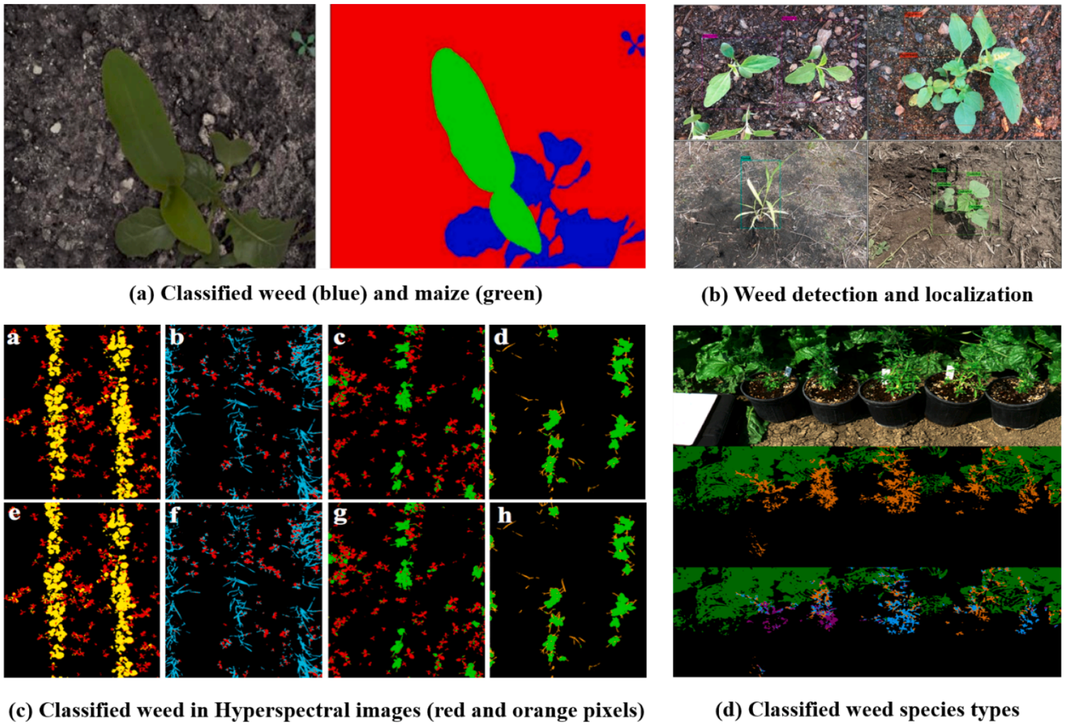


Fig. 5. Classified weeds as seen in RGB color space (a, b) and hyperspectral images (c, d).

advancements to adjust for extracting complex weed image representations. Generally, pretrained models are trained on simple images (objects around us), but when the same models are trained on weed image dataset, they may either fail to extract relevant morphological features of complex weed species or end up extracting redundant features that may lead to overfitting. Therefore, research based on extracting relevant features for weed detection will have a high scope in the future. Although these studies may have identified weeds with high accuracies, most of them have been limited to a constrained number of test images in the same field settings. Therefore, this limits the judgment on the scalability of trained models when deployed to identify weeds in real-time or on a completely different distribution of test images. To address this, experts from multiple universities should collaborate in order to develop a high-quality and a robust DL model. For example, researchers from one university can train the model based on the dataset collected on their experimental field. At the same time, the same developed model should be deployed based on the test dataset provided by some other expert from a different university. This research practice will lead to new and novel research findings based on the performance of DL models applied to a completely unseen and new locations.

3.2.1.1.2. Hyperspectral images. With all the advancements made in sensor technology, hyperspectral sensors (HS) are also looked upon as a possible solution for weed classification because of their high spectral data channels (Li et al., 2021). Although these types of sensors offer image information in narrow bands, the application of DL techniques demands intense labeling procedure and optimization on a large number of parameters to improve mode performance on the test dataset. Additionally, training high-dimensional large-sized data will demand heavy computational adequacy (Bioucas-Dias et al., 2013). But, according to the present research scenario, advances made in specifically designed GPU hardware are enabling the application of DL for hyperspectral images (Zhou and Prasad, 2020; Li et al., 2020). Numerous studies have deployed ML techniques on HS images to classify weeds from crop plants (Scherrer et al. 2019; Pantazi et al., 2017; Li et al. 2021). However, training HS data using DL techniques with the possibility of extracting spatial and spectral features together holds great benefit. As in the case of 3D CNN that has proved to increase accuracy in comparison to conventional ML methods (Yin et al., 2021). Researchers have found that using 3D CNN also eliminates the need for dimensionality reduction for the input training images (Li et al., 2017). Studies have shown that weed classification accuracy can be increased when diverse features were extracted from multiple bands by deploying CNN-based techniques on HS images (Farooq et al., 2018; Farooq et al., 2019). In short, the application of DL techniques to classify weeds from crop plants is emerging in the HS domain as well (Scherrer et al., 2019; Eddy et al., 2014) (Fig. 5 c & d). However, certain challenges such as the presence of noise in an image (adversarial image), non-uniform lighting conditions, and blurredness can easily fool a trained network to classify a class correctly (Serre, 2019). Careful attention needs to be given to the preprocessing steps as a single preprocessing pipeline cannot be applied to multiple dataset. These steps should be independent to the type of DL approach adopted to classify weeds in HS images.

The present research in developing DL algorithms for HS-based images are constrained by two limitations. These limitations can be observed in the area of open-source resources, such as, public domain weed dataset and custom application programming interfaces (APIs). Although DL techniques can be deployed on HS images, training high-dimensional image data will demand computational time as well as programming expertise. Additionally, special attention needs to be navigated to make feature selection and representation tasks more user friendly. This will help researchers understand the complex pattern learned by the model when deployed on HS images.

3.2.2. Unmanned weeding robots (UWRs) for real-time weed detection

In-field weeding operation demands two crucial steps, (1) identifying weeds amongst crop plants (Dekker, 1997) with high accuracy, and, (2) accurately localizing weeds for weeding operation (Sermanet et al., 2014). Many commercially available UWRs have emerged over the last decade to classify weeds from crop plants in real-time. These include, (a) weeding robot prototype (van Evert et al., 2011) (Fig. 6a), (b) Weedcer (Berge et al., 2012) (Fig. 6b), (c) BoniRob (Bangert et al., 2013) (Fig. 6c), (d) Dino (Naïo Technology, France) (Naïo Technologies) (Fig. 6d), (e) RIPPA (Robot for Intelligent Perception and Precision Application) (Bogue, 2016) (Fig. 6e), (f) Hortibot (Hortibot: the autonomous, GPS-

Fig. 6. Commercial robots that use computer vision techniques to perform in-field weeding tasks.

enabled weed eradicator) (Fig. 6f), (g) Avo (EcoRobotix Avo) (Fig. 6g), (h) WeLASER (WeLASER) (Fig. 6h), and (i) Robotti (Agrointelli) (Fig. 6i & 7a).

On the other hand, conventional sprayers like See and Spray (John Deere), Patriot series (Case IH), and Weed-IT have also gained market interest for in-field spraying operations. However, the in-field application spanning over multiple crop plants is limited with these conventional sprayers. For instance, John Deere's See and Spray can only identify weeds in corn, soybean, and cotton fields (Fig. 7c). Additionally, this system would work better in identifying weeds in fallow land limiting its application to classify weeds in the presence of densely vegetated crop plants. Whereas Carbon Robotic' ground robot has been tested to identify weeds in onion crop, chard, baby spinach, lettuce, cilantro, and carrot plants amongst others. Similarly, Dino (Naïo Technologies) can also be used to identify weeds in several vegetable crops such as, cabbage, cauliflower, carrots, onions, and lettuce (Fig. 7b). Although UWRs have wide variety of application in multiple fields, there are no published benchmarks or description of specific DL models that would help evaluate the performance of these technologies in real-time (Misse et al., 2020). A further advancement on the application of DL on these systems is driven by research that uses resource-constrained edge computers for on-the-go processing and decision making. Currently, many industries and university-based research are inclined towards the use of small palm-sized edge GPUs that demands less power and low latency to handle real-time weed detection.

3.2.2.1. DL on resource-constrained edge platform for on-the-go site-specific weeding operation. High-throughput edge computers integrated with a vision-based system for autonomous navigation (Mousazadeh, 2013; Roshanianfard et al., 2020) and real-time weed detection (Lee et al., 2021) are emerging. DL on resource-constrained edge computers is widely adopted due to less space requirements, low power

Fig. 7. Weed detection accomplished by in-field weeding robots.

consumption, and less latency during data transfer and processing. But one of the major challenges of implementing DL on edge computers sprawls in its requirement of training weed and crop plants each time. Since weed management in agriculture is accomplished on open farms with dynamic environment, on-board computers need to be trained with images of new weed species. This manual training or customization might slow down the adoption rate of these technologies by farmers (Serre, 2019), thereby affecting its scalability on multiple field conditions. Also, weeds need to be destroyed at a specific growth stage; therefore, a very robust perception system is required to build a DL model that is able to destroy weeds at an appropriate stage. Along the same line of thoughts, to build a very robust DL model, large amount of data is required at the training stage to identify weeds in an extreme dynamic condition. The data fed to the network needs to be carefully annotated under the expertise of a weed scientist to ensure correct weed labelling procedure is accomplished. Although an expert might be able to differentiate between look-alike crop plants and weeds at an early growth stage, a key limitation of DL algorithms might be observed in this area during real-time analysis.

A surge in the application of DL for real-time weed detection was observed after Jeon et al., (2011) showcased an effective use of machine vision system for differentiating crop plants from weeds. They used concepts from traditional image processing such as, adaptive image thresholding, and artificial neural network (ANN) to detect crop plants in uncontrolled outdoor illuminations. Although their algorithm was able to identify 72.6 % of corn plants, their work sparked the use of training models for real-time applications. The application of neural network has not been limited to detecting weeds but also segmenting them based on pixel-level information. Semantic-based segmentation was performed to classify weeds from crop plants and soil background (Milioto et al., 2018). The trained model was deployed on test images acquired using Bonirob ground robot. One-stage object detection architecture, YOLOv3, was deployed to differentiate between weeds and crop plants in real-time (Partel et al., 2019). The same architecture was inferenced on two graphical processing units (GPUs)-based systems, GTX 1070Ti and Nvidia Jetson TX2. Their results report that YOLOv3 performed better (precision of 71 %) on GTX 1070Ti (in real-time consisting of crop plants) which is a more powerful GPU when compared to a TX2 module (precision of 44 %). Similarly, a comparative test of YOLOv3 and YOLOv3-tiny was performed to identify common lambsquarters in a potato field (Hussain et al., 2020). Both the models were trained on 24,000 images of weeds, potatoes, and diseased plants. As reported in the literature, YOLOv3 had a larger mAP value (93.2 %) as compared to tiny YOLOv3 (78.2 %). But, the inference time of YOLOv3 (14.6 FPS) was less than tiny YOLOv3 (30.0 FPS) when deployed in real-time conditions. The authors suggest to use the YOLOv3-tiny model for inferencing purpose. Currently, the most common approach for real-time weed detection is inclined towards the use of lite-weight models. A majority of the literatures have deployed lightweight models that promises to achieve high accuracy with minimum latency and optimal parameters. For instance, YOLOv3 model was trained to identify, locate, and spray weeds with 96 % accuracy in in-field scenario (Ruigrok et al. 2020). Since, edge devices are resource-constrained, therefore, it is often desired that the trained DL model should have limited number of parameters that consume less GPU memory during the inferencing stage. Considering this as another research challenge, weed detection accuracy of 95.1 % was achieved by deploying 5-layer custom neural network on Raspberry Pi 4 (Razfar et al. 2022). As per the results, 5-layer CNN had 414,956 parameters with a memory usage of 1.14 GB delivering 9.85 ms latency during inference time. Integrating novel modules within the backbone layer of DL models are also becoming an area of research study. For example, block-based attention module was combined with YOLOv5 model to identify the presence of Dunal weeds (Wang et al., 2022b). The trained model was deployed on Jetson AGX Xavier and achieved a real-time precision accuracy of 94.6 % with a processing speed of 37 FPS. Hennessy et al. (2022) also deployed YOLOv3 model to identify hair rescue and sheep sorrel in wild blueberry field. The model achieved an FI-score of 97 % and 95 % in identifying hair rescue and sheep sorrel, respectively. Double-stage object detection models, such as, Faster R-CNN or Mask R-CNN is considered densely designed models that often end up consuming lot of GPU memory during inferencing stage. To address this, a comparative study of single and double-stage models for weed detection was studied (Saleem et al., 2022). Out of all the model validated on test dataset, YOLOv4 achieved the highest mAP of 79.6 % in identifying all the weed classes. Clearly, in the light of all the reported literatures, different versions of YOLO remain the best choice for real-time weed detection due to their small size, a smaller number of parameters, and optimal inference timing.

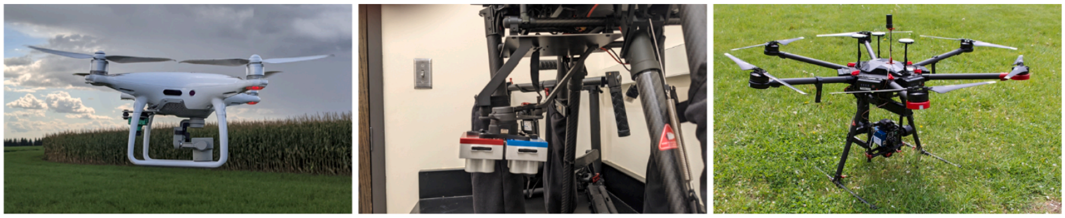
In the future, weeding robots that promise to address weed detection in a real-time environment will have to be designed efficiently that not only consumes less power but should be quick enough to make smart decisions on edge devices. The task of making smart decisions on these edge devices will be highly dependent the quality of the dataset used and training techniques applied to boost the generalization ability of the algorithm. To increase the generalization efficiency of DL, large amounts of data will be required to train DL models. This is a very crucial step as the output model will reflect the quality of input data (Dai et al., 2018). The cost of data acquisition, management, storage, and image annotation will play a big role in developing a robust DL model for real-time weed detection. Although, techniques such as active learning can relax the need to annotate images manually (Ning et al., 2022), data acquisition, management, and pre-processing still demands manual human input. Additionally, converting models to lightweight frameworks, such as TensorFlow Lite (TFLite) and TensorRT would be beneficial for real-time inferencing. These frameworks assist in reducing model size and redundant parameters through post training model quantization and pruning technique (Zhang et al., 2022). Overall, to develop successful large-scale weeding robots, expertise from the field of weed science, DL, and mechatronics engineering must work together to develop a powerful sensing and weeding solution. Expertise from these three fields will have to be coupled with farmer' experience to enhance feeding intelligent decisions to UWRs.

3.3. Remote sensing-based weed detection

The term "remote sensing" was first coined by Evelyn Pruitt in the late 1950 s after which many researchers and scientists have tried to define the precise meaning of this term (Fussell et al., 1986). Remote sensing is an indirect data acquisition process followed by data manipulation operation such as, pixel transformation or pixel clustering to convert the images into a human-readable format. Different categories of sensors used in this process include RGB camera mounted on a gimble attached with a DJI Phantom 4 Pro (Fig. 8a), 10-band multispectral sensor by Micasense (RedEdge MX) (Fig. 8b), and Headwall's Nano Hyperspec® (Headwall) (Fig. 8c). The quintessential steps required for UASs image data acquisition to weed detection includes, (1) flying missions using iOS or Android-based apps, such as, Pix4DCapture (Switzerland), DJI GO 4 Pro (China), etc.; (2) stitching all the images to generate an orthomosaic either using a commercial software like Pix4D (Switzerland) or an open-source platform like WebODM (OpenDroneMap); and finally, (3) applying DL techniques to detect weeds in the generated orthomosaic.

3.3.1. Integrated application of orthomosaic imagery and DL for weed detection

3.3.1.1. RGB orthomosaic. RGB-based weed detection on orthomosaic involves flying missions and generating a geo-registered imagery depicting the real location when projected on the earth's surface (bird's-eye view of a field). Currently, processing an orthomosaic for weed detection involves two different methodologies. These methodologies



a) DJI Phantom 4 Pro b) Multispectral sensor on M600 c) Headwall's Nano Hyperspec®

Fig. 8. Drones with sensors used for weed image acquisition.

are dependent on ML and DL-based approaches. When ML-based techniques are implemented to classify weeds from crop plants, a common approach is to develop a classifier trained on a single part of the orthomosaic (Islam et al., 2021). This classifier is further validated on the remaining portion of the whole orthomosaic. However, this review work does not discuss ML-based weed classification. On the other hand, DL-based approach demands clipped (constraint due to large dimension of the orthomosaic imagery) and annotated images of weeds and crops to train a model for validation and testing purpose (Sivakumar et al., 2020) (Fig. 9).

Research work involving early weed identification using aerial imagery and DL is challenging because of indistinct images of weeds and crop plants. However, researchers have focused on implementing DL models, like, AlexNet, VGGNet, GoogleNet, and ResNet to detect weeds at the seedling stage (Huang et al., 2020). They also compared the accuracy and inference timing of these models with object-based image analysis (OBIA), which is considered a widely adopted method to classify weeds from crop plants (López-Granados et al., 2016). Their results report that DL-based detection (using AlexNet model) achieved the highest accuracy in identifying weeds at the seeding stage. Image resolution also plays a significant role in achieving better accuracy when DL models are implemented on UASs acquired images. For this very reason, a UASs that fly close to the ground will deliver a higher resolution with distinct pixel intensities of each object when compared to UASs flying at a higher altitude. The lower the flight height, the lower the ground sample distance will be, leading to more detailed image. In order to find out the minimum flight altitude for precise weed detection, research work carried out by Lam et al., (2021) investigated the minimal flying height (at 32 ft, 50 ft, and 65 ft) required for optimal accuracy for weed detection. They deployed VGG-16 model that resulted in a classification accuracy (F1-score) of 78 % at 32 ft altitude.

Several studies state that despite early weed control methods, some weeds do dodge early weed management methods (called late season weeds) and become trouble for the subsequent growing seasons (Goplen et al., 2017). To detect late-season weeds using DL techniques and UASs imagery, Sivakumar et al., (2020) compared two object-based detection models, Faster R-CNN and single shot detector (SSD) with a patch-based CNN model. It turns out that the accuracy and inference time of object-based detection model (F1-scores of Faster RCNN and SSD was 0.6 and 0.7, respectively) performed significantly better than the patch-based CNN model. Application of single-stage object detection model, YOLOv3, has also been used to localize the presence of weeds in aerial imagery (Khan et al., 2021a). The model achieved an accuracy of 91 % in detecting and localizing weeds. Furthermore, the model developed in this study could be integrated or embedded on a UASs sprayer system or a tractor. The application of lightweight tiny model, YOLOv3-tiny, was deployed to detect weed pixel coordinate. These coordinates were further converted to geodetic coordinates to precisely locate the position of detected weeds (Zhang et al., 2018). Similarly, Etienne et al. (2021) deployed YOLOv3 model on UASs imagery to detect monocot and dicot weeds at an altitude of 10 m (32 ft). Results prove that YOLOv3 model was successful in detecting and locating the monocot (91.4 %) and dicot

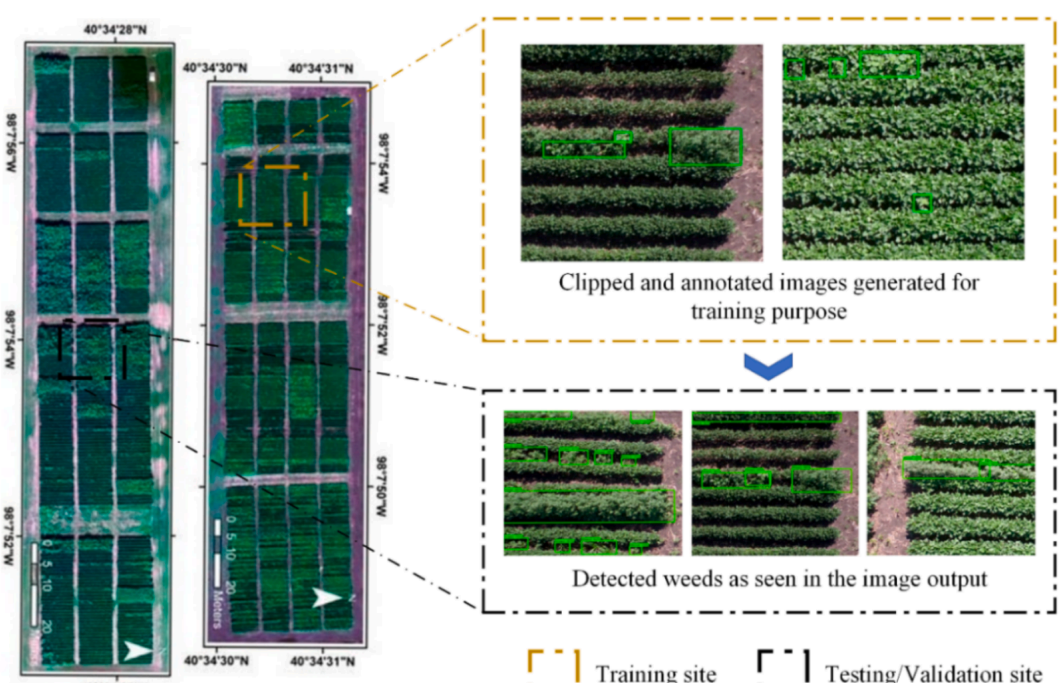


Fig. 9. Weed detection using UASs acquired imagery.

seeds (86.1 %) an average precision (AP) of 25 %. Overall, it can be noted that YOLOv3 has been a good choice for researchers to detect and locate the presence of weeds (small objects) in UASs acquired imagery.

Besides bounding-box approach, semantic segmentation, is also seen as the most common technique to classify weeds from crop plants in aerial images. This technique is mostly used to segment out the precise location of weeds in an image. U-Net model (U-shaped structure) was deployed to segment weeds from soil background (Zou et al., 2021). Further, they also developed an algorithm to quantify weed density which was also an extended application of using U-Net-based algorithm for weed classification. Results show that an R-square value of 0.94 was achieved in comparison with ground-truth data. Recently, four segmentation model, SegNet, U-Net, fully-convolutional network (FCN), DeepLabV3+, was fine-tuned and trained to segment weeds from crop plants and background (Hashemi-Beni et al. 2022). Results indicate that DeepLabV3 + model achieved high accuracy of 90.5 % as compared to U-Net (86.1 %) and SegNet (64.5 %).

3.3.1.2. Multispectral orthomosaic. Multispectral sensors are widely adopted in precision agriculture due to their flexibility in delivering object information in various spectral bands. Images captured via multispectral sensors highly depend on the environmental conditions given the fact that they deliver information about the plant's reflectance which is affected by the light absorbed by the plant. Commercial multispectral sensors (Altum, RedEdge, etc.) are expensive but image data captured using these sensors have helped researchers to extract a normalized differentiation vegetation index (NDVI). NDVI is a quantitative value that measures the greenness and vigor of vegetation (Kogan, 1995). Since, this index can be used to extract greenness, which consists of mostly crop plants and weeds, research work in the past have used NDVI as a foundational step to first segment the soil background from green foreground objects. After the segmentation process, ML-based classifiers or DL models are leveraged to map or detect weeds, respectively. For example, a common NDVI-based segmentation, analyzing crop row pattern, and OBIA-based image processing techniques were used to map out the position of weeds in UASs imagery (Peña et al., 2013).

Similarly, Pérez-Ortiz et al., (2015) flew a quadcopter mounted with a multispectral sensor to classify crop plants, soil, and weeds in a sunflower field using unsupervised (k-means, repeated k-means), semi-supervised support vector machine (SVM),and supervised learning (k-NN, linear SVM, and kernel SVM). They reported that the semi-supervised learning classification approach was best in classifying weeds. CNN-based pixel-wise classification approach was adopted to map and separate multiple classes involving weeds and crops (Sa et al., 2018a). Their results show that this approach had an acceptable F1-score of 0.8 for weed detection. Later in 2018, Sa et al., (2018b) trained a deep neural network (DNN) model, SegNet, to perform semantic-based segmentation for classifying crop, soil, and weeds in the sugar beet field. Furthermore, they also reported that segmenting images using the NDVI index significantly helped them to boost their classification accuracy. Blob-wise CNN-based approach has been used to classify weeds from sugar beet images using RGB + NIR imagery (Milioto et al., 2017). However, Osorio et al., (2020) took a step forward to implement state-of-the-art technique by deploying DL model, YOLOv3 model, to classify weeds in lettuce plantations. The authors also used ML-based histogram of oriented gradients SVM (HOG-SVM), and Mask R-CNN to test out weed classification accuracy. YOLOv3 and Mask R-CNN methods proved to deliver highest accuracy of 94 % when classifying weeds and lettuce crop plants.

Multispectral sensors have contributed significantly to weed detection and mapping in the precision agriculture domain. In the last couple of years, sensors have become compact while becoming more robust in their features. To add to this, as sensors have become complex in delivering image information, so did the DL techniques. The application of SegNet and U-Net models have proved to be one of those techniques that were widely deployed for weed segmentation tasks Apart from classifying weeds from soil background, these models also deliver object size information which can be one of the most quintessential information to estimate weed density.

3.3.2. Emerging spray drones and research in aerial-based weed detection for spot spraying application

SSWM, also termed as target-based (Liu et al., 2021), spot spraying (Yu et al., 2019a), or patch spraying (Berge et al., 2012) have inspired engineers over the decade to develop aerial robots that can accomplish the task of spot spraying weeds with desired efficacy. In fact, spot spraying treatments can reduce the amount of herbicide used thereby reducing herbicide concentration in runoff (Melland et al., 2016).

Because of the spatial heterogeneity of weeds, specific challenge pertaining to herbicide application arises. This challenge is related to the broadcast application (or blanket application) over the entire field resulting in environmental pollution leading to economic losses due to plant death. To solve this problem, a ground-robot is sent to the field for target spraying application. However, a ground robot may not be a fitting choice to scan for weed patches over a vast field since the process can be time-consuming. In that case, UASs equipped with sensors can perform spot spraying. Also, UASs-based spot spraying delivers preferred advantages over the ground-based robot, like, non-destructive to crop plants, no soil-compaction, no-fuel consumption thereby more environment friendly, economically sustainable, etc.

UASs-based spot spraying only involves postemergence for controlling weeds. As discussed before, UASs require on-site image data acquisition therefore preemergence UASs applications to control weeds will not be applicable for weed monitoring. After the postemergence of weeds in the field, two distinct methods can be applied for weed monitoring via UASs. Firstly, creating prescription maps as discussed in sections 3.3.1.1 & 3.3.1.2., and secondly, sensor-based real-time. One of the major limitations when prescription-based mapping approach is adopted is related to the timeline from data acquisition to final map generation. The total process needs to be accomplished rapidly so that the weeds dynamic does not change. Delaying this step will render the generated map obsolete (Lima and Mendes, 2020). Therefore, these days, a lot of research work are inclined towards real-time weed detection.

Drone-based spraying technology has recently gained popularity and has been commercialized by various industries. For example, DJI Agras T30 (DJI Agras T30) (Fig. 10a), which is a semi-autonomous spraying technology, requires a prerequisite flight of DJI Phantom 4 Pro drones to scout for weeds. After visually observing the presence of weeds, a user or a farmer can fly the Agras T30 drone for spot spraying application. A more advanced system by Precision AI (Precision AI) (Fig. 10b) uses computer vision to spray herbicide in row crops. Further, it can spray just the weeds based on a smart decision system built on AI. Another autonomous drone sprayer by John Deere (John Deere) (Fig. 10c) first uses a scout drone to scan for weeds from the air. After returning to its initial take-off position, it shares the weed information with the other drones in its swarm to spot and spray individual weeds. In the coming future, industrial or commercially manufactured drones for spot spraying weeds will rely heavily on DL-based techniques.

Besides industrial efforts to manufacture drones for spot spraying weeds, research efforts in the universities are also making significant effort to develop aerial-based weed detection solutions for precision spraying. For instance, an attention module was combined with YOLOv5, called YOLO-CBAM, was trained and deployed to detect the presence of Dunal seedlings in aerial images captured using DJI Mavic (Wang et al., 2022b). Similarly, a real-time weed recognition system was designed by integrating a Raspberry Pi 4 with a UASs (Khan et al., 2021c). Five custom designed CNNs were trained achieving an accuracy of 95.5 % for real-rime weed detection. Raspberry Pi 3 module was also mounted on a quadcopter for real-time identification of broadleaf and

a) Agras T30 b) Precision AI drone c) Autonomous spray drone

Fig. 10. Spray drones for spot spraying application.

grass weeds in farmland (Ukaegbu et al., 2021). Several tests were conducted by deploying a CNN model on the soybean dataset. Training and validation accuracies turned out to be 99.9 % and 98.4 %, respectively. Since UASs have payload constraints, therefore, significant research efforts should be directed in designing a network requires less power and parameters when inferencing. For example, a state-of-the-art flying robot was designed that used AGX Xavier NCS2 and Intel's Neural Compute Stick to perform onboard real-time computation (Hossain and Lee, 2019). Concepts could be borrowed to leverage the same technology in weed identification for real-time spot spraying applications. The integration of edge AI on UASs, called Ag-YOLO, demonstrated the effective application of target-based detection and spot spraying in palm plantation (Qin et al., 2021). Their research work tackled three existing problems for a drone-based spot spraying, choosing an appropriate hardware accelerator, scripting an efficient neural network algorithm, and model pruning to eliminate unnecessary computation.

More research effort is also needed in the area of the aerial spraying mechanism. For example, sprayer tip location with regards to the target weeds, ensuring if the herbicide is precisely sprayed over the weeds, controlling spray drifts by analyzing the downwash effect of the rotors on spraying mechanism. But before this research effort is worked upon, questions pertaining to DL algorithm implementation should be precisely answered. This research may involve queries such as; the effect of changing gimble angle on the detection accuracy of the DL model, optimal altitude and speed of UASs when targeting weeds in real-time scenario (Rai et al. 2022), and optimizing DL models for detecting small objects within the input frame (Wang et al. 2022a). Advanced research based on these questions will help develop an effective high level of the crop to weed differentiating algorithm for aerial-based weed detection.

4. Future directions on applying novel techniques for weed detection using DL

Progress made in the area of DL to facilitate SSWM has been evident in the last demi-decade. Considering the ongoing research, significant efforts should be directed to overcome certain challenges of DL for weed detection. These challenges mostly lie in the area of tuning models by training on a limited and diverse dataset to testing them on a completely unseen dataset with a different distribution. To accomplish this, there are five effective ways that researchers in this field may consider making advancements. These novel techniques or approaches may include:

a. Training a neural network from scratch – This basically means designing and training a novel CNN model from scratch. As mentioned, a majority of weed detection approaches have relied heavily on deploying an already pretrained CNN model. This has become one of the most common approaches in the agricultural community. Although these models have achieved an acceptable accuracy either on still image context or real-time scenario, the base layers of the pre-trained models carry weight information that may result in bias on the new and complex dataset. To tackle this challenge, more research should focus on designing neural networks based on focused learning of representations from complex training dataset. Executing this step will also demand feeding significant number of images to the network for robust learning mechanism. However, training models on diverse dataset will demand hefty hours for data collection, preprocessing, and annotation process. In some cases, training may also take weeks, provided the computational resources are high-end. Therefore, to relax this demand, few more approaches are described below that could be pursued to improve the generalization ability of the trained models for weed detection.

b. Adopting domain adaptation (DA) approach (Dev et al. 2022) – DA technique is a special type of TL technique that assists a model to generalize better on the dataset that has a different distribution than the training dataset (test images with novel context). For example, a weed image dataset that has been captured using a hand-held camera will have a very different distribution compared to the dataset that has been acquired using a UASs. Therefore, the DA technique can be used in this case by adjusting and optimizing the trained model on the new test dataset with a completely different distribution.

c. Training using adversarial approach (Bai et al. 2021) - One of the biggest challenges faced by DL algorithms is regarding adversarial images. These adversarial within an image can be present in the form of noise, or even a small pixel level perturbation can fool a DL model into classifying an object inaccurately. Recently, researchers have been working on an adversarial training technique called generative adversarial network (GAN) that promises to solve this challenge (Espejo-García et al., 2021).

d. Model and module level ensemble approach (Ganaie et al., 2022) – The ensemble approach is a technique that uses prediction results from the base of multiple models to predict an outcome for an unseen dataset (Ofori et al. 2022). Whereas, module reparameterization (a more advanced approach) splits the convolutional blocks during inferencing operation (Wang et al., 2022a).

e. Integrating attention module for DL (Zhu et al. 2021) – Nowadays, the attention mechanism approach has become popular in the DL community. The attention mechanism technique tends to enable the decoder that utilizes the best and long range of feature information from the given input sequences. For example, in a recently published work by Wang et al. (2022b), the integration of attention module with the YOLOv5 model has resulted in significant increase in detection accuracy of Dunal seedlings.

Furthermore, exploring model interpretability-based research studies are lagging in the agricultural domain (Li et al. 2021). A very common notion surrounding DL implementation is restricted by the fact that DL is nothing but a black box-based technique. To address this notion, researchers working on detecting or classifying weeds from crop plants either in an industrial setting or lab boundaries must develop techniques that will help find a pattern learned or recognized by a trained CNN model. This should also be a major focus of published technical papers in well-known journals as well. Doing this will build a deeper understanding on DL model feature learning technique or tuning models to learn focused features when classifying weeds from crop plants (Lee et al., 2017).

5. Conclusion

In this review study, 60 technical papers on weed detection using DL techniques have been surveyed. To accomplish this, three best-known academic databases were chosen, Agricola, Science Direct, and Web of Science. Moreover, to select relevant papers out of retrieved papers, abstract of each paper were read and a screening criterion were applied. After a successful literature search method, it is clear that a greater number of technical articles on weed detection using DL are published after 2017.

Furthermore, to distill the information gained after reading these papers, the outline of this review is divided into two categories, proximal and remote sensing-based weed detection. These two categories are further sub-divided and elaborated based on these sub-topics; sensors available for each sensing category and the DL techniques applied to process images acquired via these sensors. For example, Proximal-based weed detection consists of two sections, image acquisition sensors and DL techniques applied to process the images for weed detection. Similarly, remote sensing-based weed detection also consist of two sections, remote sensing image acquisition technologies and DL techniques deployed to detect and map weeds in the generated orthomosaic.

In conclusion, novel techniques in DL are still emerging and revolutionizing weed detection for SSWM. Key findings, contributions, and research gaps based on this review can be summarized as follows; a) transfer learning approach is a widely adopted technique to address weed detection in majority of research work, b) less focus navigated towards custom designed neural networks for weed detection task, c) based on the pretrained models deployed on test dataset, no one specific model can be attributed to have achieved high accuracy on multiple field images pertaining to several research studies, d) inferencing DL models on resource-constrained edge devices with limited number of dataset is lagging, e) different versions of YOLO (mostly v3) is a widely adopted model for detecting weeds in real-time scenario, f) SegNet and U-Net models have been deployed to accomplish semantic segmentation task in multispectral aerial imagery, g) less number of open-source weed image dataset acquired using drones, h) lack of research in exploring optimization and generalization techniques for weed identification in aerial images, i) research in exploring ways to design models that consume less training hours, low-power consumption and less parameters during training or inferencing, and j) slow-moving advances in optimizing models based on domain adaptation approach. Therefore, this review article will help researchers, DL experts, weed scientists, and technology extension specialist to develop novel ideas and work jointly towards advancing and improving DL-based weed detection for SSWM technologies.

Data availability

No data was used for the review study described in this article.

CRediT authorship contribution statement

Nitin Rai: Methodology, Investigation, Visualization, Writing – original draft, Writing – review & editing. **Yu Zhang:** Writing – review & editing. **Billy G. Ram:** Writing – review & editing. **Leon Schumacher:** Writing – review & editing. **Ravi K. Yellavajjala:** Writing – review & editing. **Sreekala Bajwa:** Writing – review & editing. **Xin Sun:** Conceptualization, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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References

Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., Devin, M., Ghemawat, S., Irving, G., Isard, M. & others. 2016. TensorFlow: A system for large-scale machine learning. OSDI (p./pp. 265–283). Retrieved from: https://github.com/tensorflow/tensorflow.

Agrointelli. Robotti. Retrieved from: https://www.agrointelli.com/robotti/.

Adhikari, S.P., Yang, H., Kim, H., 2019. Learning semantic graphics using convolutional encoder–decoder network for autonomous weeding in paddy. Front. Plant Sci. 10 https://doi.org/10.3389/fpls.2019.01404.

Ahmad, A., Saraswat, D., Aggarwal, V., Etienne, A., Hancock, B., 2021. Performance of deep learning models for classifying and detecting common weeds in corn and soybean production systems. Comput. Electron. Agric. 184, 106081 https://doi.org/10.1016/j.compag.2021.106081.

Ahmed, F., Al-Mamun, H.A., Bari, A.S.M.H., Hossain, E., Kwan, P., 2012. Classification of crops and weeds from digital images: A support vector machine approach. Crop Prot. 40, 98–104. https://doi.org/10.1016/j.cropro.2012.04.024.

Albanese, A., Nardello, M., Brunelli, D., 2021. Automated pest detection with DNN on the edge for precision agriculture. IEEE J. Emerg. Sel. Topics Power Electron. 11, 458–467. 10.48550/arXiv.2108.00421.

Andújar, D., Dorado, J., Fernández-Quintanilla, C., Ribeiro, A., 2016. An approach to the use of depth cameras for weed volume estimation. Sensors (Basel, Switzerland) 16, 972. https://doi.org/10.3390/s16070972.

Andújar, D., Weis, M., Gerhards, R., 2012. An ultrasonic system for weed detection in cereal crops. Sensors. https://doi.org/10.3390/s121217343.

Arun, R.A., Umamaheswari, S., Jain, A.V., 2020. Reduced U-Net architecture for classifying crop and weed using pixel-wise segmentation. In: 2020 IEEE International Conference for Innovation in Technology (INOCON). pp. 1–6. 10.1109/INOCON50539.2020.9298209.

Asad, M.H., Bais, A., 2020. Weed detection in canola fields using maximum likelihood classification and deep convolutional neural network. Inf. Process. Agric. 7, 535–545. https://doi.org/10.1016/j.inpa.2019.12.002.

Bah, M., Hafiane, A., Canals, R., 2019. CRowNet: Deep network for crop row detection in UAV images. IEEE Access 8, 1. https://doi.org/10.1109/ACCESS.2019.2960873.

Bai, T., Luo, J., Zhao, J., Wen, B. and Wang, Q., 2021. Recent advances in adversarial training for adversarial robustness. arXiv preprint arXiv:2102.01356.

Bangert, W., Kielhorn, A., Rahe, F., Albert, A., Biber, P., Grzonka, S., Hänsel, M., Haug, S., Michaels, A., Mentrup, D., Kinski, D., Möller, K., Ruckelshausen, A., Scholz, C., Sellmann, F., Strothmann, W., Trautz, D., 2013. Field-robot-based agriculture: "RemoteFarming.1" and "BoniRob-Apps". In: 2013 Tagung Land.TECHNIK - AgEng.

Beeharry, Y., Bassoo, V., 2020. Performance of ANN and AlexNet for weed detection using UAV-based images. In: 2020 3rd International Conference on Emerging Trends in Electrical, Electronic and Communications Engineering (ELECOM). pp. 163–167. 10.1109/ELECOM49001.2020.9296994.

Berge, T., Goldberg, S., Kaspersen, K., Netland, J., 2012. Towards machine vision based site-specific weed management in cereals. Comput. Electron. Agric. 81, 79–86. https://doi.org/10.1016/j.compag.2011.11.004.

Binguitcha-Fare, A.A., Sharma, P., 2019. Crops and weeds classification using convolutional neural networks via optimization of transfer learning parameters. Int. J. Eng. Adv. Technol. 8, 5.

Bioucas-Dias, J.M., Plaza, A., Camps-Valls, G., Scheunders, P., Nasrabadi, N., Chanussot, J., 2013. Hyperspectral remote sensing data analysis and future challenges. IEEE Geosci. Remote. S. 1, 6–36. https://doi.org/10.1109/MGRS.2013.2244672.

Bogue, R., 2016. Robots poised to revolutionise agriculture. Ind. Rob. 43, 450–456. https://doi.org/10.1108/IR-05-2016-0142.

Bosilj, P., Aptoula, E., Duckett, T., Cielniak, G., 2019. Transfer learning between crop types for semantic segmentation of crops versus weeds in precision agriculture. J. Field Robot. https://doi.org/10.1002/rob.21869.

Bullock, D., Mangeni, A., Wiesner-Hanks, T., DeChant, C., Stewart, E.L., Kaczmar, N., Kolkman, J.M., Nelson, R.J., Gore, M.A., Lipson, H., 2019. Automated weed detection in aerial imagery with context. arXiv preprint arXiv:1910.00652.

Butte, S., Vakanski, A., Duellman, K., Wang, H., Mirkouei, A., 2021. Potato crop stress identification in aerial images using deep learning-based object detection. Agron. J. https://doi.org/10.1002/agj2.20841.

Champ, J., Mora-Fallas, A., Goëau, H., Mata-Montero, E., Bonnet, P., Joly, A., 2020. Instance segmentation for the fine detection of crop and weed plants by precision agricultural robots. Appl. Plant Sci. 8 (7), e11373.

Chavan, T.R., Nandedkar, A.V., 2018. AgroAVNET for crops and weeds classification: A step forward in automatic farming. Comput. Electron. Agric. 154, 361–372. https://doi.org/10.1016/j.compag.2018.09.021.

Chechliński, Ł., Siemiątkowska, B., Majewski, M., 2019. A system for weeds and crops identification-reaching over 10 FPS on Raspberry Pi with the usage of MobileNets, DenseNet and custom modifications. Sensors (Basel, Switzerland) 19, 3787. https://doi.org/10.3390/s19173787.

Chen, D., Lu, Y., Li, Z., Young, S., 2021. Performance evaluation of deep transfer learning on multiclass identification of common weed species in cotton production systems. 10.48550/arXiv.2110.04960.

Chollet, F., & others. 2015. Keras. GitHub. Retrieved from https://github.com/fchollet/keras.

Chollet, Francois. 2017. Deep Learning with Python. New York, NY: Manning Publications Co., 3. United States.

Chowdhury, M.E.H., Rahman, T., Khandakar, A., Ayari, M.A., Khan, A.U., Khan, M.S., Al-Emadi, N., Reaz, M.B., Islam, M.T., Ali, S.H., 2021. Automatic and reliable leaf disease detection using deep learning techniques (special issue). AgriEngineering 3 (2), 294–312. https://doi.org/10.3390/agriengineering3020020.

Dai, W., Yoshigoe, K., Parsley, W., 2018. Improving data quality through deep learning and statistical models. 10.1007/978-3-319-54978-1_66.

David, E., Daubige, G., Joudelat, F., Burger, P., Comar, A., de Solan, B., Baret, F., 2021. Plant detection and counting from high-resolution RGB images acquired from UAVs: Comparison between deep-learning and handcrafted methods with application to maize, sugar beet, and sunflower crops. 10.1101/2021.04.27.441631.

Dekker, J., 1997. Weed diversity and weed management. Weed Sci. 45, 357–363. https://doi.org/10.1017/S0043174500092985.

Dev, K., Ashraf, Z., Muhuri, P.K., Kumar, S., 2022. Deep autoencoder based domain adaptation for transfer learning. Multimed. Tools Appl. 81, 22379–22405. https://doi.org/10.1007/s11042-022-12226-2.

DJI Agras T30. DJI Agras T10 and Agras T30 - The future of agriculture drone spraying. Retrived from: https://enterprise.dronenerds.com/agriculture/dji-agras-t10-and-agras-t30-the-future-of-agriculture-drone-spraying/.

dos Santos Ferreira, A., Matte Freitas, D., Gonçalves da Silva, G., Pistori, H., Theophilo Folhes, M., 2017. Weed detection in soybean crops using ConvNets. Comput. Electron. Agric. 143, 314–324. https://doi.org/10.1016/j.compag.2017.10.027.

Dyrmann, M., Karstoft, H., Midtiby, H.S., 2016. Plant species classification using deep convolutional neural network. Biosyst. Eng. 151, 72–80. https://doi.org/10.1016/j.biosystemseng.2016.08.024.

Dyrmann, M., Mortensen, A.K., Midtiby, H.S., Jørgensen, R.N., 2016b. Pixel-wise classification of weeds and crops in images by using a fully convolutional neural network. In: CIGR-AgEng conference.

Eddy, P.R., Smith, A.M., Hill, B.D., Peddle, D.R., Coburn, C.A., Blackshaw, R.E., 2014. Weed and crop discrimination using hyperspectral image data and reduced bandsets. Can. J. Remote. Sens. 39 (6), 481–490. https://doi.org/10.5589/m14-001.

Espejo-Garcia, B., Mylonas, N., Athanasakos, L., Fountas, S., Vasilakoglou, I., 2020. Towards weeds identification assistance through transfer learning. Comput. Electron. Agric. 171, 105306 https://doi.org/10.1016/j.compag.2020.105306.

Espejo-García, B., Mylonas, N., Athanasakos, L., Vali, E., Fountas, S., 2021. Combining generative adversarial networks and agricultural transfer learning for weeds identification. Biosyst. Eng. 204, 79–89. https://doi.org/10.1016/j.biosystemseng.2021.01.014.

Etienne, A., Ahmad, A., Aggarwal, V., Saraswat, D., 2021. Deep learning-based object detection system for identifying weeds using UAS imagery. Remote Sens. 13 (24), 5182. https://doi.org/10.3390/rs13245182.

Farooq, A., Hu, J., Jia, X., 2018. Weed classification in hyperspectral remote sensing images via deep convolutional neural network. In: IGARSS 2018 - IEEE International Geoscience and Remote Sensing Symposium. pp. 3816–3819. 10.1109/IGARSS.2018.8518541.

Farooq, A., Jia, X., Hu, J., Zhou, J., 2019. Knowledge transfer via convolution neural networks for multi-resolution lawn weed classification. In: 2019 10th Workshop on Hyperspectral Imaging and Signal Processing: Evolution in Remote Sensing (WHISPERS). pp. 1–5. 10.1109/WHISPERS.2019.8920832.

Fawakherji, M., Potena, C., Pretto, A., Bloisi, D.D., Nardi, D., 2021. Multi-spectral image synthesis for crop/weed segmentation in precision farming. 146, 103861. 10.1016/j.robot.2021.103861.

Fernández-Quintanilla, C., Peña, J.M., Andújar, D., Dorado, J., Ribeiro, A., López-Granados, F., 2018. Is the current state of the art of weed monitoring suitable for site-specific weed management in arable crops? Weed Res. 58, 259–272. https://doi.org/10.1111/wre.12307.

Fussell, J., Rundquist, D., Harrington, J.A., 1986. On defining remote sensing. Photogramm. Eng. Remote Sens. 52, 1507–1511.

Ganaie, M.A., Hu, M., Malik, A.K., Tanveer, M., Suganthan, P.N., 2022. Ensemble deep learning: A review. Eng. Appl. Artif. Intell. 115, 105151 https://doi.org/10.1016/j.engappai.2022.105151.

Gao, J., French, A.P., Pound, M.P., He, Y., Pridmore, T.P., Pieters, J.G., 2020a. Deep convolutional neural networks for image-based Convolvulus sepium detection in sugar beet fields. Plant Methods 16, 29. https://doi.org/10.1186/s13007-020-00570-z.

Gao, Z., Luo, Z., Zhang, W., Lv, Z., Xu, Y., 2020b. Deep learning application in plant stress imaging: A review. AgriEngineering. https://doi.org/10.3390/agriengineering2030029.

Goplen, J.J., Sheaffer, C.C., Becker, R.L., Coulter, J.A., Breitenbach, F.R., Behnken, L.M., Johnson, G.A., Gunsolus, J.L., 2017. Seedbank depletion and emergence patterns of giant ragweed *(Ambrosia trifida)* in Minnesota cropping systems. Weed Sci. 65, 52–60. https://doi.org/10.1614/WS-D-16-00084.1.

Guerrero, J.M., Pajares, G., Montalvo, M., Romeo, J., Guijarro, M., 2012. Support vector machines for crop/weeds identification in maize fields. Expert Syst. Appl. 39 (12), 11149–11155. https://doi.org/10.1016/j.eswa.2012.03.040.

Hashemi-Beni, L., Gebrehiwot, A., Karimoddini, A., Shahbazi, A., Dorbu, F., 2022. Deep convolutional neural networks for weeds and crops discrimination from UAS imagery. Front. Remote Sens. 3 https://doi.org/10.3389/frsen.2022.755939.

He, K., Zhang, X., Ren, S., Sun, J., 2015. Deep residual learning for image recognition. 10.48550/arXiv.1512.03385.

Hennessy, P.J., Esau, T.J., Schumann, A.W., Zaman, Q.U., Corscadden, K.W., Farooque, A.A., 2022. Evaluation of cameras and image distance for CNN-based weed detection in wild blueberry. Smart Agric. Technol. 2, 100030 https://doi.org/10.1016/j.atech.2021.100030.

Herrera, P.J., Dorado, J., Ribeiro, Á., 2014. A novel approach for weed type classification based on shape descriptors and a fuzzy decision-making method. Sensors. 14, 15304–15324. https://doi.org/10.3390/s140815304.

Hoang Trong, V., Gwang-hyun, Y., Thanh Vu, D., Jin-young, K., 2020. Late fusion of multimodal deep neural networks for weeds classification. Comput. Electron. Agric. 175, 105506. 10.1016/j.compag.2020.105506.

Hossain, S., Lee, D., 2019. Deep learning-based real-time multiple-object detection and tracking from aerial imagery via a flying robot with GPU-based embedded devices. Sensors. https://doi.org/10.3390/s19153371.

Hu, K., Coleman, G., Zeng, S., Wang, Z., Walsh, M., 2020. Graph weeds net: A graph-based deep learning method for weed recognition. Comput. Electron. Agric. 174, 105520 https://doi.org/10.1016/j.compag.2020.105520.

Huang, H., Lan, Y., Deng, J., Yang, A., Deng, X., Zhang, L., Wen, S., 2018. A semantic labeling approach for accurate weed mapping of high resolution UAV imagery. Sensors. https://doi.org/10.3390/s18072113.

Huang, H., Lan, Y., Yang, A., Zhang, Y., Wen, S., Deng, J., 2020. Deep learning versus object-based image analysis (OBIA) in weed mapping of UAV imagery. Intl. J. Remote Sens. 41, 3446–3479. https://doi.org/10.1080/01431161.2019.1706112.

Hung, C., Xu, Z., Sukkarieh, S., 2014. Feature learning based approach for weed classification using high resolution aerial images from a digital camera mounted on a UAV. Remote Sens. https://doi.org/10.3390/rs61212037.

Hussain, N., Farooque, A.A., Schumann, A.W., Abbas, F., Acharya, B., McKenzie-Gopsill, A., Barrett, R., Afzaal, H., Zaman, Q.U., Cheema, M.J.M., 2021. Application of deep learning to detect Lamb's quarters *(Chenopodium album L.)* in potato fields of Atlantic Canada. Comput. Electron. in Agric. 182, 106040 https://doi.org/10.1016/j.compag.2021.106040.

Hussain, N., Farooque, A.A., Schumann, A.W., McKenzie-Gopsill, A., Esau, T., Abbas, F., Acharya, B., Zaman, Q., 2020. Design and development of a smart variable rate sprayer using deep learning. Remote Sens. https://doi.org/10.3390/rs12244091.

Islam, N., Rashid, M.M., Wibowo, S., Xu, C.-Y., Morshed, A., Wasimi, S.A., Moore, S., Rahman, S.M., 2021. Early weed detection using image processing and machine learning techniques in an Australian chilli farm. Agriculture. https://doi.org/10.3390/agriculture11050387.

Ismail, N., Malik, O.A., 2021. Real-time visual inspection system for grading fruits using computer vision and deep learning techniques. Inf. Process. Agric. 10.1016/j.inpa.2021.01.005.

Jeon, H.Y., Tian, L.F., Zhu, H., 2011. Robust crop and weed segmentation under uncontrolled outdoor illumination. Sensors (Basel, Switzerland) 11, 6270–6283. https://doi.org/10.3390/s110606270.

Jeon, W., Ko, G., Lee, J., Lee, H., Ha, D., Ro, W.W., 2021. Chapter six - Deep learning with GPUs. In: Kim, S., Deka, G.C.B.T.-A. in C. (Eds.), Hardware Accelerator Systems for Artificial Intelligence and Machine Learning. Elsevier, pp. 167–215. 10.1016/bs.adcom.2020.11.003.

Jiang, H., Zhang, C., Qiao, Y., Zhang, Z., Zhang, W., Song, C., 2020. CNN feature based graph convolutional network for weed and crop recognition in smart farming. Comput. Electron. Agric. 174, 105450 https://doi.org/10.1016/j.compag.2020.105450.

Jiang, Y., Li, C., 2020. Convolutional neural networks for image-based high-throughput plant phenotyping: A review. Plant Phenomics, 4152816. 10.34133/2020/4152816.

Jiang, Z., 2019. A novel crop weed recognition method based on transfer learning from VGG16 implemented by Keras. In: IOP Conference Series: Materials Science and Engineering 677, 32073. 10.1088/1757-899X/677/3/032073.

Jin, X., Che, J., Chen, Y., 2021. Weed identification using deep learning and image processing in vegetable plantation. IEEE Access 9, 10940–10950. https://doi.org/10.1109/ACCESS.2021.3050296.

John Deere. Autonomous drone sprayer. Retrieved from: https://www.deere.co.uk/en/agriculture/future-of-farming/.

Junior, L.C.M., and Ulson, C.A.J., 2021. Real time weed detection using computer vision and deep learning. In: 14th IEEE International Conference on Industry Applications (INDUSCON), pp. 1131-1137, doi: 10.1109/INDUSCON51756.2021.9529761.

Kamilaris, A., Prenafeta-Boldú, F.X., 2018. A review of the use of convolutional neural networks in agriculture. J. Agric. Sci. 156, 312–322. https://doi.org/10.1017/S0021859618000436.

Khan, A., Ilyas, T., Umraiz, M., Mannan, I.Z., Kim, H., 2020. CED-Net: Crops and weeds segmentation for smart farming using a small cascaded encoder-decoder architecture. Electronics. 9 (10), 1602. https://doi.org/10.3390/electronics9101602.

Khan, S., Tufail, M., Khan, M.T., Khan, Z.A., Anwar, S., 2021a. Deep learning-based identification system of weeds and crops in strawberry and pea fields for a precision agriculture sprayer. Precis. Agric. https://doi.org/10.1007/s11119-021-09808-9.

Khan, S., Tufail, M., Khan, M.T., Khan, Z.A., Iqbal, J., Alam, M., 2021b. A novel semi-supervised framework for UAV based crop/weed classification. PLOS ONE 16 (5), e0251008.

Khan, S., Tufail, M., Khan, M.T., Khan, Z.A., Iqbal, J., Wasim, A., 2021c. Real-time recognition of spraying area for UAV sprayers using a deep learning approach. PLOS ONE 16 (4), e0249436.

Kogan, F.N., 1995. Droughts of the late 1980s in the United States as derived from NOAA polar-orbiting satellite data. Bull. Amer. Meteo. 76, 655–668. https://doi.org/10.1175/1520-0477(1995)076<0655:DOTLIT>2.0.CO;2.

Kounalakis, T., Malinowski, M.J., Chelini, L., Triantafyllidis, G.A., Nalpantidis, L., 2018. A robotic system employing deep learning for visual recognition and detection of weeds in grasslands. In: 2018 IEEE International Conference on Imaging Systems and Techniques (IST). pp. 1–6. 10.1109/IST.2018.8577153.

Kounalakis, T., Triantafyllidis, G.A., Nalpantidis, L., 2019. Deep learning-based visual recognition of rumex for robotic precision farming. Comput. Electron. Agric. 165, 104973 https://doi.org/10.1016/j.compag.2019.104973.

Krizhevsky, A., Sutskever, I., Hinton, G.E., 2012. ImageNet classification with deep convolutional neural networks. In: Pereira, F., Burges, C.J.C., Bottou, L., Weinberger, K.Q. (Eds.), Advances in Neural Information Processing Systems. Curran Associates, Inc.

Lam, O.H.Y., Dogotari, M., Prüm, M., Vithlani, H.N., Roers, C., Melville, B., Zimmer, F., Becker, R., 2021. An open source workflow for weed mapping in native grassland using unmanned aerial vehicle: using *Rumex obtusifolius* as a case study. Eur. J. Remote Sens. 54, 71–88. https://doi.org/10.1080/22797254.2020.1793687.

Laursen, M.S., Jørgensen, R.N., Dyrmann, M., Poulsen, R.N., 2017. RoboWeedSupport-Sub millimeter weed image acquisition in cereal crops with speeds up till 50 Km/H. World Academy of Science, Engineering and Technology. Int. J. Agric. Biol. Eng. 11, 317–321.

LeCun, Y., Bengio, Y., Hinton, G., 2015. Deep learning. Nature 521, 436–444. https://doi.org/10.1038/nature14539.

LeCun, Y., Boser, B., Denker, J.S., Henderson, D., Howard, R.E., Hubbard, W., Jackel, L. D., 1989. Backpropagation applied to handwritten zip code recognition. Neural Comput. 1, 541–551. https://doi.org/10.1162/neco.1989.1.4.541.

Lee, J., Wang, P., Xu, R., Dasari, V., Weston, N., Li, Y., Bagchi, S., Chaterji, S., 2021. Benchmarking video object detection systems on embedded devices under resource contention. In: Proceedings of the 5th International Workshop on Embedded and Mobile Deep Learning, EMDL'21. Association for Computing Machinery, New York, NY, USA, pp. 19–24. 10.1145/3469116.3470010.

Lee, S.H., Chan, C.S., Mayo, S.J., Remagnino, P., 2017. How deep learning extracts and learns leaf features for plant classification. Pattern Recognit. 71, 1–13. https://doi.org/10.1016/j.patcog.2017.05.015.

Li, C., Peng, Y., Su, M., Jiang, T., 2020. GPU parallel implementation for real-time feature extraction of hyperspectral images. Appl. Sci. https://doi.org/10.3390/app10196680.

Li, Y., Al-Sarayreh, M., Irie, K., Hackell, D., Bourdot, G., Reis, M.M., Ghamkhar, K., 2021. Identification of weeds based on hyperspectral imaging and machine learning. Front. Plant Sci. 11, 2324. https://doi.org/10.3389/fpls.2020.611622.

Li, Y., Zhang, H., & Shen, Q., 2017. Spectral–spatial classification of hyperspectral imagery with 3D convolutional neural network. Remote Sens., 9(1), 67. https://www.mdpi.com/2072-4292/9/1/67.

Lima, A., Mendes, K., 2020. Variable rate application of herbicides for weed management in pre-and postemergence. In: Pests, Weeds and Diseases in Agricultural Crop and Animal Husbandry Production, edited by Dimitrios Kontogiannatos, Anna Kourti, Kassio Mendes. London: IntechOpen. 10.5772/intechopen.93558.

Liu, J., Abbas, I., Noor, R.S., 2021. Development of deep learning-based variable rate agrochemical spraying system for targeted weeds control in strawberry crop. Agronomy 11. https://doi.org/10.3390/agronomy11081480.

Liu, J., Wang, X., 2021. Plant diseases and pests detection based on deep learning: A review. Plant Methods 17, 22. https://doi.org/10.1186/s13007-021-00722-9.

López-Granados, F., Torres-Sánchez, J., Serrano-Pérez, A., de Castro, A.I., Mesas-Carrascosa, Fco.-J., Peña, J.-M., 2016. Early season weed mapping in sunflower using UAV technology: Variability of herbicide treatment maps against weed thresholds. Precis. Agric. 17, 183–199. 10.1007/s11119-015-9415-8.

Lottes, P., Behley, J., Milioto, A., Stachniss, C., 2018. Fully convolutional networks with sequential information for robust crop and weed detection in precision farming. IEEE Robot. Autom. Lett. PP, 1. 10.1109/LRA.2018.2846289.

Louargant, M., Villette, S., Jones, G., Vigneau, N., Paoli, J.N., Gée, C., 2017. Weed detection by UAV: simulation of the impact of spectral mixing in multispectral images. Precis. Agric. 18, 1–20. https://doi.org/10.1007/s11119-017-9528-3.

Mahony, N.O., Campbell, S., Carvalho, A., Harapanahalli, S., Velasco-Hernández, G.A., Krpalkova, L., Riordan, D., Walsh, J., 2019. Deep learning vs. traditional computer vision. arXiv: Computer Vision and Pattern Recognition. 10.1007/978-3-030-17795-9.

Melland, A.R., Silburn, D.M., McHugh, A.D., Fillols, E., Rojas-Ponce, S., Baillie, C., Lewis, S., 2016. Spot spraying reduces herbicide concentrations in runoff. J. Agric. Food Chem. 64, 4009–4020. https://doi.org/10.1021/acs.jafc.5b03688.

Milioto, A., Lottes, P., Stachniss, C., 2018. Real-time semantic segmentation of crop and weed for precision agriculture robots leveraging background knowledge in CNNs. arXiv: Computer Vision and Pattern Recognition. 10.1109/ICRA.2018.8460962.

Milioto, A., Lottes, P., Stachniss, C., 2017. Real-time blob-wise sugar beets vs weeds classification for monitoring fields using convolutional neural networks. ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences IV-2/W3, 41–48. 10.5194/isprs-annals-IV-2-W3-41-2017.

Misse, P.T.E., Werner, A., Almond, P., 2020. Developing automated and autonomous weed control methods on vegetable crops in New Zealand. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3745319.

Mousazadeh, H., 2013. A technical review on navigation systems of agricultural autonomous off-road vehicles. J. Terramechanics. 50, 211–232. https://doi.org/10.1016/j.jterra.2013.03.004.

Mursalin, M., Mesbah-Ul-Awal, M., 2014. Towards classification of weeds through digital image. In: Fourth International Conference on Advanced Computing & Communication Technologies. Presented at the 2014 Fourth International Conference on Advanced Computing & Communication Technologies, pp. 1–4. 10.1109/ACCT.2014.101.

Nasiri, A., Omid, M., Taheri-Garavand, A., Jafari, A., 2022. Deep learning-based precision agriculture through weed recognition in sugar beet fields. Sustainable Comput. Inf. Syst. 35, 100759 https://doi.org/10.1016/j.suscom.2022.100759.

Ning, K.-P., Zhao, X., Li, Y., Huang, S.-J., 2022. Active learning for open-set annotation. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 41–49.

Ofori, M., El-Gayar, O., O'Brien, A. and Noteboom, C., 2022. A deep learning model compression and ensemble approach for weed detection. http://hdl.handle.net/10125/79470.

Olsen, A., Konovalov, D.A., Philippa, B., Ridd, P., Wood, J.C., Johns, J., Banks, W., Girgenti, B., Kenny, O., Whinney, J., Calvert, B., Azghadi, M.R., White, R.D., 2019. DeepWeeds: A multiclass weed species image dataset for deep learning. Sci. Rep. 9, 2058. https://doi.org/10.1038/s41598-018-38343-3.

Onishi, Y., Yoshida, T., Kurita, H., Fukao, T., Arihara, H., Iwai, A., 2019. An automated fruit harvesting robot by using deep learning. ROBOMECH J. 6, 13. https://doi.org/10.1186/s40648-019-0141-2.

Osorio, K., Puerto, A., Pedraza, C., Jamaica, D., Rodríguez, L., 2020. A deep learning approach for weed detection in lettuce crops using multispectral images. AgriEngineering. https://doi.org/10.3390/agriengineering2030032.

Pang, Y., Shi, Y., Gao, S., Jiang, F., Sivakumar, A.N.V., Thompson, L., Luck, J., Liu, C., 2020. Improved crop row detection with deep neural network for early-season maize stand count in UAV imagery. Comput. Electron. Agric. 178, 105766 https://doi.org/10.1016/j.compag.2020.105766.

Pantazi, X.E., Tamouridou, A.A., Alexandridis, T.K., Lagopodi, A.L., Kashefi, J., Moshou, D., 2017. Evaluation of hierarchical self-organising maps for weed mapping using UAS multispectral imagery. Comput. Electron. Agric. 139, 224–230. https://doi.org/10.1016/j.compag.2017.05.026.

Parico, A.I., Ahamed, T., 2021. Real time pear fruit detection and counting using YOLOv4 models and deep SORT. Sensors. https://doi.org/10.3390/s21144803.

Partel, V., Charan Kakarla, S., Ampatzidis, Y., 2019. Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence. Comput. Electron. Agric. 157, 339–350. https://doi.org/10.1016/j.compag.2018.12.048.

Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., … Chintala, S., 2019. PyTorch: An imperative style, high-performance deep learning library. In: Advances in Neural Information Processing Systems 32 (pp. 8024–8035). Curran Associates, Inc. Retrieved from http://papers.neurips.cc/paper/9015-pytorch-an-imperative-style-high-performance-deep-learning-library.pdf.

Pathak, H., 2021. Machine vision methods for evaluating plant stand count and weed classification using open-source platforms. Master's Thesis. In: Department of Agricultural and Biosystems Engineering, North Dakota State University, Fargo, ND, USA.

Pearlstein, L., Kim, M. and Seto, W., 2016, October. Convolutional neural network application to plant detection, based on synthetic imagery. In: IEEE applied imagery pattern recognition workshop (AIPR). pp. 1-4. IEEE. 10.1109/AIPR.2016.8010596.

Peña, J.M., Torres-Sánchez, J., de Castro, A.I., Kelly, M., López-Granados, F., 2013. Weed mapping in early-season maize fields using object-based analysis of unmanned aerial vehicle (UAV) images. PLOS ONE 8 (10), e77151.

Peng, H., Li, Z., Zhou, Z., Shao, Y., 2022. Weed detection in paddy field using an improved RetinaNet network. Comput. Electron. Agric. 199, 107179 https://doi.org/10.1016/j.compag.2022.107179.

Pérez-Ortiz, M., Peña, J.M., Gutiérrez, P.A., Torres-Sánchez, J., Hervás-Martínez, C., López-Granados, F., 2015. A semi-supervised system for weed mapping in sunflower crops using unmanned aerial vehicles and a crop row detection method. Appl. Soft Comput. 37, 533–544. https://doi.org/10.1016/j.asoc.2015.08.027.

Peteinatos, G.G., Reichel, P., Karouta, J., Andújar, D., Gerhards, R., 2020. Weed identification in maize, sunflower, and potatoes with the aid of convolutional neural networks. Remote Sens. https://doi.org/10.3390/rs12244185.

Precision AI. Precision AI raises $20M for drone-based computer vision for sustainable agriculture. Retrieved from: https://www.robotics247.com/article/precision_ai_raises_20m_for_drone_based_computer_vision_for_sustainable_agriculture/Machine_Learning.

Prema, P., Murugan, D., 2016. A novel angular textural pattern (ATP) extraction method for crop and weed discrimination using curvelet transformation. ELCVIA Electron. Lett. Comput. Vis. Image Anal. 15, 27–59. https://doi.org/10.5565/rev/elcvia.826.

Qin, Z., Wang, W., Dammer, K.-H., Guo, L., Cao, Z., 2021. A Real-time Low-cost Artificial Intelligence system for autonomous spraying in palm plantations. arXiv: Computer Vision and Pattern Recognition. 10.48550/arXiv.2103.04132.

Rai, N., Flores, P., 2021. Leveraging transfer learning in ArcGIS Pro to detect "doubles" in a sunflower field. In: 2021 ASABE Annual International Virtual Meeting, ASABE Paper No. 2100742. 10.13031/aim.202100742.

Rai, N., Zhang, Y., Quanbeck, J., Christensen, A. and Sun, X., 2022. SpotWeeds: A multiclass UASs acquired weed image dataset to facilitate site-specific aerial spraying application using Deep Learning. In: 2022 15th International Conference on Precision Agriculture (ICPA).

Rakhmatulin, I., Andreasen, C., 2020. A concept of a compact and inexpensive device for controlling weeds with laser beams. Agronomy. https://doi.org/10.3390/agronomy10101616.

Rasti, P., Ahmad, A., Samiei, S., Belin, E., Rousseau, D., 2019. Supervised image classification by scattering transform with application to weed detection in culture crops of high density. Remote Sens. https://doi.org/10.3390/rs11030249.

Razfar, N., True, J., Bassiouny, R., Venkatesh, V., Kashef, R., 2022. Weed detection in soybean crops using custom lightweight deep learning models. J. Agric. Food Res. 8, 100308 https://doi.org/10.1016/j.jafr.2022.100308.

Redmon, J., Divvala, S., Girshick, R., Farhadi, A., 2015. You only look once: Unified, real-time object detection. 10.48550/arXiv.1506.02640.

Roshanianfard, A., Noguchi, N., Okamoto, H., Ishii, K., 2020. A review of autonomous agricultural vehicles (The experience of Hokkaido University). J. Terramechanics. 91, 155–183. https://doi.org/10.1016/j.jterra.2020.06.006.

Ruigrok, T., van Henten, E., Booij, J., van Boheemen, K., Kootstra, G., 2020. Application-specific evaluation of a weed-detection algorithm for plant-specific spraying. Sensors 20 (24), 7262. https://doi.org/10.3390/s20247262.

Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., Huang, Z., Karpathy, A., Khosla, A., Bernstein, M., Berg, A.C., Fei-Fei, L., 2015. ImageNet large scale visual recognition challenge. Int. J. Comput. Vis. 115, 211–252. https://doi.org/10.1007/s11263-015-0816-y.

Sa, I., Chen, Z., Popovic, M., Khanna, R., Liebisch, F., Nieto, J., Siegwart, R., 2018a. WeedNet: Dense semantic weed classification using multispectral images and MAV for smart farming. IEEE Robot. Autom. Lett. 3, 588–595. https://doi.org/10.1109/LRA.2017.2774979.

Sa, I., Ge, Z., Dayoub, F., Upcroft, B., Perez, T., McCool, C., 2016. DeepFruits: A fruit detection system using deep neural networks. Sensors (Basel, Switzerland) 16, 1222. https://doi.org/10.3390/s16081222.

Sa, I., Popović, M., Khanna, R., Chen, Z., Lottes, P., Liebisch, F., Nieto, J., Stachniss, C., Walter, A., Siegwart, R., 2018b. WeedMap: A large-scale semantic weed mapping framework using aerial multispectral imaging and deep neural network for precision farming. Remote Sens. https://doi.org/10.3390/rs10091423.

Saleem, M.H., Velayudhan, K.K., Potgieter, J., Arif, K.M., 2022. Weed identification by single-stage and two-stage neural networks: A study on the impact of image resizers and weights optimization algorithms. Front. Plant Sci. 13 https://doi.org/10.3389/fpls.2022.850666.

Scherrer, B., Sheppard, J., Jha, P., Shaw, A.J., 2019. Hyperspectral imaging and neural networks to classify herbicide-resistant weeds. J. Appl. Rem. Sens. 13, 044516 https://doi.org/10.1117/1.JRS.13.044516.

Sermanet, P., Eigen, D., Zhang, X., Mathieu, M., Fergus, R., LeCun, Y., 2014. OverFeat: Integrated recognition, localization and detection using convolutional networks. arXiv: Computer Vision and Pattern Recognition. 10.48550/arXiv.1312.6229.

Serre, T., 2019. Deep Learning: The Good, the Bad, and the Ugly. Annu. Rev. Vis. Sci. 5, 399–426. https://doi.org/10.1146/annurev-vision-091718-014951.

Shahbazi, N., Ashworth, M.B., Callow, J.N., Mian, A., Beckie, H.J., Speidel, S., Nicholls, E., Flower, K.C., 2021. Assessing the capability and potential of LiDAR for weed detection. Sensors. https://doi.org/10.3390/s21072328.

Simonyan, K., Zisserman, A., 2014. Very deep convolutional networks for large-scale image recognition. arXiv: Computer Vision and Pattern Recognition. 10.48550/arXiv.1409.1556.

Sivakumar, A.N.V, Li, J., Scott, S., Psota, E., J. Jhala, A., Luck, J.D., Shi, Y., 2020. Comparison of object detection and patch-based classification deep learning models on mid- to late-season weed detection in UAV imagery. Remote Sens. 10.3390/rs12132136.

Subeesh, A., Bhole, S., Singh, K., Chandel, N.S., Rajwade, Y.A., Rao, K.V.R., Kumar, S.P., Jat, D., 2022. Deep convolutional neural network models for weed detection in polyhouse grown bell peppers. Artif. Intell. Agric. 6, 47–54. https://doi.org/10.1016/j.aiia.2022.01.002.

Tan, C., Sun, F., Kong, T., Zhang, W., Yang, C., Liu, C., 2018. A survey on deep transfer learning. arXiv: Computer Vision and Pattern Recognition. 10.48550/arXiv.1808.01974.

Tang, J., Wang, D., Zhang, Z., He, L., Xin, J., Xu, Y., 2017. Weed identification based on K-means feature learning combined with convolutional neural network. Comput. Electron. Agric. 135, 63–70. https://doi.org/10.1016/j.compag.2017.01.001.

Teimouri, N., Dyrmann, M., Nielsen, P.R., Mathiassen, S.K., Somerville, G.J., Jørgensen, R.N., 2018. Weed growth stage estimator using deep convolutional neural networks. Sensors. https://doi.org/10.3390/s18051580.

Ukaegbu, U.F., Tartibu, L.K., Okwu, M.O., Olayode, I.O., 2021. Development of a light-weight unmanned aerial vehicle for precision agriculture. Sensors (Basel, Switzerland) 21, 4417. https://doi.org/10.3390/s21134417.

van Evert, F. K., Samsom, J., Polder, G., Vijn, M., Dooren, H.-J. v., Lamaker, A., van der Heijden, G. W., Kempenaar, C., van der Zalm, T., & Lotz, L. A., 2011. A robot to detect and control broad-leaved dock (rumex obtusifolius l.) in grassland. J. Field Robot., 28(2), 264–277. 10.1002/rob.20377.

Wang, C.-Y., Bochkovskiy, A., Liao, H.-Y.M., 2022a. YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors. arXiv: Computer Vision and Pattern Recognition. 10.48550/arXiv.2207.02696.

Wang, Q., Cheng, M., Huang, S., Cai, Z., Zhang, J., Yuan, H., 2022b. A deep learning approach incorporating YOLO v5 and attention mechanisms for field real-time detection of the invasive weed Solanum rostratum Dunal seedlings. Comput. Electron. Agric. 199, 107194 https://doi.org/10.1016/j.compag.2022.107194.

Wiles, L., 2009. Beyond patch spraying: Site-specific weed management with several herbicides. Precis. Agric. 10 https://doi.org/10.1007/s11119-008-9097-6.

Xu, K., Zhu, Y., Cao, W., Jiang, X., Jiang, Z., Li, S., Ni, J., 2021a. Multi-modal deep learning for weeds Detection in wheat field based on RGB-D images. Front. Plant Sci. 12, 2572. https://doi.org/10.3389/fpls.2021.732968.

Xu, Y., Zhai, Y., Zhao, B., Jiao, Y., Kong, S., Zhou, Y., Gao, Z., 2021b. Weed recognition for depthwise separable network based on transfer learning. Intell. Autom. Soft. Comput. 27, 3. 10.32604/iasc.2021.015225.

Yan, X., Deng, X., Jin, J., 2020. Classification of weed species in the paddy field with DCNN-learned features. In: 2020 IEEE 5th Information Technology and Mechatronics Engineering Conference (ITOEC). pp. 336–340. 10.1109/ITOEC49072.2020.9141894.

Yang, B., Xu, Y., 2021. Applications of deep-learning approaches in horticultural research: A review. Hortic. Res. 8, 123. https://doi.org/10.1038/s41438-021-00560-9.

Yin, J., Qi, C., Chen, Q., & Qu, J., 2021. Spatial-spectral network for hyperspectral image classification: A 3-D CNN and Bi-LSTM framework. Remote Sens., 13(12), 2353. https://www.mdpi.com/2072-4292/13/12/2353.

You, J., Liu, W., Lee, J., 2020. A DNN-based semantic segmentation for detecting weed and crop. Comput. Electron. Agric. 178, 105750 https://doi.org/10.1016/j.compag.2020.105750.

Young, T., Hazarika, D., Poria, S., Cambria, E., 2018. Recent trends in deep learning based natural language processing (Review Article). IEEE Comput. Intell. Mag. 13, 55–75. https://doi.org/10.1109/MCI.2018.2840738.

Yu, J., Schumann, A.W., Cao, Z., Sharpe, S.M., Boyd, N.S., 2019a. Weed detection in perennial ryegrass with deep learning convolutional neural network. Front. Plant Sci. 10, 1422. https://doi.org/10.3389/fpls.2019.01422.

Yu, J., Sharpe, S.M., Schumann, A.W., Boyd, N.S., 2019b. Deep learning for image-based weed detection in turfgrass. Eur. J. Agron. 104, 78–84. https://doi.org/10.1016/j.eja.2019.01.004.

Zhang, R., Wang, C., Hu, X., Liu, Y., Chen, S., Su, B., 2018. Weed location and recognition based on UAV imaging and deep learning. Â 10.33440/j.ijpaa.20200301.63.

Zhang, J., Zhou, Y., Saab, R., 2022. Post-training quantization for neural networks with provable guarantees. arXiv preprint arXiv:2201.11113.

Zhou, X., Prasad, S., 2020. Advances in deep learning for hyperspectral image analysis - Addressing challenges arising in practical imaging scenarios BT - Hyperspectral Image Analysis: Advances in Machine Learning and Signal Processing. In: Prasad, S., Chanussot, J. (Eds.). Springer International Publishing, Cham, pp. 117–140. 10.1007/978-3-030-38617-7_5.

Zhu, B., Hofstee, P., Lee, J. and Al-Ars, Z., 2021. An attention module for convolutional neural networks. In Artificial Neural Networks and Machine Learning–ICANN 2021: 30th International Conference on Artificial Neural Networks, Bratislava, Slovakia, September 14–17, 2021, Proceedings, Part I 30 (pp. 167-178). Springer International Publishing.

Zhuang, F., Qi, Z., Duan, K., Xi, D., Zhu, Y., Zhu, H., Xiong, H., He, Q., 2021. A comprehensive survey on transfer learning. Proc. IEEE 109, 43–76. 10.48550/arXiv.1911.02685.

Zou, K., Chen, X., Zhang, F., Zhou, H., Zhang, C., 2021. A field weed density evaluation method based on UAV imaging and modified U-Net. Remote Sens. https://doi.org/10.3390/rs13020310.