

Neural Network Models for Weed Detection

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Abstract—This paper summarizes the neural network models developed for weed detection in agricultural production systems published up to 2021, covering the classification, object detection, and semantic segmentation schemes. Differences in performance are evaluated and discussed in terms of accuracy, precision, recall and f1 score for convolutional networks with eight layers trained on early ImageNet-scale classification work, residual networks over 50 layers, and inception-style modules in various combinations on a range of single-crop row imagery to multi-species rangeland benchmarks with over 17,000 labeled images. Detection-based frameworks, such as the single-shot and two-stage, are evaluated by means of a mean average precision and a trade-off between inference speed (seconds per frame) and inference accuracy (mean average precision), with the fourth generation of the You Only Look Once architecture showing around 91.5 percent mean average precision on real-time inference speeds of almost 23 frames per second. Under field conditions, the weed-class F1-scores of segmentation-based approaches using multispectral red-green-blue near-infrared fusion were close to 0.80. The single most useful optimization strategy investigated was identified as transfer learning, which led to an accuracy increase of around 5.8 percentage points over networks trained from a random initialization of weights, whereas synthetic oversampling of minority weed classes resulted in an accuracy increase of around 3.2 percentage points. Comparative analysis shows that deep learning fares better than all traditional machine learning classifiers that rely on hand-crafted shape and texture features when evaluated under similar assessment conditions, achieving between 8 and 13% increase in accuracy. Neural network models are an effective and growing mature platform for site-specific weed management with a potential for further development in lightweighting the architecture, fusion of multispectral sensors, and generalization across environments.

Keywords—convolutional neural networks, weed detection, precision agriculture, deep learning, semantic segmentation, object detection, transfer learning, multispectral imaging, site-specific weed management, image classification, unmanned aerial vehicles, agricultural robotics

I. INTRODUCTION

Weeds continue to be one of the most widespread limitations to crop productivity and quality globally in crop production systems. Weeds are also a source of competition for the essential resources of agricultural crops, such as nutrients, water and photosynthetically active radiation, and can cause significant yield losses when not controlled, depending on species mix and density. Weed management has historically been based on using herbicides on entire fields, which is an inefficient use of time and money, and poses increasing environmental and regulatory issues with chemical wash-off, herbicide resistance and biodiversity loss. Thus, site specific weed management, where weed control is practiced only in the area where weed infestation is detected, has become a preferred method and the ability to accurately locate and detect weeds in real-time is a fundamental requirement for the practical implementation of this method.

Weed detection has been revolutionized by artificial neural networks, and particularly by convolutional neural networks (CNNs). The hierarchical representations learned by CNNs, in contrast, are not

based on handcrafted features like colour indices or shape descriptors or texture statistics but are extracted from labelled image data and capable of generalizing over variable lighting conditions, occlusion, growth stages, and crop-weed morphological similarity [1][2]. The number of published research papers that used deep learning to weed detection has grown substantially from 2015 to 2021, as shown in Fig. 1, in parallel with the increasing availability of graphics processing unit (GPU) hardware and the development and extension of open-source deep learning frameworks.

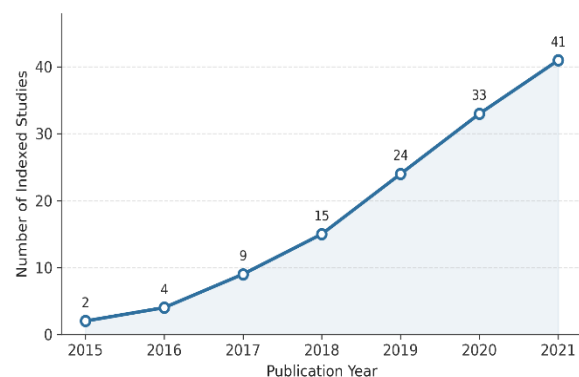


Fig. 1. Growth in the number of published studies applying deep learning to weed detection, 2015 to 2021.

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This paper reviews, summarizes and combines methodologies, datasets and reported performance results from published neural network-based weed detection studies up to 2021. In Section II, the fundamentals of the architecture of the neural networks employed in this field are presented. In Section III classification-, detection and segmentation-based methodologies are reviewed. In Section IV the datasets and sensing platforms used are reviewed [3][4]. The performance comparison between the architectures is given in Section V. Section VI presents some challenges and optimization strategies, while Section VII presents some future directions found in the reviewed literature, and Section VIII provides concluding remarks.

II. NEURAL NETWORK FOUNDATIONS FOR IMAGE-BASED WEED RECOGNITION

The most common family of architectures used for weed recognition based on images is the convolutional neural networks. CNNs are made up of stacked convolutional layers, which use learnable filters to learn features that are localized in space across an image; pooling layers, which shrink the spatial dimension of the input while preserving significant information; and fully connected layers that convert the extracted features into probabilities for the classes. For large-scale image classification, an eight-layer network shown to be trained on the ImageNet corpus was able to significantly outperform previous hand-crafted feature pipelines, with a top-five error rate close to 15.3 percent, which spurred the use of deep convolutional architectures in computer vision applications (including agriculture). Later architectures added the idea of residual connections, which made it possible to have networks with hundreds of layers without the gradients dying out and still have them train well. Later, they added the concept of residual connections to allow gradients to flow through networks deeper than a hundred layers, allowing for much deeper and more expressive models to be trained in a stable way [5].

Categorical cross-entropy loss function is usually minimized for the classification of weeds in a CNN. The loss function commonly minimized in training a CNN for weed classification is called a categorical cross-entropy loss function.

$$L = - \sum_i y_i \log(\hat{y}_i)$$

Note that the summation is over all the C classes, y_i is the ground truth indicator for class i , and $\hat{y}_i$ is the predicted probability for class i that is put out by the softmax output layer denoted as (1). For detection approaches, the model quality is also evaluated using Intersection over Union (IoU) metric,

$$IoU = \text{Area of Overlap} / \text{Area of Union}$$

denoted as (2), which quantifies the spatial agreement between a predicted bounding box and its corresponding ground-truth annotation; a prediction is typically deemed a true positive when the IoU value exceeds a threshold of 0.5.

The overall processing pipeline common to most neural network-based weed detection systems is depicted in Fig. 2, proceeding from image acquisition through preprocessing, convolutional feature extraction, task-specific inference, and generation of an actionable weed distribution map suitable for guiding site-specific herbicide application or mechanical intervention [7].

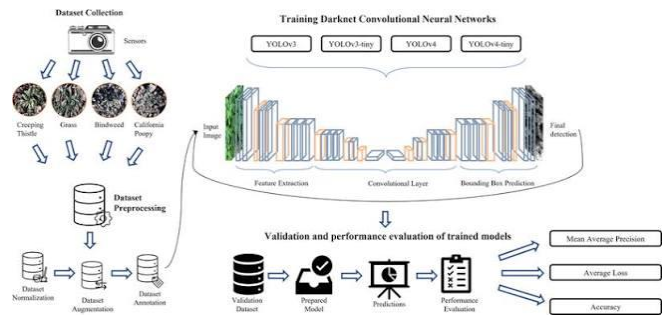


Fig. 2. Conceptual processing pipeline for neural network-based weed detection systems. (ResearchGate,2021)

III. NEURAL NETWORK METHODOLOGIES FOR WEED DETECTION

A. Classification-Based Approaches

Early attempts to weed recognition in CNNs classified the whole image or image patch, assigning each area-of-interest in the crop to one of three categories: crop, grass weed, or broadleaf weed. A study that compared the performance of a ConvNet-based classifier with a baseline SVM program on the soybean field imagery with the same feature space achieved accuracies above 99 percent when distinguishing between soil, soybean, grass and broadleaf classes, far outperforming the baseline SVM program [8][9]. Table 1 shows a summary of the average performance of equivalent classification pipelines applied to rangeland images containing eight weed species within a large multiclass benchmark, with a residual network showing an average accuracy of ~95.1 percent, and Inception-based architecture an average accuracy of ~95.7 percent. The average accuracies of equivalent classification pipelines applied to images of rangelands containing eight weed species within a large multiclass benchmark are approximately 95.1 percent with a residual network and approximately 95.7 percent with Inception-based architecture (see Table 1), as shown in Fig. 3. Transfer learning – using convolutional weights trained on huge natural-image corpora and fine-tuning them on smaller corpora in agricultural applications – has been especially successful for applications with limited labeled data, one of which that combined an Xception feature extractor with a support vector machine for tomato-crop weed discrimination achieved an F1-score of 99.29 percent [10].

B. Detection-Based Approaches

Detection based approaches are used to identify specific weed occurrences in a picture using bounding boxes and give spatial information for targeted intervention. Mean average precision values around 91.5 percent were obtained, and real-time inference speeds were around 23 frames per second, for a fourth-generation version of the You Only Look Once (YOLOv4) architecture applied to corn and soybean field images, outperforming the previous version and a two-stage Faster R-CNN baseline in a speed-accuracy trade-off analysis in Section V. Object detection systems trained to identify weeds in row crops also achieved near 0.94 F1-scores on UAS-collected images, highlighting the appropriateness of a detection framework for UAV-scale field surveying.

TABLE 1
REPRESENTATIVE CNN ARCHITECTURES APPLIED TO WEED DETECTION TASKS

Architecture	Task Type	Crop / Environment	Reported Metric (%)
AlexNet	Classification	Soybean field (4-class)	99.07 (Acc.)
VGG16	Classification	Corn and soybean	97.80 (Acc.)
GoogLeNet	Classification	Turfgrass (broadleaf)	96.90 (Acc.)
ResNet-50	Classification	Rangeland (8 species)	95.10 (Acc.)
Inception-v3	Classification	Rangeland (8 species)	95.70 (Acc.)
Xception + SVM	Classification (transfer)	Tomato crop	99.29 (F1)
YOLOv3	Detection	UAV corn/soybean imagery	90.00 (mAP)
YOLOv4	Detection	UAV corn/soybean imagery	91.48 (mAP)
SegNet-based CNN	Semantic segmentation	Sugar beet (multispectral)	80.00 (F1, weed)

C. Segmentation-Based Approaches

Semantic segmentation assigns a class label to each pixel in an image, which allows for a more detailed description of the weed and crop canopy boundaries [11]. Despite a strong class imbalance, favouring background vegetation, a dense semantic segmentation network combining red-green-blue and near infrared channels developed for sugar beets performed at high levels of accuracy in the field; the F1-scores obtained in the field were close to 0.80 for the weed and sugar beet classes respectively when deployed on a micro air vehicle. A similar large-scale mapping approach expanded this segmentation process to multiple aerial surveys, and created field level weed pressure maps, showing that the fusion of visible and near-infrared bands of the image resulted in a better discrimination between spectrally similar crop and weed canopies when compared to only using visible and red bands of the image as input (as quantified later in Table 7).

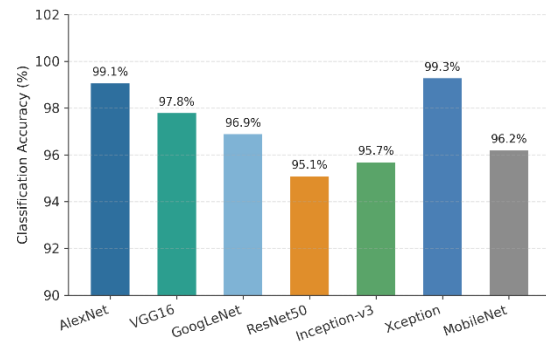


Fig. 3. Classification accuracy achieved by representative CNN architectures across reviewed studies.

IV. DATASETS, SENSING PLATFORMS, AND DATA ACQUISITION

Weed detection performances of neural network models largely rely on scale, variety, and annotation quality of the training sets. Table 2 provides a summary of representative data sets cited as part of the literature reviewed. The benchmark includes 17,509 labeled images across eight weed species that are important in the rangeland and pasture systems of Australia, captured in natural lighting and different background conditions in order to make the model robust; the class-wise composition of this benchmark is shown in Fig. 4 and the background is mostly a large class of negative images [12][13][14]. Other datasets are based on ground-based robotic platforms that fly at very low altitudes (5 to 30 m depending on the sensor configuration), generating very high-resolution images that allow fine-grained texture and shape analysis, but at small spatial scale, which is not suitable for large areas.

TABLE 2
CHARACTERISTICS OF REPRESENTATIVE WEED DETECTION DATASETS

Dataset / Study	Platform	Sensor	Images	Classes
Rangeland multiclass benchmark	Ground robot	RGB	17,509	9
Soybean field ConvNet study	Ground camera	RGB	15,336	4
Canola field study	Ground camera	RGB	~2,000 patches	2
Sugar beet segmentation (MAV)	Micro air vehicle	RGB + NIR	~1,400	3
Large-scale weed mapping	UAV	Multispectral	Multi-field surveys	3
Turfgrass broadleaf detection	Ground camera	RGB	~26,000 patches	2
UAS corn/soybean detection	Fixed-wing UAS	RGB	~5,000 annotated	2

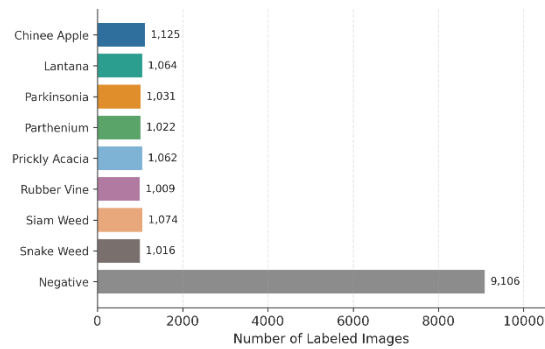


Fig. 4. Class-wise image composition of a representative multi-species rangeland weed dataset.

The type of sensation used has a significant effect on the discrimination accuracy that can be achieved, as indicated in Table 3. While the most common and affordable sensing option is the standard RGB camera, multispectral sensors with filters for near-infrared and red-edge bands offer complementary discriminative information associated with the amount of chlorophyll in the crop canopy and the vigor of the vegetation, especially when crop and weed foliage are similarly colored in the visible spectrum [15]. For large field areas, coverage is important, but for small areas, spatial resolution is more important, which is why micro air vehicles with multispectral payloads have been employed to build fine-grained weed maps at the sub-meter level, and larger fixed-wing MAVs sacrifice spatial resolution for coverage [16]. Acquisition protocols described in the literature generally involve multiple imaging acquisitions at different growth stages, as the morphology of weeds and crops varies significantly throughout the entire growing season, and often data sets are divided into separate training, validation, and test sets in order to retain a balance of classes between the sets.

**TABLE 3
SENSING PLATFORMS AND SPECTRAL CONFIGURATIONS USED FOR WEED IMAGING**

Platform	Spectral Bands	Typical Range	Primary Advantage
Ground-based camera/robot	RGB	0.3–1 m	High spatial resolution, low cost
UAV (multirotor)	RGB	5–20 m	Field-scale coverage, flexible scheduling
UAV, multispectral sensor	RGB+NIR+Red-edge	10–30 m	Vegetation index discrimination
Micro air vehicle (MAV)	RGB + NIR	2–5 m	Fine-grained mapping in small plots
Fixed-wing (large-scale)	Multispectral	>100 m	Regional-scale weed pressure mapping

V. COMPARATIVE PERFORMANCE ANALYSIS

The classification accuracy, precision, recall and F1-score make comparison among the five

representative architectures as shown in Tab. 4. The ability of classification models to obtain high accuracy depends on the number of classes, as well as on the imaging conditions [17]. In this study, the classifiers were tested on the relatively limited number of classes, 4, and on relatively uniform close-range images, and the overall accuracy achieved by the 8-layer AlexNet was 99.1 percent, while the deeper networks, ResNet-50 and Inception-v3, were tested on a much more diverse set of 8 classes and achieved comparatively lower but still strong accuracy values, near 95 percent, indicating that the imaging conditions were a key to obtaining high accuracy, and that greater intra-class morphological variability led to increased classification difficulty rather than any architectural deficiency [18].

**TABLE 4
CLASSIFICATION METRICS FOR REPRESENTATIVE ARCHITECTURES**

Model	Acc. (%)	Prec. (%)	Recall (%)	F1 (%)
AlexNet	99.1	98.9	98.7	98.8
VGG16	97.8	97.3	96.9	97.1
Inception-v3	95.7	95.2	94.9	95.0
ResNet-50	95.1	94.6	93.8	94.2
MobileNet	96.2	95.8	95.1	95.4

This trade-off between inference speed and the localization accuracy of detection frameworks is clearly observed in the tables and figures below [19]. Two-stage detectors like Faster R-CNN and Mask R-CNN typically achieve competitive mean average precision (mAP) scores between 88.6 to 89.1 percent and can only process imagery 5 to 7 frames per second, which makes them less appropriate for real-time field robotic applications. YOLO family and Single Shot Detector (SSD) are single-shot detectors with lower accuracy levels but much higher throughput, with YOLOv4 having the best compromise of the frameworks discussed, because it can achieve a mean average precision of 91.5 percent while delivering more than 20 frames per second of inference [20].

**TABLE 5
DETECTION FRAMEWORK SPEED-ACCURACY TRADE-OFF**

Model	mAP (%)	Speed (FPS)	Hardware
SSD	82.4	22	Desktop GPU
Faster R-CNN	89.1	7	Desktop GPU
YOLOv3	90.0	20	Desktop GPU
YOLOv4	91.5	23	Desktop GPU
Mask R-CNN	88.6	5	Desktop GPU

Per-class confusion performance is shown in Fig. 6 for a representative confusion matrix and suggests that there are relatively few confusions between crop and background soil classes, typically < 3%, and that most mistakes occur between the classes grass-type and broadleaf-type weed, as the foliar morphology of these

classes can become similar under some growth conditions and imaging incident angles. This pattern is found in several independent studies making fine-grained weed species discrimination (and not crop-weed separation) the more difficult classification sub-problem within this domain [21].

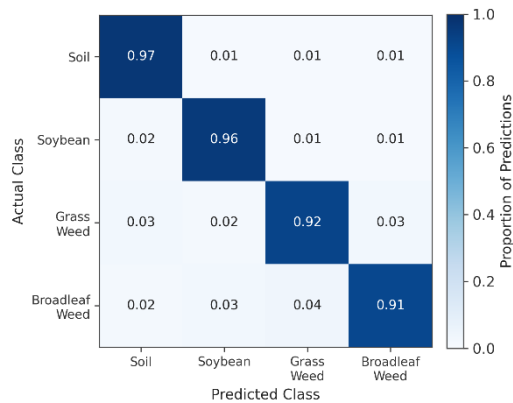


Fig.5. Representative confusion matrix illustrating per-class discrimination performance.

However, the accuracy advantage of CNN-based approaches over traditional machine learning classifiers—such as shallow artificial neural networks and support vector machines using hand-crafted shape and texture descriptors—has been consistently found, though to varying extents with different levels of shape and texture feature engineering; for sugar beet field imagery, a maximum likelihood (baseline) achieved a 92.92 percent accuracy, whereas a shape-feature-based SVM achieved a 95.00 percent accuracy, well exceeded by CNN-based approaches operating on canola field imagery, which achieved approximately 94 percent accuracy [22].

VI. CHALLENGES, TRAINING DYNAMICS, AND OPTIMIZATION STRATEGIES

Although the reported results show high accuracy, several common issues hinder the deployment of weed detection systems based on neural networks in the field. Weed occurrence is often sparse when compared with crop canopy and background soil in a field, creating a class imbalance that may lead to models being falsely represented toward the weed class. This may require either a targeted sampling or loss reweighting approach to avoid bias from class imbalance [23].

**TABLE 6
TRADITIONAL MACHINE LEARNING VERSUS DEEP LEARNING APPROACHES**

Method	Feature Type	Accuracy (%)
Support vector machine	Hand-crafted shape (Hu moments, Fourier)	95.00
Artificial neural network	Hand-crafted shape	92.92
Wavelet texture classifier	Hand-crafted texture	91.00

Maximum likelihood classifier	Spectral / statistical	82.00
Deep CNN (SegNet-based)	Learned hierarchical features	94.00

Table 7 presents the numerical results of the commonly used data augmentation and data preprocessing techniques applied to increase the model accuracy, with synthetic oversampling of the minority weed classes contributing to an accuracy gain of around 3.2 percentage points, and initializing the convolutional weights with transfer learning from large pretrained corpora producing the largest single improvement observed in the studies reviewed, at approximately 5.8 percentage points, which highlights the importance of external image knowledge when training data in agriculture is comparatively limited [24].

**TABLE 7
EFFECT OF AUGMENTATION AND PREPROCESSING ON MODEL ACCURACY**

Technique	Accuracy Gain (pp)
Rotation and flipping	+2.1
Color jittering / HSV shift	+1.4
Random cropping	+1.8
Synthetic oversampling (minority classes)	+3.2
Multispectral band fusion (RGB+NIR)	+4.5
Transfer learning initialization	+5.8

Table 7 presents the numerical results of the commonly used data augmentation and data preprocessing techniques applied to increase the model accuracy, with synthetic oversampling of the minority weed classes contributing to an accuracy gain of around 3.2 percentage points, and initializing the convolutional weights with transfer learning from large pretrained corpora producing the largest single improvement observed in the studies reviewed, at approximately 5.8 percentage points, which highlights the importance of external image knowledge when training data in agriculture is comparatively limited [25].

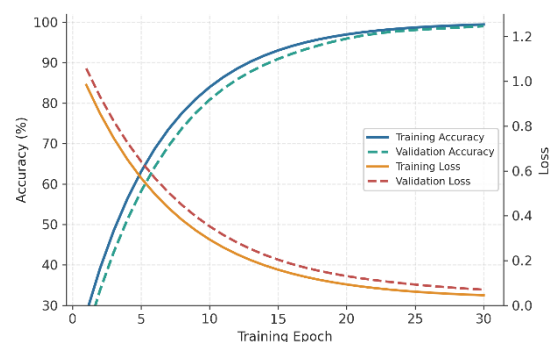


Fig. 6. Representative training and validation accuracy and loss curves across thirty training epochs.

The other challenge is computational limitations, because of the fact that deeper architectures tend to produce higher rates of accuracy, but consume more memory and processing power than can be delivered by field robots and UAVs with mounted architectures, there is a need for lightweight architectures like MobileNet that have been found to produce a competitive 96.2 percent classification accuracy, with significantly fewer parameters than those of deeper residual networks. Lastly, the reduction of herbicide use volume (that is possible by site-specific application, using guidance from a neural network to detect the plants) has been cited as a key motivating outcome, although concrete environmental impact assessments have been less common within the studies reviewed, up until 2021.

VII. FUTURE DIRECTIONS

A number of possible future courses for research are discernible in the literature surveyed up to 2021. These architectures will become more refined and lightweight, and will enable real-time inference on board autonomous field robots and unmanned aerial vehicles (UAVs) that lack reliable connectivity with external computing infrastructure. Further discrimination of spectrally similar crop and weed canopies is expected with the expansion of multispectral and hyperspectral sensing, and with the use of sensor fusion techniques, which will not be possible with visible-spectrum imagery alone. Other active lines of research include semi-supervised and unsupervised labeling approaches that lessen the reliance on time-intensive manual annotation, especially since the creation of extensive training sets of species can be costly [26]. Finally, a natural next step is the integration of neural network-based detection with robotic systems of mechanical or chemical intervention for targeted, site-specific weed management in commercial production environments, which would complete the loop between detection and site-specific weed management.

VIII. CONCLUSION

This paper has compiled neural network methods, data sets, and comparisons of performance for weed detection up to 2021. Depending on the operational requirement, between classification and detection and computation, and spatial localization and accuracy, each of the two approaches has its own benefits; deeper architectures sacrifice inference speed for small increments of accuracy. Comparative analysis shows that convolutional neural networks consistently outperform traditional machine learning methods based on hand-crafted features, whereas the best strategies to enhance the accuracy in low data availability scenarios are transfer learning, and sensor fusion using multispectral data. Despite the challenges faced, in-class imbalance, cross-environment generalization, and embedded computational constraints continue to drive current research

directions. The overall evidence presented here suggests that neural network models provide a well-developed and well-proven basis for site-specific weed management, and future architectural and sensing innovations of the neural network are likely to further enhance the performance of future field-deployable weed-management systems.

REFERENCES

- [1] A. Ahmad, D. Saraswat, V. Aggarwal, A. Etienne, and B. Hancock, "Performance of deep learning models for classifying and detecting common weeds in corn and soybean production systems," *Computers and Electronics in Agriculture*, vol. 184, p. 106081, 2021.
- [2] M. H. Asad and A. Bais, "Weed detection in canola fields using maximum likelihood classification and deep convolutional neural network," *Information Processing in Agriculture*, vol. 7, no. 4, pp. 535–545, 2020.
- [3] M. D. Bah, A. Hafiane, and R. Canals, "Deep learning with unsupervised data labeling for weed detection in line crops in UAV images," *Remote Sensing*, vol. 10, no. 11, p. 1690, 2018.
- [4] A. Bakhshipour and A. Jafari, "Evaluation of support vector machine and artificial neural networks in weed detection using shape features," *Computers and Electronics in Agriculture*, vol. 145, pp. 153–160, 2018.
- [5] A. Bakhshipour, A. Jafari, S. M. Nassiri, and D. Zare, "Weed segmentation using texture features extracted from wavelet sub-images," *Biosystems Engineering*, vol. 157, pp. 1–12, 2017.
- [6] Y. Beeharry and V. Bassoo, "Performance of ANN and AlexNet for weed detection using UAV-based images," in *Proc. 2020 3rd Int. Conf. Emerging Trends Elect., Electron. Commun. Eng. (ELECOM)*, 2020, pp. 163–167.
- [7] A. dos Santos Ferreira, D. M. Freitas, G. G. da Silva, H. Pistori, and M. T. Folhes, "Weed detection in soybean crops using ConvNets," *Computers and Electronics in Agriculture*, vol. 143, pp. 314–324, 2017.
- [8] A. dos Santos Ferreira, D. M. Freitas, G. G. da Silva, H. Pistori, and M. T. Folhes, "Unsupervised deep learning and semi-automatic data labeling in weed discrimination," *Computers and Electronics in Agriculture*, vol. 165, p. 104963, 2019.
- [9] B. Espejo-Garcia, N. Mylonas, L. Athanasakos, S. Fountas, and I. Vasilakoglou, "Towards weeds identification assistance through transfer learning," *Computers and Electronics in Agriculture*, vol. 171, p. 105306, 2020.
- [10] A. Etienne, A. Ahmad, V. Aggarwal, and D. Saraswat, "Deep learning-based object detection system for identifying weeds using UAS imagery," *Remote Sensing*, vol. 13, no. 24, p. 5182, 2021.
- [11] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. 2016 IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2016, pp. 770–778.
- [12] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," *Computers and Electronics in Agriculture*, vol. 147, pp. 70–90, 2018.

- [13] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," *Communications of the ACM*, vol. 60, no. 6, pp. 84–90, 2017.
- [14] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.
- [15] A. Milioto, P. Lottes, and C. Stachniss, "Real-time blob-wise sugar beets vs weeds classification for monitoring fields using convolutional neural networks," *ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci.*, vol. IV-2/W3, pp. 41–48, 2017.
- [16] A. Olsen et al., "DeepWeeds: A multiclass weed species image dataset for deep learning," *Scientific Reports*, vol. 9, no. 1, p. 2058, 2019.
- [17] K. Osorio, A. Puerto, C. Pedraza, D. Jamaica, and L. Rodríguez, "A deep learning approach for weed detection in lettuce crops using multispectral images," *AgriEngineering*, vol. 2, no. 3, pp. 471–488, 2020.
- [18] G. G. Peteinatos, P. Reichel, J. Karouta, D. Andújar, and R. Gerhards, "Weed identification in maize, sunflower, and potatoes with the aid of convolutional neural networks," *Remote Sensing*, vol. 12, no. 24, p. 4185, 2020.
- [19] I. Rakhmatulin, A. Kamilaris, and C. Andreassen, "Deep neural networks to detect weeds from crops in agricultural environments in real-time: A review," *Remote Sensing*, vol. 13, no. 21, p. 4486, 2021.
- [20] I. Sa et al., "weedNet: Dense semantic weed classification using multispectral images and MAV for smart farming," *IEEE Robotics and Automation Letters*, vol. 3, no. 1, pp. 588–595, 2018.
- [21] I. Sa et al., "WeedMap: A large-scale semantic weed mapping framework using aerial multispectral imaging and deep neural network for precision farming," *Remote Sensing*, vol. 10, no. 9, p. 1423, 2018.
- [22] A. Wang, W. Zhang, and X. Wei, "A review on weed detection using ground-based machine vision and image processing techniques," *Computers and Electronics in Agriculture*, vol. 158, pp. 226–240, 2019.
- [23] J. Yu, A. W. Schumann, Z. Cao, S. M. Sharpe, and N. S. Boyd, "Weed detection in perennial ryegrass with deep learning convolutional neural network," *Frontiers in Plant Science*, vol. 10, Art. 1422, 2019.
- [24] J. Yu, A. W. Schumann, S. M. Sharpe, X. Li, and N. S. Boyd, "Detection of grassy weeds in bermudagrass with deep convolutional neural networks," *Weed Science*, vol. 68, no. 5, pp. 545–552, 2020.
- [25] J. Yu, S. M. Sharpe, A. W. Schumann, and N. S. Boyd, "Deep learning for image-based weed detection in turfgrass," *European Journal of Agronomy*, vol. 104, pp. 78–84, 2019.
- [26] J. Yu, S. M. Sharpe, A. W. Schumann, and N. S. Boyd, "Detection of broadleaf weeds growing in turfgrass with convolutional neural networks," *Pest Management Science*, vol. 75, no. 8, pp. 2211–2218, 2019.