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TOPICAL REVIEW

Deep Learning Techniques for Weed Detection in Agricultural Environments: A Comprehensive Review

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ABSTRACT Agriculture has been completely transformed by Deep Learning (DL) techniques, which allow for quick object localization and detection. However, because weeds and crops are similar in color, form, and texture, weed detection and categorization can be difficult. Advantages in object detection, recognition, and image classification can be obtained with deep learning (DL), a vital aspect of machine learning (ML). Because crops and weeds are similar, ML techniques have difficulty extracting and choosing distinguishing traits. This literature review demonstrates the potential of various DL methods for crop weed identification, localization, and classification. This research work investigates the present status of Deep Learning based weed identification and categorization systems. The majority of research employs supervised learning strategies, polishing pre-trained models on sizable, labeled datasets to achieve high accuracy. Innovations are driven by the need for sustainable weed management methods, and deep learning is demonstrating encouraging outcomes in image-based weed detection systems. To solve issues like resource scarcity, population increase, and climate change, precision agriculture holds great promise for the integration of AI with IoT-enabled farm equipment.

INDEX TERMS Agriculture, artificial intelligence, deep learning, weed detection, neural networks.

NOMENCLATURE

AI	Artificial Intelligence.
ASFF	Adaptive Spatial Feature Fusion.
CBAM	Convolutional Block Attention Module.
CFFI	Channel Feature Fusion with Involution.
CLAHE	Contrast Limited Adaptive Histogram Equalization.
DCGAN	Deep Convolutional Generative Adver-sarial Network.
DCNN	Deep Convolutional Neural Network.
DL	Deep Learning.
FPN	Feature Pyramid Network.
GAN	Generative Adversarial Network.
KNN	K Nearest Neighbor.
M− Unet	Multispectral U-net.
ML	Machine Learning.
MSR	Multi Scale Retinex.
MT− Unet	Multispectral Thermal U-net.
RCNN	Regional Convolutional Neural Network.
RF	Random Forest.
Soft− NMS	Soft-Non-Maximum Suppression.
SSR	Single Scale Retinex.
SV M	Support Vector Machine.
XGB	eXtreme Gradient Boosting.

I. INTRODUCTION

Agriculture is the art and science of cultivating soil for the growth of crops that will supply people with food, fiber, and other goods to buy and consume [1], [2]. The global populace is predicted to rise quickly to nine billion people by the year 2050. To meet the projected demand, agricultural output

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needs to expand by nearly 70% [3]. Nevertheless, agriculture encounters several substantial challenges, including the risk of diseases, a critical shortage of cultivable land and water resources, and the impact of a changing climate as well as threats from weeds and pests [4]. Implementing intelligent farming practices is essential to addressing the problems associated with agricultural production including sustainability, food security, productivity, and environmental impact [5].

Plants that spread quickly and negligently are known as weeds, and they can negatively impact crop production and quality [6]. They contend with crops for nutrients, water, sunlight, and growth space, necessitating farmers to allocate resources to control them [7]. To mitigate the impact of weeds, various management tactics are employed, which can be categorized into five main groups according to [8]: ''preventative'' (preventing weed establishment), ''cultural'' (preserving field cleanliness) to reduce the weed seed bank), ''mechanical'' (utilizing techniques such as mulching, tilling, and cutting), ''biological'' (employing natural enemies like insects, grazing animals, or diseases), and ''chemical'' (using herbicides). Despite their effectiveness, each strategy has drawbacks, typically being costly, time-consuming, and labor-intensive. Additionally, control measures may have adverse effects on the health of humans, plants, soil, animals, or the environment [9]. Until now, various techniques and technologies have been employed for weed detection.

II. TRADITIONAL METHODS AND CHALLENGES IN WEED REMOVAL

1) Manual Inspection: Traditional weed detection involves labor-intensive and time-consuming manual inspection and removal by human workers. Despite its drawbacks, this method is still utilized in certain situations.
2) Chemical herbicides: They are frequently used in agriculture to suppress weeds, however, their application can have detrimental effects on the environment and be non-selective, which could hurt crops as well as weeds.
3) Mechanical weed control techniques: Plowing, tilling, and mechanical weeding equipment, are useful for getting rid of weeds from fields, but they can be inaccurate and harm crops.
4) Crop rotation: To increase soil fertility, nutrient levels, and control weeds and pests, crop rotation is the practice of growing various crops one after another. The distinct growth requirements of various crops, however, may present difficulties for farmers.
5) Mulching: To efficiently inhibit the growth of weeds, organic materials such as leaves, wood chips, or straw are added to the soil [10], [11], [12].

Figure 1 depicts various weed management techniques.

A. LIMITATIONS OF TRADITIONAL WEED CONTROL STRATEGIES

Herbicides work well to manage weeds, however because of the shortcomings of traditional spraying systems, they also have disadvantages [13]. Herbicide resistance, environmental contamination, and ecological imbalance can result from using the same class of herbicides repeatedly over time. Overuse can lead to herbicide-resistant weed populations, which lowers farmland biodiversity and dominates hard-to-control weed species in agricultural settings. Negative side effects from chemical pesticides include contaminating ground and surface waters and releasing residues into the food chain [14]. This puts the long-term sustainability of the farming industry and biodiversity conservation at risk by increasing contamination of the environment from agricultural chemical inputs.

Because of the higher bulk density and compaction of topsoil, little tillage or non-tillage can also raise the phytotoxicity of the soil. Reducing tillage may force farmers to use additional pesticides and herbicides to counter these risks. The criteria of soil quality, such as biological diversity, soil structure, and water storage capacity, are negatively impacted by overuse of tillage. Tillage causes soil erosion and degradation by depriving microorganisms of carbon and nitrogen resources. This leads to an increase in agricultural contamination of the environment.

There are restrictions on other ground cover techniques as well, like fire, mulching, and cattle grazing. Mulching can induce soil alterations, be costly, and have allelopathic impacts on crops if certain organic mulches are used [15]. Living mulches compete with other plants for nutrients and water, they can stunt crop development and yield and raise the danger of disease and pest infestation. Livestock grazing can disperse weed seeds, harm non-target species and the soil's structure, and even result in an animal's condition or liveweight being lost.

Precision Weed Management (PWM) technology can be integrated to reduce or eliminate these constraints, opening the door where precision is the norm [16].

III. TECHNOLOGICAL PROGRESS IN WEED DETECTION

In expansive agricultural regions, the use of remote sensing technology—such as drones and satellite imaging is essential for identifying and monitoring weed infestations [17]. By differentiating between weeds and crops, computer vision and machine learning enhance weed detection, with accuracy being continuously enhanced through training [18].

With cameras and automated equipment, robotic weed eaters provide real-time weed detection and elimination, which might cut down on manual labor and the need for herbicides [19], [20], [21], [22].

With the use of precision agricultural technologies, such as GPS-guided equipment, farmers may spray herbicides selectively, sparing areas that are not affected by weed infestations while focusing on those that are instruments for chemical sensing that identify biological fingerprints, such as changes in chlorophyll content, indicate the presence of weeds [23], [24].

Additionally, weed management apps utilizing image recognition technology assist farmers in identifying and

FIGURE 1. Various weed management techniques [26].

managing weeds, often based on photos provided by users [25].

A. ROBOTIC TECHNOLOGY

Expected to transform farming, the agriculture robot, or agribot, is driving an exponential increase in global investment and research in robotics, science, and engineering [27]. Robots that carry out in-field weeding operations using computer vision techniques are shown in Figure 2, 3, 4 and 5.

FIGURE 2. BoniRob terrestrial robot [28].

FIGURE 3. Tertill weeding robot [29].

Several researchers have made progress in the development of robotic systems for controlling and detecting weeds, although the practical application is still a significant challenge [30].

Reference [32] created a robot with dual-gimbal capabilities, successfully identifying and targeting weeds indoors, achieving a high hit rate of 97% with specific laser parameters. Reference [22] designed a weed-detecting robot using

FIGURE 4. Solar powered weeding robot [31].

a Raspberry Pi microcontroller and achieved 92.9% accuracy in identifying sugarcane crops among various weed species. Reference [33] demonstrated the Adigo robot platform for autonomous herbicide application. The Ladybird robot from the University of Sydney, equipped with a spraying end actuator and a machine learning algorithm, effectively controls weeds with targeted herbicide application.

FIGURE 5. Agricultural robotic platform with four wheel steering for weed detection [20].

[34] developed the AgBotII, a modular weeding robot that identifies crops and weeds using image processing techniques and removes weeds with different tools. Reference [35] merged a multifunctional agricultural automated terrain vehicle with the aerial survey capability of a small UAV to achieve thorough weed management. Reference [36] proposed a weeding robot that navigates autonomously in paddy fields, disrupting soil to remove weeds and inhibiting their growth. The Sinobot prototype, equipped with independently steered wheels, was designed for weeding and route planning.

These advancements indicate progress in robotic weed control, but practical implementation remains challenging.

B. PRECISION AGRICULTURE AND AI INTEGRATION

Precision agriculture combines the advancements of the information age with an established agricultural sector [37]. It serves as a comprehensive crop management system, aiming to align input types and quantities with the specific requirements of small sections within a farm field.

Although the objective is not novel, recent technological developments have made precision agriculture feasible in practical farming scenarios. Precision agriculture is frequently identified by the enabling technologies, commonly known as GPS (Global Positioning System) agriculture or variable-rate farming [38]. Despite the significance of devices, it becomes evident upon reflection that information is the crucial element for achieving accuracy in farming practices.

To enhance the efficiency of modern agriculture, the integration of drones for aerial applications is crucial. This approach standardizes chemical spraying processes and addresses the labor shortage in rural areas. The use of drones ensures precise deposition of products on target areas, minimizing environmental losses. Reference [39] proposed that UAVs enable the monitoring of individual plants and weed patches, a capability previously unavailable.

References [40] and [41] presented a method involving UAV imagery to apply herbicides selectively, demonstrating the identification of weeds in row crops through aerial image analysis.

The concept put out by [42] suggests that weed management tactics have evolved to use drones equipped with cameras and Geographic Information Systems (GIS).

Improved results may be achieved by optimizing agricultural activities linked to weed detection and eradication through the combination of drones, robots, artificial intelligence, and sensors, as proposed by [43], [44], [45], and [46].

Reference [47] argued that technology not only reduces manual labor but also enhances food quality by utilizing drones for various agricultural purposes.

C. UTILIZING DRONES FOR WEED CONTROL

The assertion made by [48] in the area of weed management is that drones play a crucial role in detecting and identifying weed patches efficiently. They use near-infrared and visible light for crop condition assessment, offering a significant advantage of reduced surveying time, especially among crop rows. The capacity of UAVs to cover large areas quickly and generate photographic images facilitates weed patch identification. The processing of these images involves advanced technologies such as deep neural networks and convolutional neural networks.

RGB, multispectral, and hyperspectral cameras are the three primary types of cameras used in [49]'s research on UAV-based weed identification. Still, other parameters like drone kind, flight height, and camera resolution affect how well these cameras identify weed patches. Differentiating between crop seedlings and weeds is crucial for designing an effective automated weed management system. Specific UAV models equipped with GPS and cameras, like the md4-1000 quadcopter, are employed for weed detection and mapping. These systems utilize object-based image analysis (OBIA) frameworks to create accurate herbicide application maps. Color analysis methods have been implemented for detecting specific weed types in various environmental conditions efficacy and limits of unmanned aerial vehicle (UAV) technology for weed seedling detection as affected by sensor resolution.

For example, in a vineyard field, a quadcopter UAV with RGB photos mapped weed patches using an OBIA approach, optimizing site-specific weed control. Reference [50] argued that the md4-1000 quadcopter employs a weed mapping rule set method to categorize crop rows, differentiate between crop plants and weeds, and develop a weed infestation map. This technique aims to reduce herbicide applications by tailoring doses based on observed weed infestation levels Weed mapping in early-season maize fields using object-based analysis of unmanned aerial vehicle (UAV) images. Figure 6 depicts an image of a drone utilized for data collection procedure in agricultural domain.

FIGURE 6. Pictures taken of the drone at various points during the data collection procedure [51].

The detection capability of algorithms, indicating the accuracy in classifying pixels as crops or weeds, reaches 91% with a spatial resolution of 21.6 mm/pixel.

Reference [52] carried out research on UAVs equipped with visible and multispectral cameras, utilizing automated OBIA approaches, effectively map weed patches such as Johnsongrass.

Overall, the integration of drones and advanced imaging technologies enhances the precision and efficiency of weed management in agriculture.

IV. SENSOR TECHNIQUE IN WEED CONTROL

Reference [53] focused on digital video cameras called Robocrop inter-row and Robocrop Inrow® that are used in agricultural techniques to control weeds particular to a given place. They help to reduce the amount of herbicide used in spraying applications and to steer mechanical weeding equipment. These methods use shape, color, and crop row spacing data to increase classification rates for transplanted crops. Variable herbicide rates depend on online sensors for weed detection. Comparing field trials with traditional application, cereal, and pea trials revealed average pesticide savings of 24.6%, no yield reduction, and no variations in weed density between lowered and standard dosage areas.

A. NON IMAGING SENSORS

Using spectral and height features, non-imaging sensors (e.g., spectrometers and fluorescence sensors) quantify weed spots in fields [17].

From the ultraviolet (UV) to the near-infrared (NIR), spectrum analyzers measure the strength of reflections at different electromagnetic spectrum wavelengths [54]. Although they can't tell different species of plants apart, they can provide information that can help separate plants from soil. The reflectance of bare soil increases linearly from blue to near-infrared light, whereas green leaves have low reflectivity in the red and blue spectra and high reflectance in the green and near-infrared wavelengths.

A plant's spectrum response varies with its growth stage, and the signal that is received is a blend of various plant species and soil composition. Approaches to spectral identification are intricate and necessitate appropriate prior knowledge, which is unavailable in the field. For weed identification and quantification, chemometrics works well; however, it is not effective for weed detection.

Optoelectronic sensors distinguish between the presence and absence of plants by focusing on particular spectral bands in the red/near-infrared (R/NIR) spectrum. In rows of crops, these sensors can identify weeds in between the rows. To calculate an index similar to the NDVI, commercial sensors evaluate reflectance characteristics in the NIR and R wavelengths.

The DetectSpray spot-spraying system and the WeedSeeker, GreenSeeker, WEEDit, and Crop Circle ACS-470 are a few examples. When paired with a sprayer, these active sensors indicate a high level of vegetation cover. Underestimating weed coverage is the most common inaccuracy that has been reported.

Because of flavonol anthocyanins, polyphenols, and chlorophyll, plants' leaves generate fluorescent light, which is detected by fluorescence sensors. While chlorophyll a and b emit fluorescence in the red to the far-red range, UV light causes blue-green fluorescence (BGF) to be stimulated in leaves. Identification of plants can be done using the ratio of BGF to CLa fluorescence, which has a strong relationship with plant species.

B. IMAGING SENSORS

For more than thirty years, the use of image sensors for weed identification has been an important area of research. In agricultural fields, portable imaging and analysis tools like RGB sensors and NDVI cameras have been used to identify weed patches, distinguish weeds from crops, and identify various weed species. The procedure entails capturing digital images, segmenting them, and then extracting plant properties.

Using red and NIR wavelengths, [55] created a bi-spectral camera to identify different species of weeds. They produced high-resolution images with pixel sizes of 0.23 mm and a classification accuracy of 95%. They also employed RGB imagery and the active shape models (ASM) matching technique to get comparable outcomes. The RGB color space was converted to HSI values to apply the color co-occurrence method (CCM) for species differentiation.

Reference [56] classified soil with 100% accuracy and detected weeds with over 90% accuracy in other circumstances. These systems are not yet commercially available, despite their shown ability to distinguish between different species of weeds. Certain devices, like the H-sensor, use different pictures of the red and infrared wavebands taken under active illumination to implement shape-based species discrimination.

V. WEED MANAGEMENT APPLICATIONS

Below are the few innovative weed management apps that bring enhanced control right to our fingertips [57].

1) Site of Action Lookup Tool:
   Purpose: Swiftly identify the site of action (SOA) of commonly used herbicides and diversify your approach.
   Available on: Android, iPhone, iPad
2) ID Weeds:
   Purpose: Quickly and easily identify weeds with this app from the University of Missouri, offering a list of suspects based on characteristics.
   Available on: Android, iPhone, iPad
3) Windfinder:
   Purpose: A weather app displaying wind speed and direction, crucial information for spray preparation.
   Available on: Android, iPhone, iPad
4) Calibrate My Sprayer:
   Purpose: User-friendly app by Clemson University for sprayer calibration, optimizing weed control and minimizing crop damage.
   Available on: Android, iPhone, iPad
5) Agrian:
   Purpose: Access chemical labels, including supplemental labels and updates, quickly. Note: Information covers the entire U.S., and product registration varies by state.
   Available on: Android, iPhone, iPad
6) Mix Tank:
   Purpose: Determine the right order for adding products to the spray tank for compatibility, featuring integrated weather data and GPS information in spray logs.
   Available on: Android, iPhone, iPad
7) SpraySelect:
   Purpose: Easily select the appropriate spray tip by entering speed, tip spacing, and target rate, providing a list of recommended tips.
   Available on: Android, iPhone, iPad

VI. DEEP LEARNING

By incorporating hierarchical functions and adding depth to data, deep learning (DL) is a technique that increases the complexity of machine learning (ML). Because of its intricate models, which enable large parallelization, it is very good at addressing complicated issues [58]. When extensive datasets are available, deep learning (DL) can improve classification accuracy or decrease errors in regression studies. Depending on which network architecture is being utilized, DL might consist of different components (Unsupervised Pre-trained Networks, Convolutional Neural Networks, Recurrent Neural Networks, and Recursive Neural Networks). It can handle many different complicated data analysis problems due to its huge learning capacity and hierarchical structure [59]. Although natural language processing (DL) is widely used in systems that work with raster-based data, it may be used with any type of data, including speech, audio, natural language, weather data, and soil chemistry. Figure 7 depicts the CNN architecture.

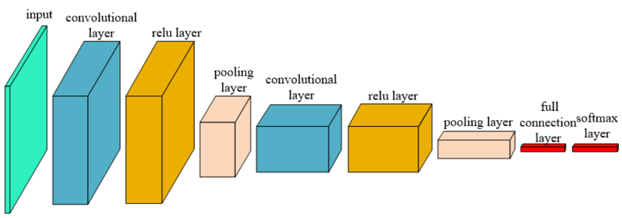

FIGURE 7. CNN architecture [60].

VII. IMPORTANCE OF DEEP LEARNING IN AGRICULTURE

Deep learning has found many applications in agriculture and has changed various aspects of the field as mentioned below:

1) Crop monitoring and yield forecasting: Deep learning models process data from drones, satellites, and IoT devices to monitor crop health, detect disease, estimate yields, and optimize irrigation and fertilization.
2) Weed and pest detection: Deep learning algorithms help identify and differentiate plants from unwanted plants (weeds) or pests, enabling targeted and precise management strategies.
3) Crop disease detection: Deep learning models employ plant image analysis to identify illnesses early on, allowing for prompt intervention to avoid crop loss.
4) Soil Health Management in Harvest Automation: Technologies such as harvest automation and soil health management, identify ripe crops and suggest crops that are appropriate for specific soil types, increase agricultural production, and lower labor expenses.
5) Climate Forecasting and Management: To forecast climate change, deep learning models examine past weather patterns and historical data. This information helps farmers decide when to plant and harvest their crops.
6) Optimization of supply chains: Deep learning enhances distribution efficiency, cuts waste, and optimizes supply chains by evaluating a variety of data points, such as demand forecasting and transportation logistics.
7) Genomics and breeding: By forecasting desired traits and genetic combinations, deep learning assists in genotype and phenotype prediction and speeds up agricultural breeding procedures.
8) Precision Agriculture: Utilizing real-time data to improve resource use and minimize environmental effects, precision agriculture, grounded on deep learning, allows for the targeted application of resources (fertilizers, herbicides, and water).
9) Market Analysis and Decision Making: Farmers may make well-informed choices about crop selection and production by employing deep learning to analyze market trends, pricing data, and consumer preferences.

Figure 8 depicts the application of Deep Learning in Agriculture.

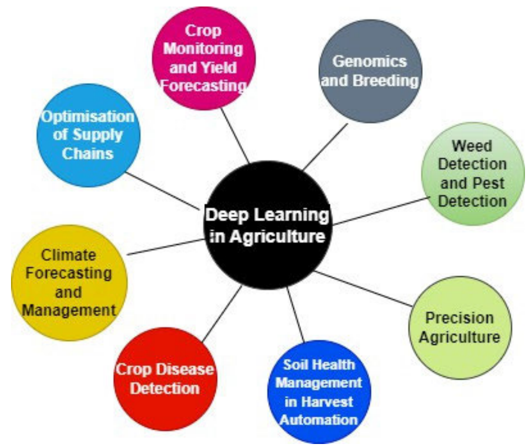

FIGURE 8. Deep learning in agriculture.

VIII. EVOLUTION OF DEEP LEARNING IN WEED DETECTION

Reference [61] quoted that the gathering of weed data and weed management strategies are determined by sensing technologies. Weed data is essential for creating and comparing weed identification techniques.

Thanks to developments in imaging techniques including multispectral imaging, near-infrared imaging, and depth imaging, interest in image-based weed identification has increased. The development of novel algorithms for weed identification tasks is facilitated by the availability of extensive public datasets in the field [62], [63], [64].

Figure 9 depicts various approaches considered in weed detection using deep learning.

Although the public datasets provide useful annotation data and photos for benchmarking, they are not consistent in terms of metadata reporting requirements or contextual information. Comprehending the types of weeds is essential to creating weed management strategies that work.

In weed control scenarios, annotated dataset construction is time-consuming and can result in overfitting and inadequate diversity. Several data augmentation techniques, such as rotation, random cropping, and generative approaches, have been used to improve the quantity and quality of training sets to solve this.

Depending on the identification method, different criteria are used to evaluate the effectiveness of weed identification algorithms. Based on the categorization of an input sample,

FIGURE 9. Deep learning in weed detection.

four different outcomes for binary image classification can be derived: true positive (TP), false positive (FP), true negative (TN), and false negative (FN).

Four categories of studies exist for weed identification: categorization of weed images, detection of weed objects, segmentation of weed objects, and segmentation of weed instances.

IX. RELATED WORK

The accuracy of mapping infestations of maize weed was evaluated by Villiers et al. [65] through the use of a multitemporal UAV and data from PlanetScope. During the mid-to-late stages of maize crop growth, they employed machine learning techniques such as support vector machine and random forest to identify weeds. For PlanetScope, accuracy of less than 49% was attained out of eight experiments. A greater comprehension of the relationships between weeds and maize throughout their life cycles is necessary, which is the study's shortcoming.

In this research, Vijayalaksmi et al. [66], proposed a novel crop-monitoring system based on machine learning-based categorization and UAVs is presented. The proposed architecture is depicted in Figure 10. It uses CNN to track crops in remote areas with below-average cultivation and local climate, classifying them as either crops or weeds. Metrics like accuracy, precision, and specificity are used to evaluate the accuracy of the system.

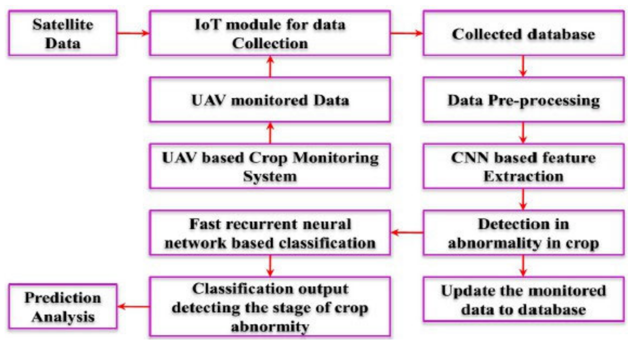

FIGURE 10. Architecture for machine learning-based crop monitoring system classification [66].

A lightweight YOLO v4-tiny model for weed detection in maize seedlings is proposed in this paper [67]. Corn and weed data photos were manually labeled and then separated into three sets: test, validation, and training. The training set was preprocessed and input into enhanced network models. After training, the ideal weights were determined, and the models were tested using the test set.

In an Australian chilli crop field, UAV photographs are analyzed for weed identification. Three machine learning algorithms are tested for this task: random forest (RF), support vector machine (SVM), and k-nearest neighbors (KNN). Results for weed detection accuracy with UAV photos indicate 96%, 94%, and 63%, respectively, suggesting that RF and SVM algorithms work well and are useful [68].

In soybean fields, the authors in this paper [69] used image datasets to create an edge-based vision system for weed identification. After testing three CNN architectures—ResNet50, MobileNet, and others—they discovered that a five-layer CNN architecture had the greatest results in terms of performance, lowest latency, and maximum accuracy of 97.7%. Custom lightweight deep learning models were used in the system's design, and Raspberry Pi images were used for training and inference. Precision, recall, and F1 score criteria were used to assess the system's correctness.

This study [70] focuses on object detection models in inpasture environments, specifically weed identification. Three dataset types were created using synthetic methodology. Tuning experiments improved model performance, achieving over 95% accuracy for testing photos and 93% mAP accuracy for training images. The leaf-based model performed marginally better.

Figure 11 shows an illustration of deep learning and transfer learning process.

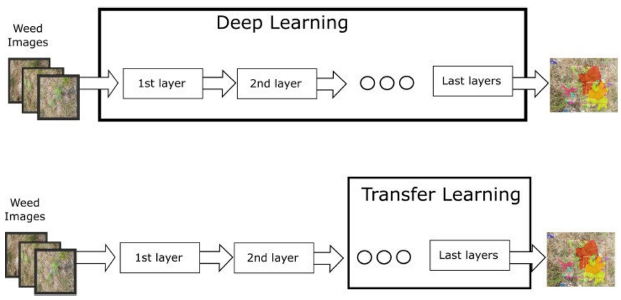

FIGURE 11. Deep learning and transfer learning process illustration [70].

The study [71] proposes a multiscale detection and attention mechanism-based weed identification model called EM-YOLOv4-Tiny, based on YOLOv4-Tiny. It uses a Feature Pyramid Network with an Efficient Channel Attention module, soft Non-Maximum Suppression, and Complete Intersection over Union loss. The model detects a single image in 10.4 ms and achieves a 94.54% mAP, making it suitable for rapid and precise weed identification in peanut fields.

This paper [72] demonstrated the effectiveness of Deep Convolutional Neural Networks (DCNN) in identifying weeds in perennial ryegrass. AlexNet and VGGNet showed similar performance on datasets with one weed species. However, VGGNet showed the highest MCC values for multiple weed species, demonstrating increased precision and improved F1 score.

The study [73] compared SVM and VGG16 classification models using RGB picture texture data to categorize weeds and crop species. The researchers used 3792 RGB photos from a greenhouse and selected crucial features for prediction models. Six crop species and four weeds were classified using SVM and VGG16 classifiers. The VGG16 model had an average f1-score of 93% to 97.5%, showing promising outcomes for site-specific weed management in precision agriculture. Figure 12 shows the Captured images of weed species and crops from a greenhouse, preprocessed to extract the green component, allowing for a better interpretation of color references.

YOLOv4-Tiny and an improved model were used by the authors to create a weed recognition framework that outperformed 33,572 labels for 1000 pictures, with a mean average precision of 86.89% [74].

The study [75] used images of paddy crops and broadleaved and sedge-type weeds to segment them using the semantic segmentation models PSPNet, UNet, and SegNet. PSPNet fared better than SegNet and UNet, suggesting its potential for safe food production and weed control at the site level. It may also be able to advise farmers on the appropriate herbicides.

Utilizing data from an unmanned aerial aircraft in a barley field, the study offers a rule-based approach for classifying perennial weed data. The multispectral-thermal-canopy-height model yielded the best F1 score when used in conjunction with the Normalized Difference Vegetation Index (NDVI) and U-net models [76].

The paper [77] offers a faster R-CNN-based technique that uses the CBAM module and field photographs to detect weeds in soybean seedlings. With VGG19 having the best structure, the model gets an accuracy rate of 99.16% on average. Using one hundred soybean data samples, the generalizability of the model is verified.

The authors in this paper [78] propose a pixel-level synthesization data augmentation technique and a TIA-YOLOv5 network for weed and crop detection in complex field environments. The pixel-level synthesization method creates synthetic images, while the TIA-YOLOv5 network adds a transformer encoder block and a channel feature fusion with an involution strategy to increase sensitivity to weeds and minimize information loss.

The study [79] uses a remotely piloted airplane to map weed-occupied areas, calculate percentages, and provide field-based treatment and control measures. Data is analyzed using R, QGIS, and PIX4D, with random forest and support vector machine methods used for classification.

The study [80] proposes a soybean field weed recognition model using an enhanced DeepLabv3+ model, incorporating a Swin transformer for feature extraction and a convolution block attention module. The model outperformed traditional semantic segmentation models in identifying densely distributed weedy soybean seedlings, with an average intersection ratio of 91.53%. The study suggests further use of transformers in weed recognition.

The study [81] trained convolutional neural networks (CNNs) on images of various plant species, resulting in a Top-1 accuracy of 77% to 98% in plant detection and weed species discrimination, using three different CNNs(VGG16, ResNet-50, and Xception)from a pool of 93,000 photos.

TABLE 1. Challenges and gaps in crop and weed detection: Addressing dataset limitations and controlled environment studies.

Citation	Aim of the Paper	Models or Algorithms	Dataset	Limitations
[68]	Explores the efficiency of three ML algorithms in weed identification using UAV images.	RF SVM KNN	Images were taken from Chilli Field, Australia	The study, conducted in a controlled environment, may not apply to different farms due to soil, weather, and crop varieties. Detection of weeds conducted during the initial phase of crop development.
[77]	Suggests an enhanced approach based on Faster R-CNN for detecting weed presence in soybean seedlings.	Faster R-CNN algorithm VGG19-CBAM	Images were taken from a soybean field located in China	This study collects data on grassy and broadleaf weeds at a small identification scale.
[82]	Suggest an enhanced model based on YOLOv4 for detecting weeds in potato fields.	Improved YOLOv4 algorithm	Images were taken from the test site in China	Data set collected from an experimental field not from the real field.
[83]	The study used multispectral data from UAVs to identify hawkweed leaves and flowers using traditional machine learning techniques.	XGB SVM RF KNN	New Zealand	The study did not explore deep learning techniques using CNN and the data used is not publicly available, limiting reproducibility and analysis.
[84]	Proposes a Faster R-CNN network architecture for identifying weeds in cropping region images.	Faster RCNN FPN Improved ResNeXt101	V2 Plant Seedlings Dataset	The paper lacks details on the potential effects of lighting conditions or image quality on the model's performance.
[73]	The study compared SVM and VGG16 classification models using texture data from RGB images for the classification of weed and crop species.	SVM VGG16	Images were collected in the Waldron greenhouse at North Dakota State University (NDSU)	The study focuses on greenhouse conditions.
[78]	Proposes the use of a pixel-level synthesis data augmentation approach and a TIA-YOLOv5 network for detecting weeds and crops in intricate pasture conditions	TIA-YOLOv5 CFFI ASFF	Publicly available sugarbeet dataset	Model is not tested on a real-time dataset.
[85]	This study uses the Weed-ConvNet model to integrate IoT and digital image processing for weed plant detection in agriculture	IoT Weed-ConvNet	Public image dataset	Not applicable
[86]	Introduces WeedGan, a new generative adversarial network, to augment a weed dataset.	WeedGAN ESRGAN	Synthetic dataset + Public dataset	Not tested on other crop datasets as well as on real field datasets.
[87]	Proposes a method using GANs to generate synthetic images and transfer learning for early weed identification in agriculture.	DCGAN	Public dataset	Study is evaluated on a relatively small dataset. Further research is needed to evaluate its performance on larger and more diverse datasets to test its generalizability.
[88]	Proposes an extensive dataset and benchmarks for semantic interpretation of images in the farming sector, with high-quality annotations of crops, weeds, and crop leaves.	Semantic Segmentation Panoptic Segmentation Leaf Instance Segmentation	Sugar beet field	Not Mentioned
[89]	Presents a plant dataset, Chicory Plant (CP), and tests deep weed object detection using YOLOv7.	YOLOv7	Lincoln beet dataset (UK) Chicory Plant dataset (Belgium)	Not Mentioned

Table 1 addresses dataset limitations and controlled environmental studies.

This study [85] uses the Weed-ConvNet model to integrate IoT and digital image processing for weed plant detection in agriculture. The model achieves higher accuracy with colorsegmented images (0.978) than with grayscale-segmented images (0.942).

This paper [87] presents a two-stage methodology combining GANs and transfer learning to improve weed identification in real environment images with complex backgrounds. It analyzes the performance of DCGANs using various architectural configurations, compares transfer learning approaches like Random, ImageNet, and Agricultural datasets, and compares traditional and GAN-based data augmentation techniques. The optimal configuration achieved 99.07% performance on a tomato and black nightshade dataset, with other designs achieving similar results. Future research should focus on larger, more complicated datasets.

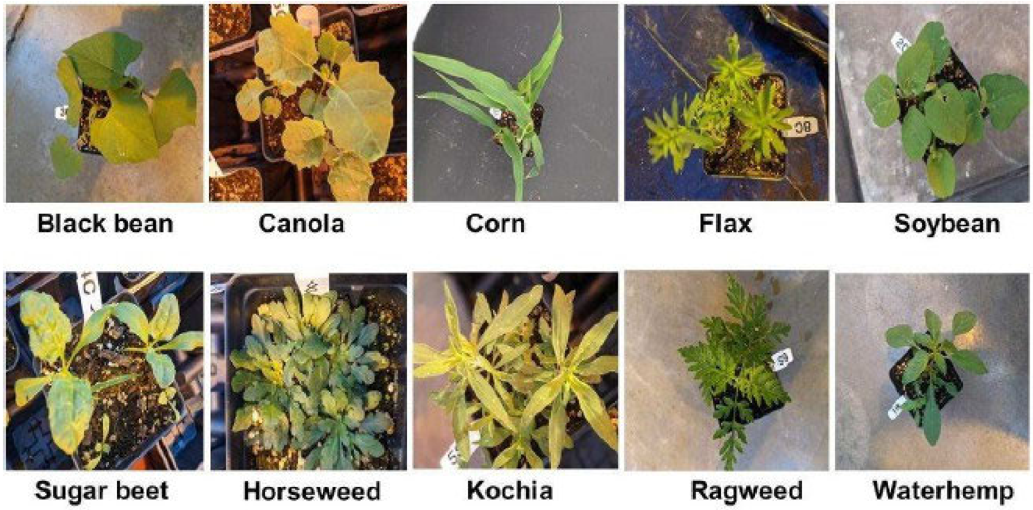

FIGURE 12. Captured images of weed species and crops from a greenhouse, preprocessed to extract the green component, allowing for better interpretation of color references [73].

In order to enhance a weed dataset, this work [86] presents WeedGan, a novel generative adversarial network. It generates synthetic images with low resolution, which are then processed by ESRGAN to produce high resolution versions. The process comprises gathering datasets, enhancing images, identifying images, and evaluating them. The study validates the efficacy of the dataset using seven transfer learning approaches.

The study [90] used device visualization and deep learning to detect weeds in wheat crop fields in real-time. Using 6000 images from PMAS Arid Agriculture University research farm, the study found that the PyTorch framework outperformed other networks in terms of speed and accuracy. The study also compared the inference time and detection accuracy of various deep learning models, with the NVIDIA RTX2070 GPU showing the best results.

This study [82] proposes an improved YOLOv4 model for weed detection in potato fields. The model uses Depthwise separable convolutions, convolutional block attention module, K-means++ clustering algorithm, and image processing techniques to improve detection accuracy. The model's learning rate is modified using cosine annealing decay, and the MC-YOLOv4 model has a 98.52% mAP value for weed detection in the potato field.

A GCN graph was created using recovered weed CNN characteristics and Euclidean distances. The GCN-ResNet-101 strategy outperformed leading techniques, achieving recognition accuracy scores of 97.80%, 99.37%, 98.93%, and 96.51% on four weed datasets. This CNN feature-based method is effective for real-time field weed control [91].

This research [92] proposes a crop row recognition system using low-cost cameras to detect field variations. It uses a deep learning-based method to segment crop rows and extracts the central crop using a new central crop row selection algorithm. The system outperforms industry standards in difficult field settings, demonstrating its effectiveness and capacity for visual servoing.

Figure 13 shows different types of data collection methods. The authors in this paper [93] developed a unique crop row identification algorithm for visual servoing in agricultural fields, outperforming the baseline by 37.66%. They identified weed population and row discontinuities as the most challenging conditions. They also developed an EOR detector to safely direct robots away from crop rows.

The paper [94] presents a system design for an autonomous agricultural robot aimed at real-time weed identification, potentially extending to other farming applications like weed removal and plowing.

The research [95] presents a base model framework for an instructor framework to improve semantic segmentation models for crops and weeds in uncontrolled field settings. It suggests using a teacher model trained on various target crops and weeds to instruct a student model, and a meta-architecture to enhance performance.

Figure 14 depicts different models used for weed detection.

This study [96] proposes a multi-layer attention technique using a transformer and fusion rule to interpret deep neural network decisions. The fusion rule integrates attention maps based on saliency. The model uses the Plant Seedlings Dataset (PSD) and Open Plant Phenotyping Dataset (OPPD) to train and assess the model. Attention maps are marked with red needs and misclassification information for cross-dataset analyses. Modern comparisons show improved classification, with an average gain of 95.42% for negative and positive explanations in PSD test sets and 97.78% and 97.83% in OPPD evaluations. High-resolution information is also included in visual comparisons.

This research [97] aims to develop a new crop row recognition technique using orthomosaic UAV photos. Using wheat and nitrogen field trials, the new crop detection technique

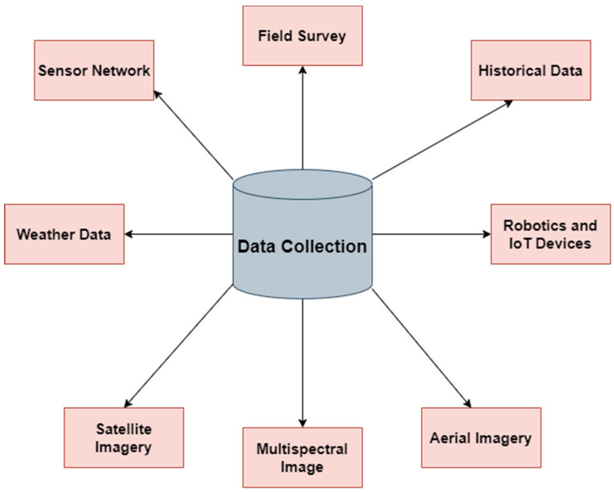

FIGURE 13. Different data collection methods used.

CNN	Faster RCNN	YOLO
Mask RCNN	MobileNet	GoogleNet
ResNet	UNet	DeepLab

FIGURE 14. Different models used for weed detection.

based on least squares fitting was compared to the Hough transform method. The new approach showed better crop row detection accuracy (CRDA) for cotton nitrogen levels and wheat nitrogen and water levels, outperforming the Hough transform method.

The first RGB-D photo dataset for the semantic segmentation of plant species in crop farming is presented by the authors as WE3DS. The dataset consists of a benchmark, 2568 images, and hand-annotated ground-truth masks. The trained models are capable of distinguishing between 10 weed species, seven crop species, and soil [98].

The authors [99] propose a new framework for data augmentation based on the random image cropping and patching (RICAP) technique for semantic segmentation and categorization of weeds and crops as shown in Figure 15. The framework enhances segmentation accuracies, with improvements over the original RICAP. Experiments show that the proposed method improves deep neural network mean accuracy and intersection over union, but has limitations, especially when using large training data.

The study evaluated deep learning-based weed identification methods from RGB photographs of a bell pepper field. The models, trained using different epochs and batch sizes, achieved varying accuracy rates. InceptionV3, with 97.7% accuracy, 98.5% precision, and 97.8% recall, outperformed others, enabling accurate weed management integration with image-based pesticide applicators [100]. Figure 16 shows the presence of weeds in bell paper grown in polyhouse.

The study [101] reveals that deep learning CNN (DL-CNN) models are effective in identifying broadleaf weeds in turfgrasses. VGGNet was the best model for detecting various broadleaf weeds in dormant bermudagrass, while DetectNet was the best for detecting cutleaf evening primrose in bahiagrass. These models have high recall values, strong F1 scores, and overall accuracy, indicating their potential for turfgrass weed detection.

The research carried out in this paper [102] used object identification Convolutional Neural Networks to detect weed species and differentiate between broadleaved and grasses. YOLOv3 outperformed other networks for spotting grass weeds. Faster R-CNN and YOLOv3 were outperformed by GoogleNet and VGGNet. VGGNet was the most successful for spotting grass and broadleaf plants in alfalfa.

The authors in this paper [103] recommend the RetinaNet-based WeedNet-R model for sugar beet fields, enhancing weed recognition accuracy without significant parameter increase. They also implemented an untuned exponential warmup schedule for the Adam optimizer and manually relabeled nearly 5,000 photos for object detection.

Three deep learning-based image processing techniques are compared in this study [104] to detect weeds in lettuce fields. First, YOLOV3 is used for object identification, followed by Mask R-CNN for instance segmentation, and last, histograms of oriented gradients (HOG) as a feature descriptor in the second. Remove non-photosynthetic elements using the NDVI index. For edge detection and crop identification, the methods additionally make use of CNN features and masks.

The study [105] presents a method for identifying weed species threatening tomato crops using RetinaNet neural networks for object detection. The technique was tested against popular models like YOLOv7 and Faster-R Results showed RetinaNet performed best with an AP ranging from 0.900 to 0.977, while Faster-RCNN and YOLOv7 also achieved good results. The study suggests CNN-based weed recognition techniques could be more relevant for real-time applications. The research [106] aims to create a lightweight weed detecting system for laser weeding robots using a dataset of 9,000 photos from six Pakistani fields. The YOLO5 single-shot object detection model was chosen due to its superior performance in predicting true positives and false negatives. The model is used to identify and categorize crops and weeds, with the YOLO model being the best choice due to its strong performance in frame extraction and detection. The system is implemented using an embedded Nvidia Xavier AGX chip for high-performance and low-power operation.

The study [83] used multispectral data from UAVs to identify hawkweed leaves and flowers using traditional Machine Learning techniques. Results showed that RF, KNN, and XGB models accurately identified flowers at 0.65 cm/pixel, demonstrating the potential of ML and remote sensing for large-scale hawkweed detection.

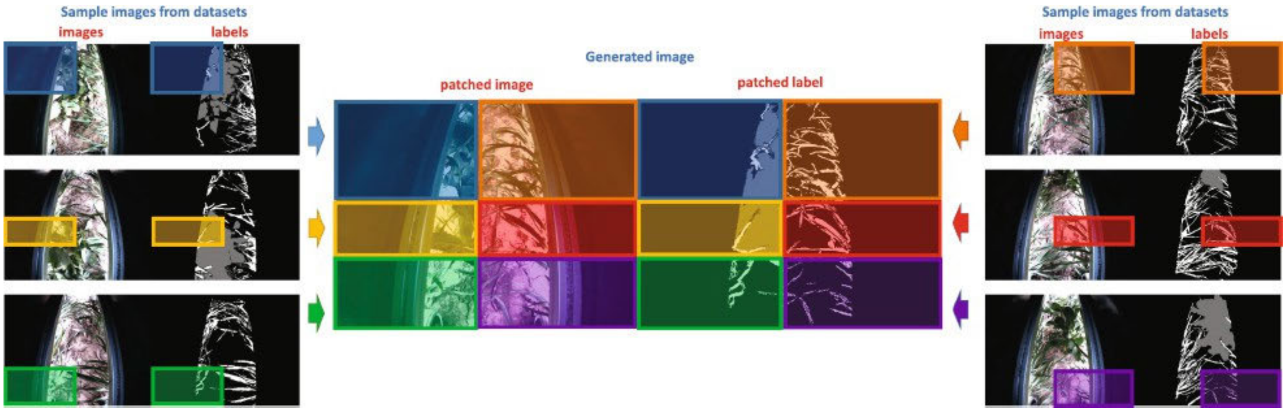

FIGURE 15. The proposed method divides an image region into horizontal and vertical parts, randomly selecting 6 images and labels from the dataset, and cropping and patching these parts to create new images and labels [99].

FIGURE 16. Presence of weeds in bell paper grown in polyhouse [100].

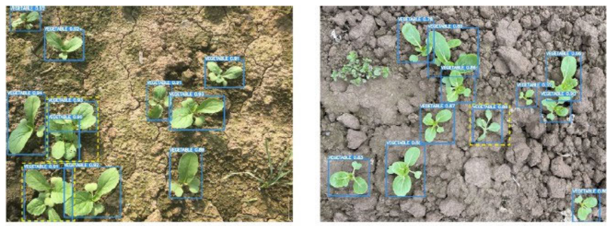

FIGURE 17. YOLO-v3 failed to cover all vegetables due to occlusion, with yellow dashed boxes representing missed detection and yellow dashed boxes representing erroneous detection [108].

The Faster R-CNN network model is proposed for weed identification in cropping region images. It incorporates the feature pyramid network (FPN) method for increased recognition precision. The model combines the ResNeXt network with FPN for feature extraction. Tests show a recognition accuracy of over 95%, making it suitable for weed management systems. The model outperforms the ResNet feature extraction network in terms of quick and accurate target recognition, demonstrating the high effectiveness of deep learning techniques in this area [84].

This paper [107] introduces ''DenseHHO'', a deep learning framework for weed identification using pre-trained CNNs. The model's architecture is chosen based on weed images from sprayer drones, and the model's hyperparameters are automatically adjusted using HHO for binary class classification.

Table 2 and 3 addresses the need for a deep learning framework in detail.

The study [108] demonstrates that deep learning can indirectly detect weeds by identifying vegetables. The strategy involves detecting vegetable instances and creating bounding boxes, then identifying plants growing outside these boxes as weeds. Three deep learning models (CenterNet, YOLO-v3, and Faster R-CNN) were tested, with YOLO-v3 being the best. YOLO-v3 failed to cover all vegetables due to occlusion, with yellow dashed boxes representing missed detection and yellow dashed boxes representing erroneous detection as shown in Figure 17. The approach can be used in robotic weeders for machine vision control. Further research is needed to refine the deep learning models for improved accuracy in weed detection.

In this paper [109] the author addresses the issue of occlusion, the Efficient Channel Attention Network ECA module was incorporated into the Spatial Pyramid Pooling (SPP) structure layer, which resolves the SPP layer's channel compression issue, and enhances PSPnet's capacity to access global context information and also uses a semi-supervised semantic segmentation was used to increase the effectiveness of small datasets.

A new Generative Adversarial Network called WeedGan is introduced in the study to enhance weed recognition in real-world photos of the cotton Weed ID15 dataset. Low resolution synthetic images are produced by WeedGan and then processed with ESRGAN to produce super-resolution versions. In the cotton weed dataset, federated learning and generative adversarial network principles are being applied for the first time. The two-stage system enhances the resolution and characteristics of generated synthetic images by combining innovative generative adversarial networks with transfer learning techniques [86].

The study [110] suggests three techniques to lessen the requirement for manual image annotation. While the second includes constructing false datasets from a single plant image (dataset B) and genuine field datasets from several plants of a single weed species (dataset C), the first requires altering real image datasets (dataset A).

TABLE 2. Challenges and gaps in crop and weed detection: Addressing the need for a deep learning framework.

Citation	Aim of the Paper	Models or Algorithms	Dataset	Limitations
[69]	The author developed an edge-based vision system for soybean field weed identification.	MobileNetV2 ResNet50 5-layer CNN on a Raspberry Pi	Open Source Datasets	The system's performance was evaluated on soybean crops, revealing potential variations in other crops and its limited application in controlled environments influenced by lighting and weather conditions.
[75]	The research employed semantic segmentation models including PSPNet, UNet, and SegNet to classify images of broadleaved weeds, sedge-type weeds, and paddy crops.	PSPNet UNet SegNet ResNet-50	Images were taken from paddy field in Manipal, India	The paper does not provide details regarding the applicability of the suggested semantic segmentation method to different types of crops or varieties of weeds.
[106]	Focuses on creating a lightweight weed detecting system to help laser weeding robots.	YOLOv5 SSD-ResNet5	Images were taken from six agriculture fields across Pakistan	The paper does not discuss the limitations or challenges faced during the development of the lightweight weed detection mechanism.
[107]	Introduces "DenseHHO", a deep learning framework for weed identification using pre-trained CNNs.	DenseNet121 DenseNet201 HHO algorithm	public dataset	Real field images are not used Only one crop is used for the study
[71]	Suggests a weed identification model named EM-YOLOv4-Tiny, utilizing a multiscale detection and attention mechanism, derived from the YOLOv4-Tiny architecture.	EM-YOLOv4-Tiny Soft-NMS Algorithm	Images were taken from Henan Province, China	Only one crop, ie, the peanut is used for the study. The information in this research exclusively covers weeds during the peanut seedling phase, with no consideration given to subsequent growth stages.
[65]	The research assessed the precision of mapping maize-weed infestations by employing machine learning techniques with multi-temporal UAV and PlanetScope data.	RF SVM	Images were taken from a farm in South Africa	PlanetScope satellite data lacks precise weed identification in maize crops.
[67]	Suggests a YOLOv4-tiny model with reduced complexity for identifying weed-infested maize seedlings.	Lightweight YOLO v4-tiny model CSPDarknet53-tiny network FPN.	Images were taken from the maize field in China.	The ability of the suggested model to detect certain objects is limited.
[72]	The study showcased the efficacy of DCNN in identifying weeds in perennial ryegrass.	DCNN (AlexNet and VGGNet)	Canada United States	not applicable
[74]	Developed a new weed detection framework using YOLOv4-Tiny and an enhanced model based on YOLOv4.	YOLOv4-Tiny Meta-ACON activation function CBAM Soft-NMS	Images were taken from a farm in Shangdong Province, China	Study was conducted in a specific context (maize fields) and with a specific dataset. Therefore, the results and conclusions may not be directly applicable to other crops or environments
[76]	The study presents a method based on rules to label data related to perennial weeds, utilizing unmanned aerial vehicle data collected from a barley field.	M-Unet MT-Unet MTCHM-Unet	Helsinki, Finland	The study did not investigate the resilience and transferability of this approach to other agricultural fields.
[79]	RPA (Remotely Piloted Aircraft) is used to map weed-occupied areas, calculate percentages, and implement field-based treatment and control measures.	RF SVM	Images were taken from a coffee plantation located at Minas Gerais, Brazil	Research was focused on coffee farms.

This research [111] aims to use a deep learning model to accurately identify weeds in rice crop images, achieving real-time identification and low machine cost. A dataset of rice and eight weed types is created, and a model called WeedDet is proposed to address overlap issues. The authors propose a new detection network, WeedDet, that outperforms RetinaNet by 5.5% mAP and 5.6 frames per second, with a high mAP of 94.1% and a frame rate of 24.3 fps. They suggest using Det-ResNet to reduce detailed information loss and ERetina-Head for more potent feature maps. The network also outperforms YOLOv3 by slightly slower fps and higher mAP.

This study [112] developed deep-learning models for weed development phase classification, focusing on Consolida regalis weeds. Three models were created, each with a different backbone, using a weed dataset. The models were trained using RetinaNet, YOLOv5 models, and Faster R-CNN. The results showed Yolo had the highest precision in identifying growth stages, while RetinaNet with ResNet-101-FPN achieved the highest average precision. RetinaNet with ResNet-101-FPN,the final model is suggested for real-time performance.

This paper [113] analyzes the Faster Region-based Convolutional Neural Network (RCNN) with ResNet-101, focusing on weed classification and localization. The model's performance is influenced by anchor box generation. Enhancements to scales and aspect ratios were made, resulting in the best classification and localization for all weed classes, with a 24.95% enhancement in Chinee apple weed.

The study introduces Conditional Random Field (CRF)-based post-processing for the ResNet-50 U-Net model as shown in Figure 18, enhancing crop/weed segmentation using a publicly available sunflower dataset. U-Net improves accuracy in underrepresented weed classes and is ideal for real-time weed detection due to its computational efficiency and limited parameters. However, future work should explore deep learning models to reduce misclassification [114].

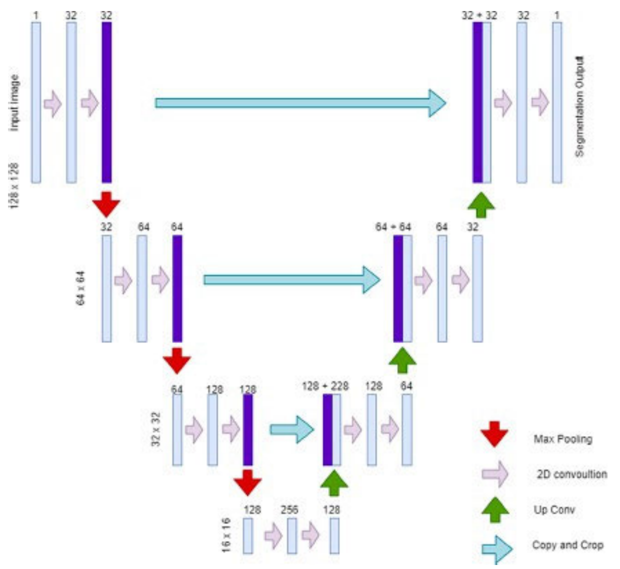

FIGURE 18. U-Net architecture [114].

To detect crops from weeds in challenging natural situations, such as high weed concentrations on organic farms, this research introduces a revolutionary crop signaling technique that uses machine vision. The technology is made for a vision-based weeding robot with a micro-jet herbicide-spraying system and uses a machine-readable signaling chemical to create visual features [115].

Crop signaling is a novel idea that enables automated onfarm plant care tasks by creating a machine-readable signal on crop plants at planting. Under excitation lights, the fluorescence crop signaling material excites fluorochrome, which facilitates its easy detection by machine vision algorithms. Systemic markers, plant labels labeled with fluorescence signaling compounds, expressing a fluorescence gene through agrobacterium transformation into plants, and topical markers are the four crop signaling techniques that have been successfully applied. Promising outcomes emerged from in-field trials, with 100% and 99.7% classification accuracy, respectively, and low false positive error rates. This method could assist in removing technical obstacles in the way of completely automated weed-control robots [116].

The authors developed an automated method for measuring maize seedling growth using RGB imagery from unmanned aerial vehicles (UAVs). They improved the color difference between young and old leaves, created a maize seedling center detection index, and used morphological processing and a dual-threshold technique to eliminate weed noise. The study calculates quantity, canopy coverage, emergence uniformity, and rate of maize emergence [117].

The authors propose a method using drone photos to automatically identify weeds using Convolutional Neural Networks and unsupervised training data. The technique involves finding crop rows, and weeds growing between them, creating a training dataset, and creating a Deep Learning model. This method is robust and adaptive, allowing for field adaptation without feature selection [118].

CRowNet is a deep network designed for crop row recognition in UAV photos, a crucial task in precision agriculture as depicted in Figure 19. It uses Convolutional Neural Networks to analyze images and recognize crop rows based on their visual characteristics. Compared to other approaches like semantic segmentation and Hough transform, CRowNet outperformed them in terms of Intersection over Union (IoU) scores. In a maize field with shadows, CRowNet achieved an IoU score of 93.58% for crop rows in a beet field [119].

This research proposes a method using GANs to generate synthetic images and transfer learning for early weed identification in agriculture. It compares the performance of different architectural configurations and conventional vs. GAN-based data augmentation strategies for weed detection. The methodology combines different techniques for early weed identification, addressing the lack of real-world datasets in agricultural areas [87].

This research [120] proposes a method using GANs to generate synthetic images and transfer learning for early weed identification in agriculture. It compares the performance of different architectural configurations and conventional vs. GAN-based data augmentation strategies for weed detection. The methodology combines different techniques for early weed identification, addressing the lack of real-world datasets in agricultural areas.

Using a single-leaf labeling method, the research [121] provides a deep-learning methodology for crop seedling detection in challenging field situations. Examined on a dataset of four crops, the technique demonstrated excellent

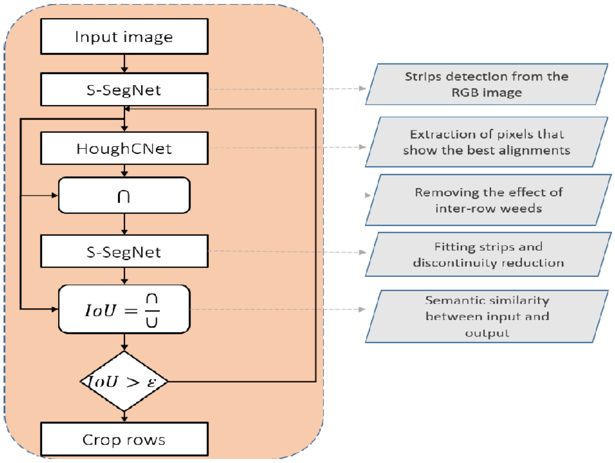

FIGURE 19. Flowchart for crop row detection with CNN (CRowNet) [119].

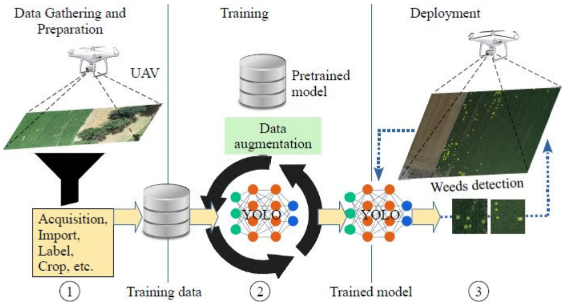

FIGURE 20. The weed detection process involves labeling images with the Roboflow tool, training the YOLOv7 model, and detecting weeds in the input images, resulting in a final output map [89].

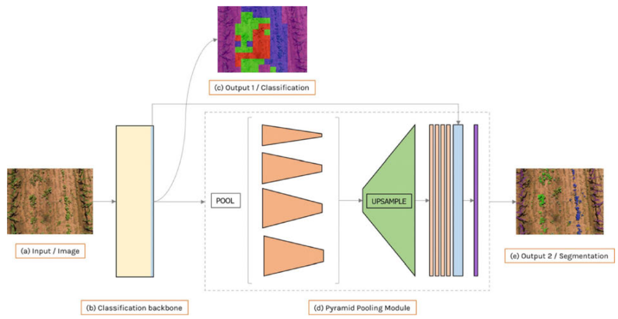

FIGURE 21. DUAL PSPNet scheme [110].

accuracy under dense planting circumstances and enhanced the model's mAP 0.5 by 1.2%, resolving difficulties with missed detection. Farmers can gain from this strategy by increasing crop output and decreasing weed interference, and it is more appropriate for high-density farms.

The research carried out in the paper [122] introduces a metaheuristic optimization method for weed detection in wheat fields. It uses an optimal voting ensemble model, ADSCFGWO algorithm for feature selection, and transfer learning for feature extraction. The method outperforms current optimization techniques, with a detection accuracy of 97.70%, F-score of 98.60%, specificity of 95.20%, and sensitivity of 98.40%.

In order to facilitate the development of visual perception algorithms for tasks such as semantic segmentation, panoptic segmentation, leaf instance segmentation, and plant and leaf recognition, the paper [88] provides a sizable dataset and standards for semantic interpretation of agricultural imagery. Using You Only Look Once version 7 (YOLOv7), the article [89] tests deep weed object detection on a new weed and crop dataset named Chicory Plant (CP). Using more than 3000 RGB photos of chicory plantings, the dataset provides 12,113 bounding box annotations. With strong mAP@0.5 scores, the YOLOv7 model surpasses other YOLO variations in CP and LB. Figure 20 represents the weed detection process invloving labeling images using Roboflow tool and training using YOLOv7 model.

According to the paper [123], machine learning techniques are used to assess the normal RGB or 4-channel NIR + RGB images that serve as the input for weed detection on robots. To improve the model's ability to accurately and precisely detect weeds, the authors train it on a large dataset of cotton crop weeds (which can subsequently be applied to many different crops). Here, the authors employed a machine learning algorithm with an accuracy of up to 90% to 95% as the SSD MobileNet model.

A deep learning segmentation model that can differentiate between different plant species at the pixel level is presented in this paper [110]. Targeting species of grass, broadleaf, and crop, three datasets were created. Real field photos made up the first dataset, single-species plots made up the second, and artificially generated images made up the third. An additional classification loss was added to a PSPNet architecture to create a semantic segmentation architecture as shown in Figure 21. The research shows that augmenting the real field images dataset with other datasets improves network performance without human annotation, surpassing the state-of-the-art method.

The Figure 22 shows various steps involved in weed detection using deep learning.

X. ANALYSIS OF THE RELATED WORKS

Dataset limitations are revealed by the identified research papers on weed detection in agriculture. The majority of studies rely on datasets gathered from particular experimental fields or controlled environments, which restricts the applicability of their conclusions to a variety of real-world agricultural scenarios. These artificial settings might not accurately capture the diversity found in various geographic regions, soil types, weather patterns, and crop types.

Furthermore, some study's inability to make their datasets publicly available compromises the reproducibility and comparability of their findings across various research projects. To overcome these dataset constraints, further research is required that integrates more representative and diverse datasets that depict the intricacies of real-world agricultural contexts. Figure 23 depicts different models or algorithms

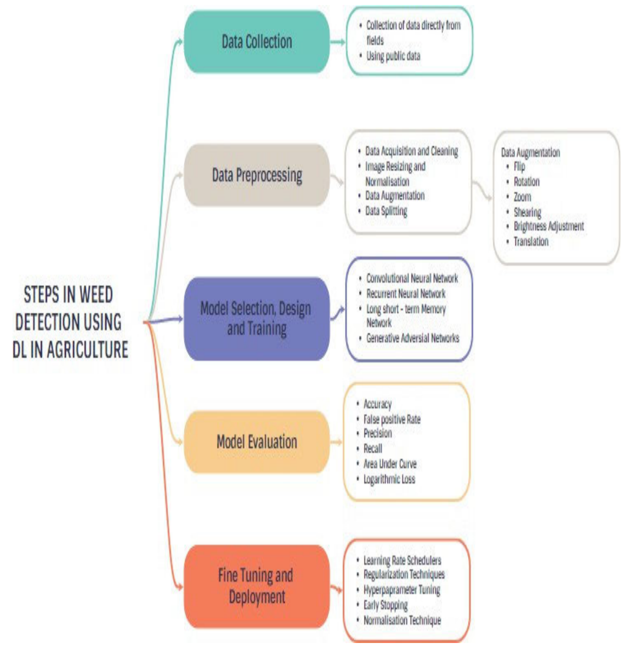

FIGURE 22. Steps involved in weed detection using deep learning.

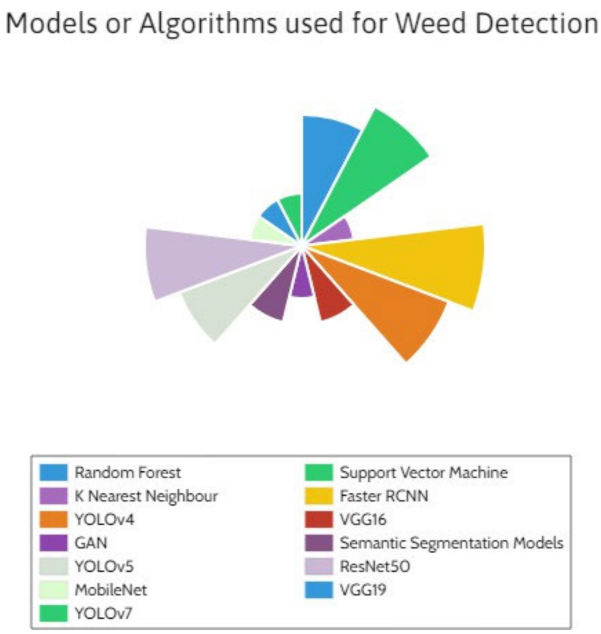

FIGURE 23. Different models or algorithms used for weed detection in agricultural fields.

used for weed detection in agricultural fields and Figure 24 depicts various types of crops used for the study.

Despite advancements in deep learning and machine vision technology, research on weed detection in agriculture concentrates on specific or limited crops. Given their great diversity, the proposed model's narrow scope raises questions regarding their application in other agricultural environments, requiring the creation of extended models to recognize and classify weeds in different crops.

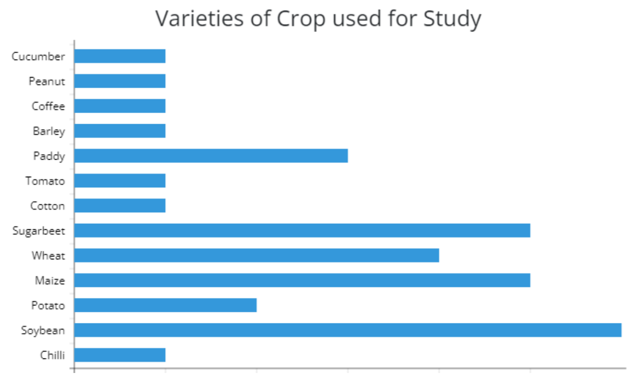

FIGURE 24. Different crops used for the study.

Creating models that can adapt to different crops and field conditions can significantly enhance the practical utility of weed detection systems in various agricultural settings.

XI. CROP STUDY INSIGHTS: MODALITY AND DATA COLLECTION METHODS IN FOCUS

A key strategy for combating herbicide misuse is site-specific weed management (SSWM), which focuses on weed control implementation, decision-making algorithms for herbicide administration, and crop and weed detection systems [124], [125]. According to [126], high spatial resolution images are ideal for precision weed management and customizable spraying systems. Digital image-based weed detection is a crucial technological tool for precise weed identification and localization in agricultural areas. Conventional machine learning is utilized in wheat fields to detect weeds which frequently call for manual characteristics including color, position, morphology, and texture. These techniques, however, are sensitive to sample variation, have a high time complexity, and are ineffective for multi-scale object detection tasks [127], [128]. Deep learning approaches based on CNNs have significantly improved recognition efficiency in weeds detection. The Figure 25 depicts the visual representation of words based on frequency and relevance.

XII. THE SCARCITY OF DATA AND POTENTIAL SOLUTIONS

Researchers have investigated diverse approaches to tackle the issue of data scarcity in agricultural systems. The first is data augmentation, which enhances the quality of images by applying geometric and color transformations. The second tactic is transfer learning, which is using knowledge gained in one context to another, frequently in agricultural settings. Weed identification and disease categorization systems have been made more functional with the use of modern architectures such as Xception, ResNet, VGGNets, Inception, or DenseNet. Generative Adversarial Networks (GANs), which generate synthetic data from preexisting datasets, constitute the third tactic.

In several fields, including the creation of synthetic samples of plants and the classification of plant illnesses in

TABLE 3. Challenges and gaps in crop and weed detection: Addressing the need for a deep learning framework (contd..).

Citation	Aim of the Paper	Models or Algorithms	Dataset	Limitations
[80]	Introduces a model for recognizing weeds in soybean fields.	The DeepLabv3+ model, incorporating a Swin transformer and CBAM.	Images were taken from Agricultural University in China	Research did not focus on other crop weed datasets.
[112]	Developed deep-learning models for weed development growth stage classification, focusing on Consolida Regalis weed	YOLOv5 Faster R-CNN RetinaNet	Turkey	This paper considers only one type of Consolida Regalis weed. Every growth stage is underrepresented in the training dataset's sample count.
[70]	Focuses on object detection models in inpasture environments, specifically weed identification.	SSD SSD Lite Fast RCNN MaskRCNN	Synthetic Dataset	The model doesn't incorporate additional weed species commonly found in pastures, expanding its applicability and usefulness.
[81]	This study trained CNN on images of various plant species	VGG16 ResNet–50 Xception	Images were taken from an experimental field in southwest Germany	Misclassifications occurred between S. nigrum and C. album due to similar morphological characteristics.
[115]	Proposes a crop signaling technique that uses machine vision.	Crop signaling machine vision	Santa Clara, USA	The algorithm's applicability to other crops and weed control technologies may be limited because it was created especially for a lettuce field and a micro-jet herbicide spraying technique. Focus on integrating advanced technologies like artificial intelligence and deep learning algorithms was not done.
[110]	Suggested a segmentation model based on deep learning capable of distinguishing between various plant species at the pixel level.	PSPNet	Limburgerhof (DE) and Utrera (ES) + synthetic dataset	The limitations of the proposed method in terms of generalization to other weed species or crops are not explicitly discussed.
[108]	Demonstrates that DL can indirectly detect weeds by identifying vegetables.	CenterNet YOLO-v3 Faster R-CNN	Collected pictures of bok choy from various vegetable fields across China.	Not employed for identifying weeds amidst other vegetables.

FIGURE 25. Word cloud, visual representation of words based on frequency and relevance.

authentic settings, Deep Convolutional GAN (DCGAN) has demonstrated encouraging outcomes. For instance, a neural network design with two stages was utilized to achieve a final accuracy of 93.67% using conventional data augmentation and GANs approaches.

However, more experimental results are needed to fully understand the effectiveness of these deep learning-based techniques. As GANs are a relatively young topic, more through empirical investigations comparing various designs and setups in comparable benchmarks are also required. Overall, these methods offer promising solutions for addressing data scarcity in agricultural systems.

A. DATA AUGMENTATION

Utilizing modified versions of current data or producing synthetic data from existing data, data augmentation techniques expands the actual amount of available data. It is used to apply random, realistic data transformations like flipping or rotating images, to a model's training sets to increase their diversity. By providing variants of the data that the model would meet in the real world, data augmentation techniques help deep learning models become more accurate and robust.

On the other hand, data augmentation may be detrimental if it produces inferior prediction outcomes. It's vital to find equilibrium between bias and variance and experiment with different combinations of data augmentation to determine which works best for the issue statement to prevent this.

When a model fits too closely to the training dataset and is unable to generalize, this is known as overfitting.

The data's variability, the model's potential for generalization, the reduction of overfitting, the cost savings associated with gathering and labeling extra data, and the enhanced prediction accuracy of the deep learning model are all advantages of data augmentation. However, because augmented datasets contain the biases of current datasets, mechanisms must be put in place to monitor and evaluate their quality.

Adding Gaussian noise, brightness, hue, contrast, saturation, flipping, rotating, scaling, cropping, and translating are examples of common data augmentation techniques. Data augmentation can greatly increase the accuracy of deep learning models by creating methods to reduce bias and boost neural network learning capacity.

B. GENERATIVE ADVERSARIAL NETWORK

A deep learning architecture known as a Generative Adversarial Network (GAN) pits two neural networks against one another in an attempt to produce more genuine new data from a given dataset [129]. Up until it is unable to discriminate between fake and original data, the predicting network generates newer, better versions of the fake data values in an attempt to ascertain whether the generated data is part of the original dataset.

Mathematical formulas and the relationship between the generator and discriminator serve as the foundation for GAN models. The simplest model, known as vanilla GAN [130], generates data variation without feedback. By introducing conditionality, conditional GAN enables the production of tailored data. Using transposed convolutions to upscale data distribution and convolutional layers for data classification, deep convolutional GAN incorporates convolutional neural networks (CNNs) into GANs. The goal of super-resolution GANs (SRGANs) [131] is to upsample low-resolution photos to high resolution while preserving detail and quality. Laplacian Pyramid GANs (LAPGANs) employ a hierarchical method with several generators and discriminators operating at various sizes or resolutions to divide the problem into stages. The procedure starts with producing a low-resolution image, whose quality increases as the GAN phases advance.

C. TRANSFER LEARNING

By using knowledge from a related area, transfer learning helps learners in one domain become better. To comprehend why transfer learning is feasible, we might take inspiration from non-technical, real-world events. Take the case of two individuals who aspire to become proficient pianists. While one individual has never played an instrument before, the other has played the guitar for a long time and has a vast knowledge of music. A person with a strong foundation in music will be able to pick up the piano more quickly because they will be able to use their prior understanding of music to the challenge of learning how to play the instrument. An individual can effectively apply knowledge from a previously acquired task to acquire a related task [132].

XIII. DISCUSSION

Regarding the identification and classification of crop weeds, the Deep Learning model works incredibly well. RGB images are captured for most research using a digital camera; some use multi-spectral or hyper-spectral data. By using detection accuracy as the primary parameter, researchers train the model using supervised learning techniques. The application of new technology and different spectrum indices are two areas where there is still opportunity for advancement. Vast datasets are required for weeds and crops, however, the cost of annotating these vast datasets is high. This issue can be solved by using weakly supervised or semi-supervised techniques. Large datasets can be produced for automated weed detection systems using deep learning techniques and Generative Adversarial Networks (GAN). Nevertheless, class imbalance is present in most datasets, which causes biases and over-fitting. To address this issue, future research should use class-balancing classifiers, cost-sensitive learning, or data redistribution. The main objective is to increase crop yields while reducing expenses.

XIV. FUTURE SCOPE

Further studies in this area could enhance intercropping models for smallholder farmers by adding more sensors and cloud computing, integrating a larger range of color spaces, vegetation indexes, and spectral bands, and expanding their use to other crops for yield prediction and disease detection. One interesting direction for the development of intelligent weeding technology is the integration of machine learning algorithms with robotic systems, which will increase the efficiency of weed detection and removal.

Subsequent investigation could improve real-time herbicide administration by integrating more weed species in pastures and refining models of deep convolutional neural networks for weed identification in turfgrass species.

WeedGan is a suggested semantic segmentation model that might be made better by adding new versions, growing the dataset, and improving training results on real-world datasets. Both the study's coverage of weed species and the experimental field setting might be lacking in disruptive elements. Down the line, more research is necessary to determine whether the performance of the suggested data augmentation strategy decreases with larger training photos.

XV. CONCLUSION

The research publications on identification and categorization of weed species using deep learning in value crops are reviewed in this study. The majority of research employs supervised learning strategies and uses plant datasets to refine pretrained models. When enough labeled data is provided, high accuracy can be reached. However, the excellent accuracy and processing speed achieved by current research are limited to tiny datasets. Future work should focus on class imbalance issues, weed growth phase identification, large-scale datasets with a variety of crop and weed species, efficient detection approaches, and comprehensive field testing for commercial deployments.

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