Research Article

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A deep learning-based method for classification, detection, and localization of weeds in turfgrass

Xiaojun Jin,[a,b] Muthukumar Bagavathiannan,[c] Patrick E McCullough,[d] Yong Chen[a*] and Jialin Yu[b*]

Abstract

BACKGROUND: Precision spraying of synthetic herbicides can reduce herbicide input. Previous research demonstrated the effectiveness of using image classification neural networks for detecting weeds growing in turfgrass, but did not attempt to discriminate weed species and locate the weeds on the input images. The objectives of this research were to: (i) investigate the feasibility of training deep learning models using grid cells (subimages) to detect the location of weeds on the image by identifying whether or not the grid cells contain weeds; and (ii) evaluate DenseNet, EfficientNetV2, ResNet, RegNet and VGGNet to detect and discriminate multiple weed species growing in turfgrass (multi-classifier) and detect and discriminate weeds (regardless of weed species) and turfgrass (two-classifier).

RESULTS: The VGGNet multi-classifier exhibited an F_1 score of 0.950 when used to detect common dandelion and achieved high F_1 scores of ≥0.983 to detect and discriminate the subimages containing dallisgrass, purple nutsedge and white clover growing in bermudagrass turf. DenseNet, EfficientNetV2 and RegNet multi-classifiers exhibited high F_1 scores of ≥0.984 for detecting dallisgrass and purple nutsedge. Among the evaluated neural networks, EfficientNetV2 two-classifier exhibited the highest F_1 scores (≥0.981) for exclusively detecting and discriminating subimages containing weeds and turfgrass.

CONCLUSION: The proposed method can accurately identify the grid cells containing weeds and thus precisely locate the weeds on the input images. Overall, we conclude that the proposed method can be used in the machine vision subsystem of smart sprayers to locate weeds and make the decision for precision spraying herbicides onto the individual map cells.

Keywords: deep learning; machine vision; precision herbicide application; weed detection

1 INTRODUCTION

Turfgrass is a form of vegetation cover in urban landscapes, including athletic fields, commercial areas, institutional lawns, golf courses, residential lawns and parks. Weeds are troublesome in turfgrass because they compete for sunlight, nutrients and water, reducing turf aesthetics and functionality. Weed management in turfgrass relies predominantly on herbicides broadcast-applied over the turfgrass, including the area without weeds.[1,2] Many herbicides currently used in turfgrass pollute the environment.[3] For example, atrazine, a photosystem II inhibiting herbicide, is used widely for weed control in warm-season turfgrasses,[4,5] but it is one of the most frequently detected herbicides in underground water.[3,6] Monosodium methylarsenate is one of the few effective herbicides for controlling difficult-to-control weeds such as dallisgrass (*Paspalum dilataum* Poir.) in golf courses;[7–9] however, in the United States, only a single application is permitted to be used in newly constructed golf courses or used as spot-application as a consequence of concern over its contamination of groundwater.[10,11]

Machine vision-based precision herbicide application can substantially reduce herbicide input, thereby mitigating the adverse impact on the environment and reducing weed control cost.[12,13] Accurate weed detection is a prerequisite for automatic weed control with smart sprayers.[13] Previous studies documented a variety of machine vision technologies, such as fluorescence,[14] LiDar sensor,[15] hyperspectral imaging[16,17] and spectral reflectance[18,19] for weed detection. In recent years, deep learning, particularly deep convolutional neural networks (DCNNs), has demonstrated extraordinary capabilities in object detection and image classification,[20,21] and is employed for real-time weed

* Correspondence to: Y Chen, College of Mechanical and Electronic Engineering, Nanjing Forestry University, Nanjing, 210037, China, E-mail: chenyongjsnj@163.com; or J Yu, Peking University Institute of Advanced Agricultural Sciences, Shandong Laboratory of Advanced Agricultural Sciences, Weifang, Shandong 261325, China. Email: jialin.yu@pku-iaas.edu.cn

a College of Mechanical and Electronic Engineering, Nanjing Forestry University, Nanjing, China

b Peking University Institute of Advanced Agricultural Sciences, Shandong Laboratory of Advanced Agricultural Sciences, Weifang, Shandong, China

c Department of Soil and Crop Sciences, Texas A&M University, College Station, TX, USA

d Department of Crop and Soil Sciences, University of Georgia, Griffin, GA, USA

detection.[13,22,23] Recent studies documented that DCNNs can effectively detect weeds in various cropping systems, such as corn (*Zea mays* L.),[24] soybean (*Glycine max* L. Merrill),[24,25] and plastic-mulched small fruiting and vegetable crops.[26,27] Sharpe *et al*. performed goosegrass (*Eleusine indica* L.) detection in strawberry (*Trifolium fragiferum* L.) and tomato (*Solanum lycopersicum* L.) with tiny YOLO-v3.[28] Sivakumar *et al*. reported that Faster R-CNN reliably identified late-season weeds in soybean fields.[29] Recently, Jin *et al*. trained and evaluated the performance of YOLO-v3, CenterNet and Faster R-CNN to detect bok choy (*brassica rapa* spp. chinensis) and identify all other green objects as weeds.[30]

The feasibility of using DCNNs for weed detection in turfgrass was first documented by Yu *et al*.,[31] who reported that DetectNet effectively detected cutleaf evening-primrose (*Oenothera laciniata* Hill) growing in bahiagrass (*Paspalum notatum* Flugge), whereas VGGNet effectively detected various broadleaf weeds growing in dormant bermudagrass (*Cynodon dactylon* L. Pers.). Later, Yu *et al*.[32,33] evaluated various object detection and image classification neural networks, including AlexNet, DetectNet, GoogLeNet and VGGNet, for weed detection in perennial ryegrass (*Lolium perenne* L.) and bermudagrass, and found that image classification DCNNs are well-performed in classifying and discriminating the images containing weeds growing in turfgrass and the images containing turfgrass exclusively. For example, VGGNet achieved an outstanding performance (overall accuracy = 1.00) at detecting crabgrass (*Digitaria* spp.), doveweed [*Murdannia nudiflora* (L.) Brenan], dallisgrass and tropical signalgrass [*Urochloa distachya* (L.) T.Q. Nguyen] in bermudagrass.[33] In more recent studies, Xie *et al*.[34] and Medrano[35] demonstrated the effectiveness of using object detection neural networks, including Faster R-CNN, Mask R-CNN and You Only Look Once, for the detection of nutsedges (*Cyperus* spp.) and common dandelion (*Taraxacum officinale* Web.) in bermudagrass.

Despite all recent success, image classification DCNNs for detecting weeds in turfgrass still present challenges.[31–33,36] For example, Yu *et al*.[31] trained neural networks using a total of 36 000 images containing 18 000 positive (images containing weeds) and 18 000 negative (images containing turfgrass only) images for detection of multiple weed species including dollar weed (*Hydrocotyle* spp.), old world diamond-flower (*Hedyotis cormybosa* L. lam.) and Florida pusely (*Richardia scabra* L.) growing in bermudagrass. Although the developed neural networks achieved excellent performance for weed detection,[31] manually classifying a large amount of images for preparing the training datasets is time-consuming and labor-intensive. Moreover, previous studies evaluated the use of image classification DCNNs to detect a single weed species or simultaneously detect multiple weed species.[31–33,36] None of the previous studies attempted to train DCNNs to discriminate different weed species growing in turfgrass. Common dandelion, dallisgrass, purple nutsedge (*Cyperus rotundus* L.) and white clover (*Trifolium repens* L.) are commonly found in turf landscapes.[37,38] Synthetic auxin herbicides (e.g. 2,4-D, dicamba and MCPP) only control broadleaf weeds,[39,40] Acetyl-CoA carboxylase inhibitors (e.g. pinoxaden) only control grass weeds[41,42]; and halosulfuron-methyl, an acetolactate synthase inhibitor, can effectively control purple nutsedge, but provides erratic control of dallisgrass in bermudagrass turf.[43] Effective discrimination of these weed species may allow the smart sprayer to spray particular herbicides to control the susceptible weeds and reduce herbicide use.

Both object detection and image classification neural networks can be employed as the machine vision system of a smart herbicide sprayer. Object detection neural networks permit the localization of individual weeds, but the training of object detection neural networks is labor-intensive and time-consuming because it requires labeling individual weeds with bounding boxes.[23] Moreover, in most cases, nozzles generate a specific size of spraying outputs whereas the size of the bounding boxes around individual weeds varies. Therefore, the outputs of object detection neural networks cannot be used to directly guide and control the nozzles. In previous research, image classification neural networks were only used to identify whether or not the input images contained weeds and did not attempt to locate weed infestation zones on the images.[31–33,36] The exact position of weeds in the input image needs to be determined to realize precision herbicide application with a smart sprayer. In this study, weed infestation zones (in terms of grid cells) were detected and localized instead of identifying each individual weed in turf. Grid cells were created on the input images, and image classification neural networks were employed to detect if the grid cells contained the target weeds. The objectives of this research were to examine the feasibility of using the proposed method to: (i) build grid cell maps on the input images and detect precise locations of weeds by identifying if the grid cells contain weeds; (ii) classify multiple weed species while growing in turfgrass and identify the exact location of each weed species in the input images; and (iii) classify weeds and turfgrass, and identify the location of weeds, regardless of weed species, in the input images.

2 MATERIALS AND METHODS

2.1 Overview

Five image classification DCNN architectures, including Densely Connected Convolutional Networks (DenseNet),[44] EfficientNet,[45] ResNet,[46] RegNet[47] and VGGNet,[48] were investigated for the capability of weed detection in bermudagrass. DenseNet alleviates the vanishing-gradient issue, strengthens feature propagation, promotes feature reuse and decreases the number of parameters.[44] It can compute dense, multiscale features from the convolutional layers of a DCNN-based object classifier.[44] EfficientNet is a straightforward yet efficient compound scaling method that consistently scales network depth, width and resolution with a set of fixed scaling coefficients.[45] ResNet introduced the concept of residual learning by employing identity-based skip connection in each residual unit to build very deep networks, which ease the flow of information across units and can gain accuracy from considerably increased depth.[46] RegNet is capable of training deeper networks due to its shortcut connection mechanism in which the gradient can directly flow through the block.[47] VGGNet is composed of 16 weight layers.[48] VGGNet utilizes a stack of convolution layers with small receptive fields in the first layer.[48] ResNet and VGGNet are two of the most classic neural networks and have been widely used in various research fields. DenseNet has been developed specifically to improve the declined accuracy caused by the vanishing gradient issue and is less prone to overfitting. RegNet and EfficientNetV2 are the most recent state-of-the-art neural networks and have not been investigated previously for detecting weeds in turfgrass. These three types of DCNN architectures were used for training multi-classifiers or two-classifiers. The multi-classifier neural networks were used for classifying and discriminating if the grid cells contain common dandelion, dallisgrass, purple nutsedge or white clover growing in bermudagrass, or exclusively contain bermudagrass without weeds; and the two-classifier was used for discriminating and identifying if the grid cells contain weeds (regardless of species) or exclusively contain bermudagrass without weeds.

2.2 Image acquisition

The training images of common dandelion, dallisgrass and white clover growing in bermudagrass were acquired at the University of Georgia Griffin Campus in Griffin, Georgia, USA (33.26°N, 84.28°W), whereas the testing images were taken primarily in multiple golf courses in Peachtree City, Georgia, USA (33.39°N, 84.59°W). The training images of purple nutsedge were acquired at sod farms in Jiangning District, Nanjing, Jiangsu, China (31.95° N, 118.85°E), whereas the testing images were taken in sod farms in Shuyang, Jiangsu, China (34.12°N, 118.79°E). The training and testing images of common dandelion (mature stage but before inflorescence emergence), dallisgrass (mature stage before inflorescence emergence) and white clover (mostly rosette phase) were acquired in autumn 2018 using a digital camera (DSC-HX1, SONY®, Cyber-Shot Digital Still Camera; SONY Corp., Minato, Tokyo, Japan). The training and testing images of purple nutsedge (mostly three-leaf stage) were acquired in spring 2021 using a digital camera (DMC-ZS110; Panasonic®, Xiamen, Fujian, China). The images were adjusted at a height to obtain a ground-sampling distance of 0.05 cm pixel^{-1}. The training and testing images at a ratio of 16:9, with a resolution of 1920 × 1080 pixels, were taken in various light conditions, including clear, cloudy and partially cloudy weather.

2.3 Image classification and weed detection

The training images containing a single weed species at the original resolution of 1920 × 1080 pixels were randomly selected for populating the training datasets. For each weed species, a total of 100 images were randomly selected, and each was equally cropped to 40 subimages of 240 × 216 pixels using IRFANVIEW (v5.50, Irfan Skijan, Jajce, Bosnia), resulting in a total of 1640,

Table 1. Hyper-parameters used for training the neural networks

Neural network	Optimizer	Base learning rate	Learning rate policy	Batch size	Training epochs
DenseNet	SGD	0.001	LambdaLR	16	24
EfficientNetV2	SGD	0.01	LambdaLR	2	24
ResNet	Adam	0.0001	StepLR	16	24
RegNet	SGD	0.001	LambdaLR	16	24
VGGNet	Adam	0.0001	StepLR	16	24

SGD, stochastic gradient descent.

Table 2. Weed detection validation and testing results when the neural networks were trained with the multi-classifier system

		Validation			Testing		
Neural network	Weed species	Precision	Recall	F_1 score	Precision	Recall	F_1 score
DenseNet	Bermudagrass	0.997	0.997	0.997	0.994	0.983	0.988
	Common dandelion	0.989	1.000	0.994	0.974	0.949	0.961
	Dallisgrass	0.983	1.000	0.991	0.991	1.000	0.995
	Purple nutsedge	1.000	0.993	0.996	0.977	0.992	0.984
	White clover	1.000	0.976	0.988	0.983	0.994	0.988
EfficientNetV2	Bermudagrass	1.000	0.992	0.996	0.997	0.974	0.985
	Common dandelion	1.000	1.000	1.000	0.974	0.974	0.974
	Dallisgrass	0.973	1.000	0.986	0.982	0.991	0.986
	Purple nutsedge	1.000	1.000	1.000	0.977	1.000	0.988
	White clover	1.000	0.984	0.992	0.972	0.994	0.983
ResNet	Bermudagrass	0.987	0.987	0.987	0.991	0.937	0.963
	Common dandelion	1.000	1.000	1.000	0.973	0.923	0.947
	Dallisgrass	0.967	0.978	0.972	0.982	1.000	0.991
	Purple nutsedge	1.000	0.993	0.996	0.984	0.992	0.988
	White clover	0.992	0.984	0.988	0.902	0.994	0.946
RegNet	Bermudagrass	0.995	0.997	0.996	0.994	0.957	0.975
	Common dandelion	0.968	1.000	0.984	0.975	1.000	0.987
	Dallisgrass	0.994	0.978	0.986	1.000	0.982	0.991
	Purple nutsedge	1.000	0.993	0.996	0.984	1.000	0.992
	White clover	0.976	0.976	0.976	0.930	0.994	0.961
VGGNet	Bermudagrass	0.995	0.997	0.996	0.994	0.980	0.987
	Common dandelion	0.968	1.000	0.984	0.927	0.974	0.950
	Dallisgrass	1.000	0.966	0.983	0.991	0.982	0.986
	Purple nutsedge	1.000	1.000	1.000	0.969	1.000	0.984
	White clover	0.977	0.992	0.984	0.989	0.989	0.989

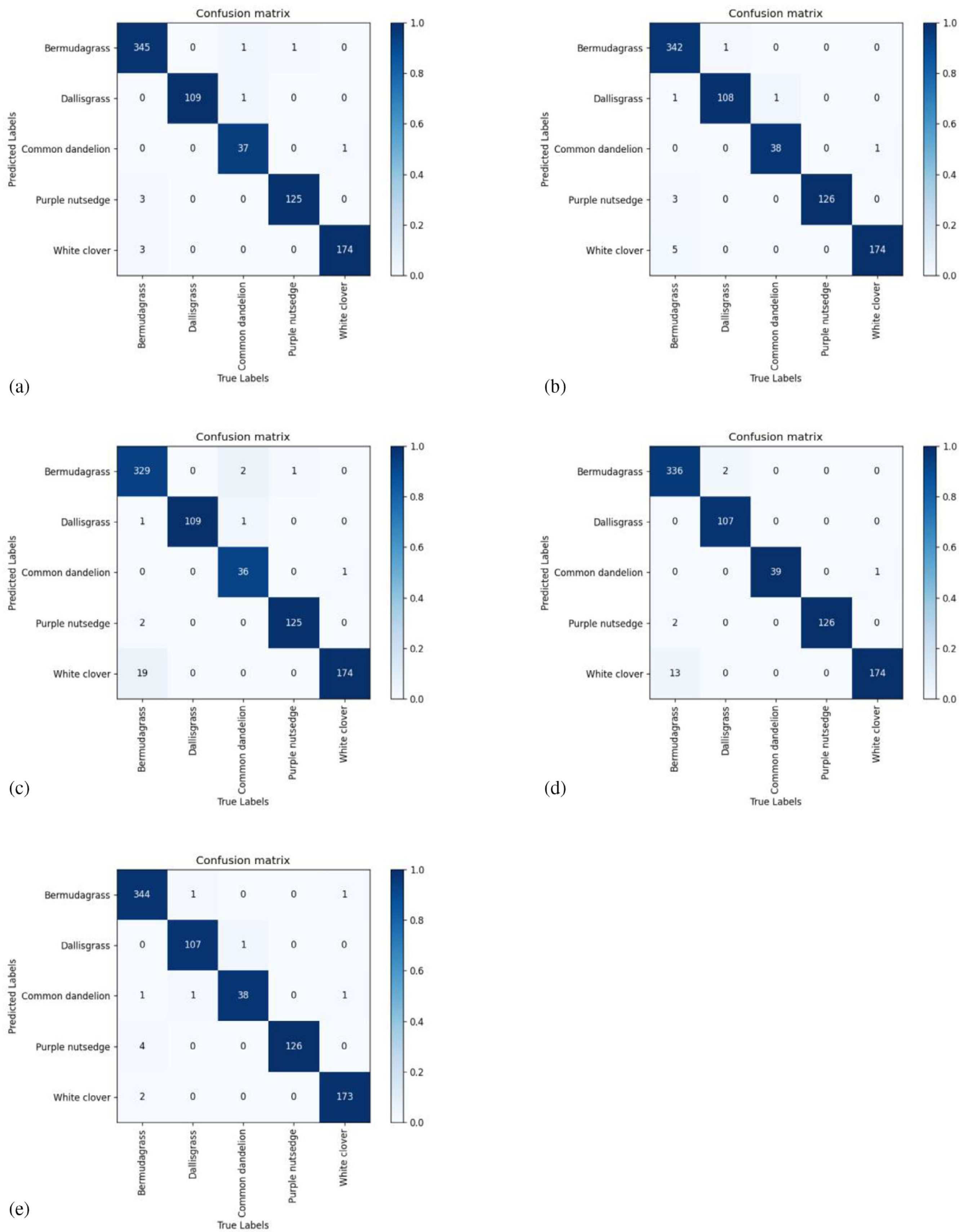

Figure 1. Confusion matrices of the multi-classifiers: (a) DenseNet, (b) EfficientNetV2, (c) ResNet, (d) RegNet and (e) VGGNet.

2010, 2066 and 1492 subimages contained common dandelion, dallisgrass, purple nutsedge or white clover growing in bermudagrass, respectively, and a total of 8113 subimages exclusively contained bermudagrass.

In order to constitute the training dataset of the multi-classifier neural networks, a total of 1490, 1810, 1866 and 1342 subimages (240 × 216 pixels) containing common dandelion, dallisgrass, purple nutsedge or white clover growing in bermudagrass were randomly selected and used as the true positive images (labeled as *common dandelion*, *dallisgrass*, *purple nutsedge* or *white clover*, respectively); and a total of 7313 subimages containing bermudagrass exclusively were randomly selected and used as the true negative images (labeled as *bermudagrass*). The two-classifier neural networks were used to discriminate turfgrass area containing weeds from the area without weeds. To constitute the training dataset of the two-classifier neural networks, the aforementioned subimages containing weeds (for training the multi-classifier neural networks) were pooled and used as the true positive images (labeled as *spray*), whereas the aforementioned subimages containing bermudagrass only (for training the multi-classifier neural networks) were used as the true negative images (labeled as *nonspray*).

In order to constitute the validation dataset of the multiclassifier neural networks, a total of 150, 200, 200 and 150 subimages containing common dandelion, dallisgrass, purple nutsedge or white clover growing in bermudagrass were randomly selected and used as the true positive images, respectively; and a total of 800 subimages containing bermudagrass only were randomly selected and used as true negative images. To constitute the testing dataset of the multi-classifier neural networks, a total of five images (1920 × 1080 pixels) for each weed species were randomly selected, and each image was cropped to 40 subimages (240 × 216 pixels) using IRFANVIEW, resulting in a total of 39, 109, 126, and 175 subimages containing common dandelion, dallisgrass, purple nutsedge, or white clover growing in bermudagrass (true positive images), respectively; and 351 subimages containing bermudagrass only (true negative images).

In order to constitute the validation dataset of the two-classifier neural networks, the aforementioned subimages containing common dandelion, dallisgrass, purple nutsedge or white clover growing in bermudagrass (used in the validation dataset of the multi-classifier neural networks) were combined and used as the true positive images, whereas the aforementioned subimages containing bermudagrass only (used for the validation of the multi-classifier neural networks) were used as the true negative images. To constitute the testing datasets of the two-classifier, the subimages containing weeds (used in the testing dataset of the multi-classifier neural networks) were combined and used as the true positive images, whereas the subimages containing bermudagrass only (used for testing the multi-classifier neural networks) were used as the true negative images.

Because we used a relatively small dataset to train the neural networks, data augmentation techniques, including rotation, flip, brightness and blur, were performed to enrich the training dataset. The neural network training and testing were performed on the Pytorch deep learning framework (available at https://pytorch.org/; Facebook, San Jose, California, United States). The training and testing were carried out on a GeForce RTX 2080 Ti with 64 Gb memory. To ensure a fair comparison between the results of all deep learning models, default hyperparameters of each neural network were used and configured (Table 1).

The neural network classification results for the multi-classifier or two-classifier neural networks were arranged in a binary classification confusion matrix under four categories including true positive (TP), false positive (FP), true negative (TN) and false negative (FN). A TP represents the neural network that correctly identified the target; an FP represents the neural network that incorrectly predicted the target; a TN represents the neural network that correctly identified the images without the target; and an FN represents the neural network that failed to predict the true target. Precision, recall and F_1 score were calculated according to the confusion matrices to assess neutral network effectiveness.

Precision measures the capability of the neural network to accurately identify the target and was computed using the following equation:[49]

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{1}$$

Recall measures the effectiveness of the neural network identified the target and was computed with the following equation[49]:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2}$$

F_1 score is the harmonic mean of the precision and recall values and was calculated using the following equation[49]:

Table 3. Validation and testing results when the neural networks were trained with the two-classifier system

		Validation			Testing		
Neural network	Herbicide spraying	Precision	Recall	F_1 score	Precision	Recall	F_1 score
DenseNet	nonspray	0.992	0.997	0.994	0.988	0.934	0.960
	spray	0.998	0.994	0.996	0.951	0.991	0.971
EfficientNetV2	nonspray	0.989	0.995	0.992	0.988	0.974	0.981
	spray	0.996	0.993	0.994	0.980	0.991	0.985
ResNet	nonspray	0.997	0.995	0.996	0.988	0.943	0.965
	spray	0.996	0.998	0.997	0.957	0.991	0.974
RegNet	nonspray	0.992	0.995	0.993	0.972	0.977	0.974
	spray	0.996	0.994	0.995	0.982	0.978	0.980
VGGNet	nonspray	0.992	0.989	0.990	0.991	0.972	0.981
	spray	0.993	0.994	0.993	0.978	0.993	0.985

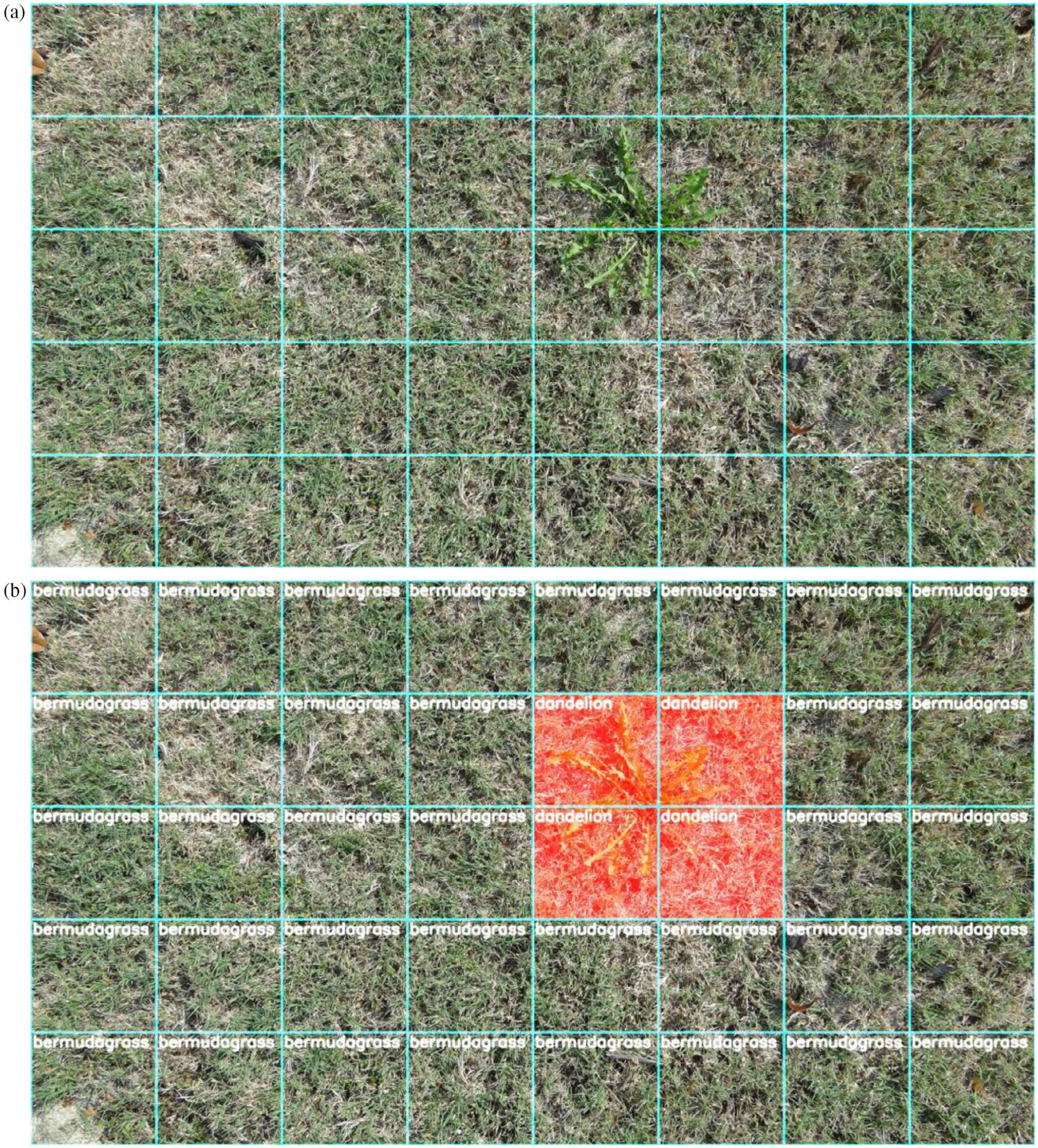

Figure 2. Common dandelion patch localization using the proposed method: (a) grid mapping of the input image (1920 × 1080 pixels) containing common dandelion, and (b) the neural network successfully predicted the grid cells (240 × 216 pixels) containing common dandelion while growing in bermudagrass (red) and bermudagrass only.

$$F_1\ \text{score} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \qquad (3)$$

2.4 Inference for weed location

A custom software integrated with OpenCV-Python and the neural network model was utilized to generate the grid cells on the input images and infer if the grid cells contained weeds. The custom software cropped each input image (1920 × 1080 pixels) to a total of 40 equal-size grid cells (240 × 216 pixels subimages). In a practical precision sprayer design, the physical size represented by each grid cell (depending on image resolution and the distance between the camera and the ground) should be equal to or slightly smaller than the size of the area in which one nozzle

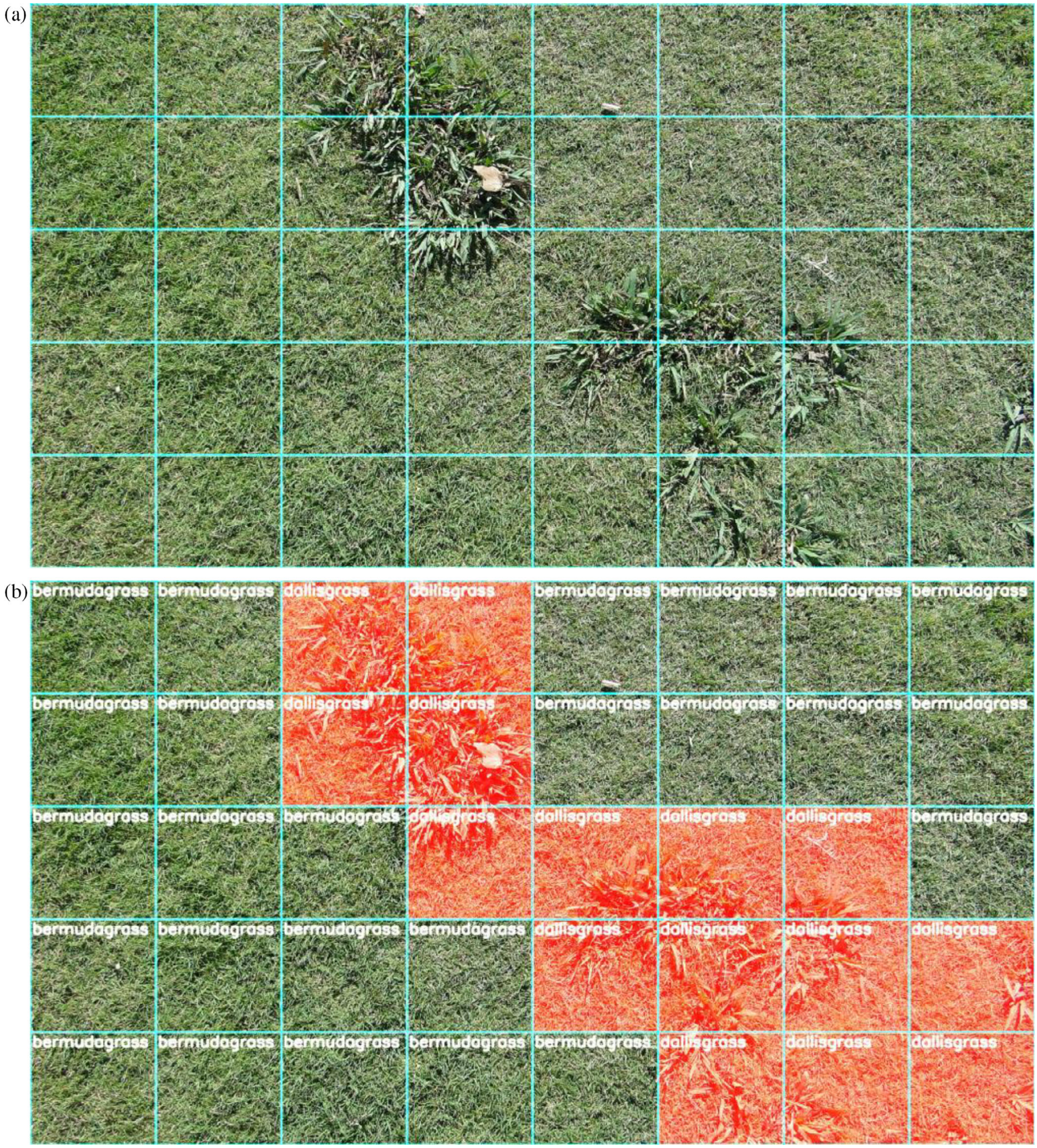

Figure 3. Dallisgrass patch localization using the proposed method: (a) grid mapping of the input image (1920 × 1080 pixels) containing dallisgrass, and (b) the neural network successfully predicted the grid cells (240 × 216 pixels) containing dallisgrass while growing in bermudagrass (red) and bermudagrass only.

is covered. However, higher accuracy should be possible by using a smaller cell size.[50] In this study, each nozzle represents a 240 × 216-pixels control zone in the images.

The trained neural networks were employed to infer if the grid cells contained weeds. The grid cells were marked as spraying areas if the inference result indicated they contained weeds. With a subsequent decision-making system, a binary input decision could be made to turn off the spray nozzle over all the weed-free cells (on/off nozzle control). By applying this strategy, each individual spray nozzle is controlled separately.

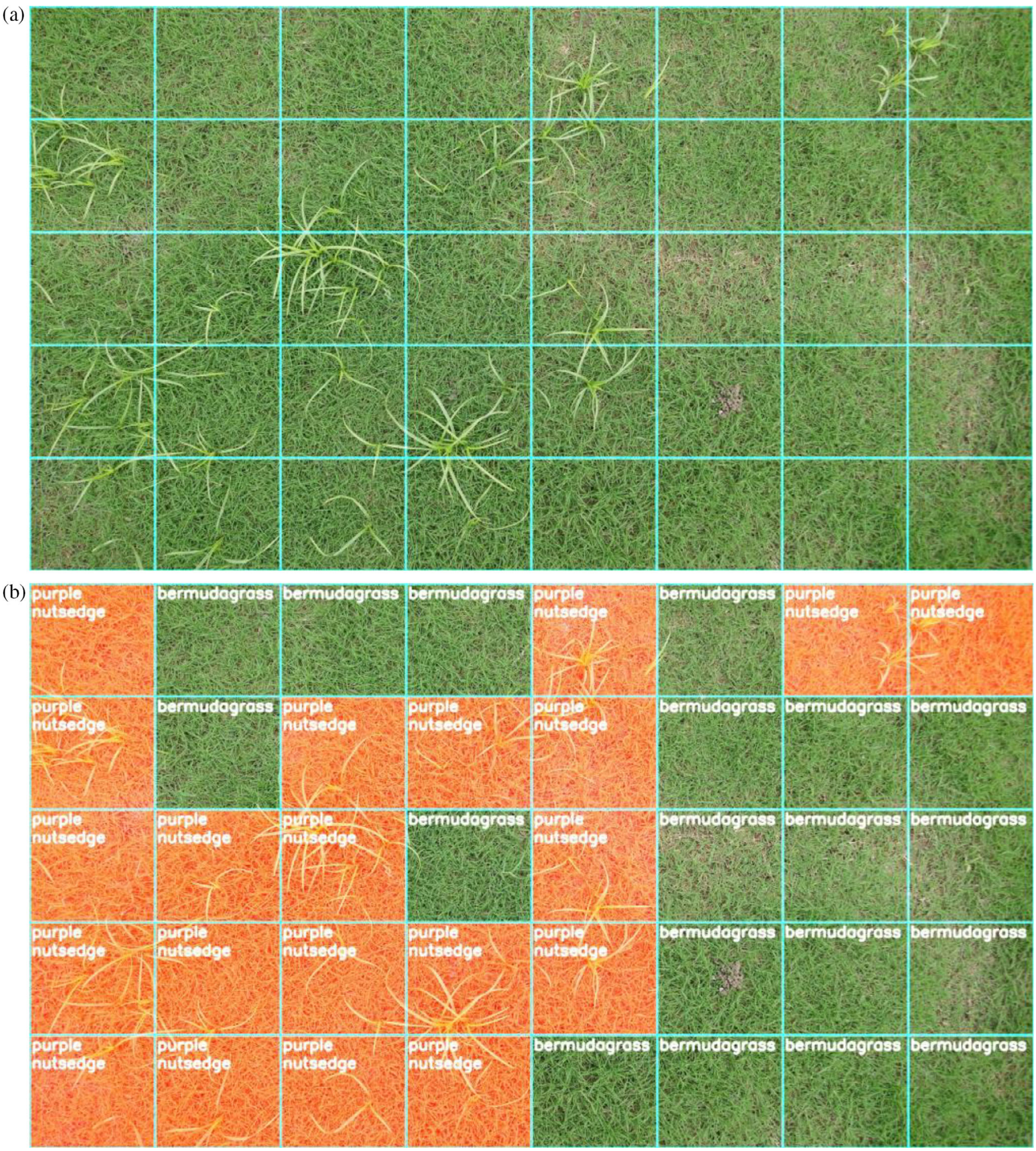

Figure 4. Purple nutsedge patch localization using the proposed method: (a) grid mapping of the input image (1920 × 1080 pixels) containing purple nutsedge, and (b) the neural network successfully predicted the grid cells (240 × 216 pixels) containing purple nutsedge while growing in bermudagrass (red) and bermudagrass only.

3 RESULTS

3.1 Weed detection

No obvious differences were observed among the multi-classifier neural networks for detecting and discriminating different weed species growing in turfgrass (Table 2). All multi-classifier neural networks, including DenseNet, EfficientNetV2, ResNet, RegNet and VGGNet, exhibited excellent F_1 scores (≥0.972) with high precision and recall values in the validation datasets for discriminating different weed species growing in turfgrass. In general, the performances of weed detection were slightly reduced in the testing datasets compared to the validation datasets for all neural networks.

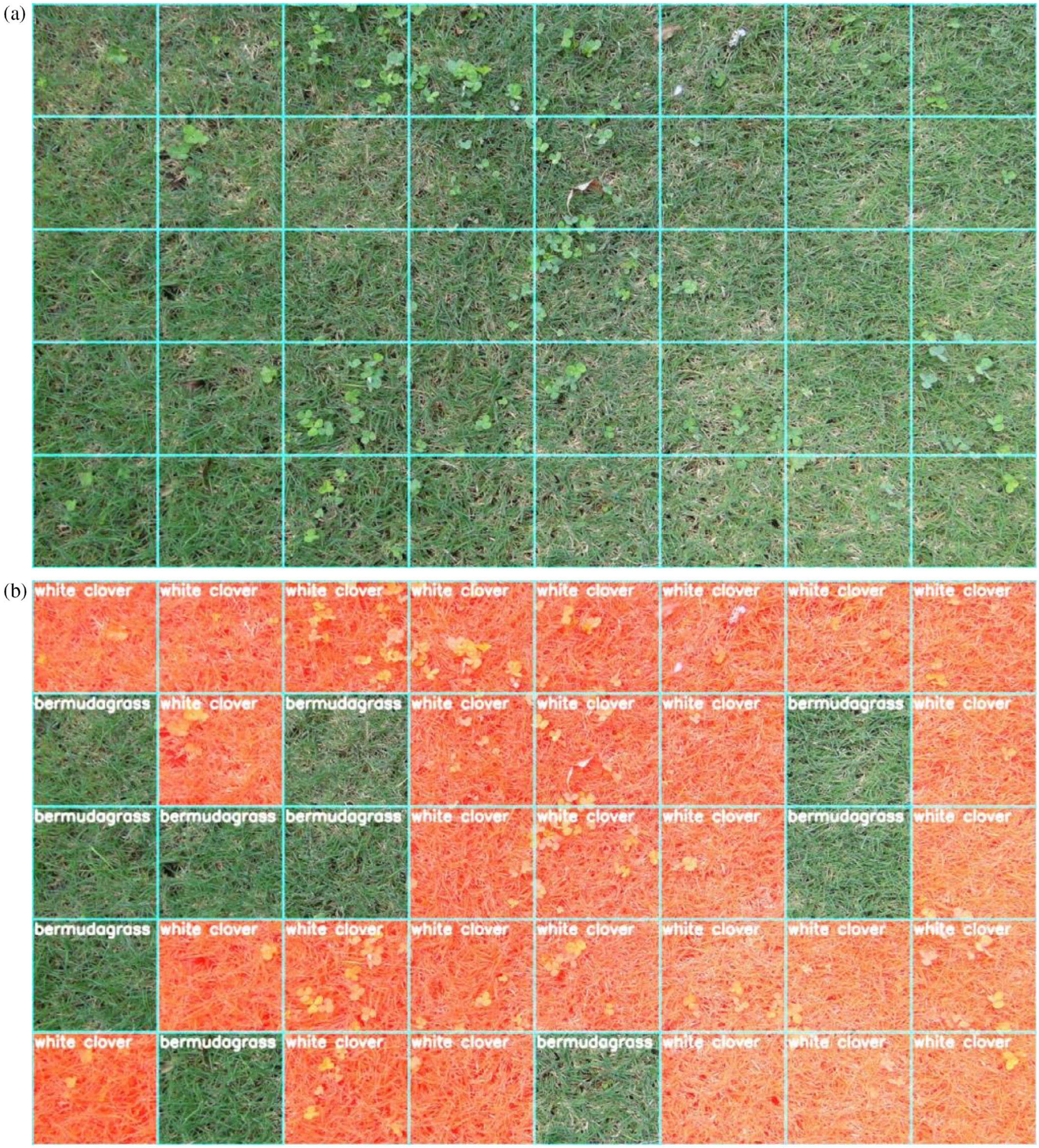

Figure 5. White clover patch localization using the proposed method: (a) grid mapping of the input image (1920 × 1080 pixels) containing white clover, and (b) the neural network successfully predicted the grid cells (240 × 216 pixels) containing white clover while growing in bermudagrass (red) and bermudagrass only.

Among the evaluated neural networks, the RegNet multi-classifier exhibited the highest F_1 score (0.987) in the testing dataset when detecting common dandelion growing in turfgrass. For detecting and discriminating white clover, the F_1 score of ResNet multi-classifier was 0.946 in the testing dataset, whereas the F_1 scores of all other multi-classifier neural networks never fell below 0.961. DenseNet, EfficientNetV2 and RegNet showed high F_1 scores (≥0.984) in the validation and testing datasets to detect dallisgrass or purple nutsedge.

A further analysis of the confusion matrices of multi-classifier neural networks showed that RegNet and ResNet had low classification accuracy mainly due to the misclassification of bermudagrass and

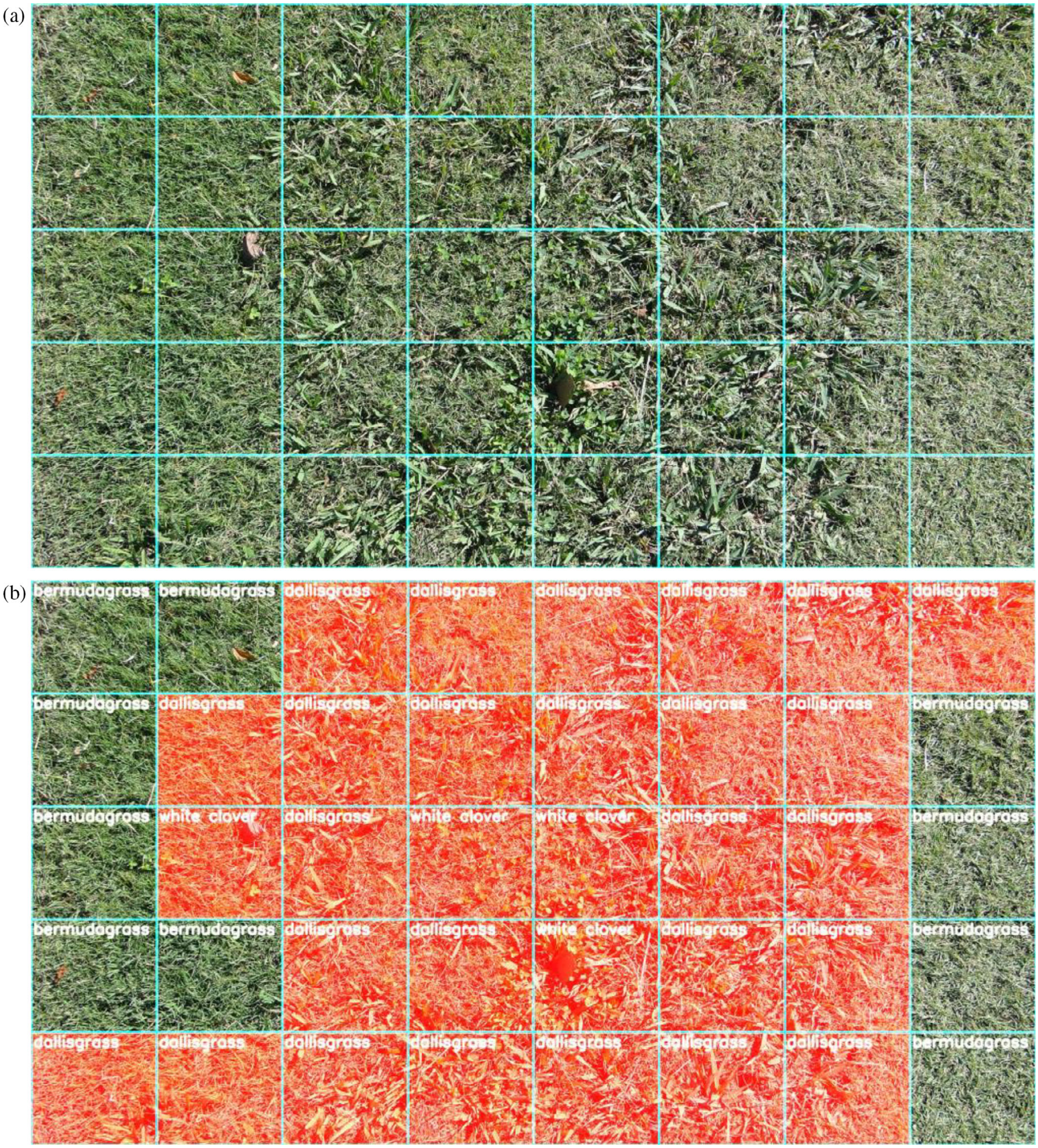

Figure 6. Dallisgrass and white clover patch localization using the proposed method: (a) grid mapping of the input image (1920 × 1080 pixels) containing dallisgrass and white clover, and (b) the neural network successfully predicted the grid cells (240 × 216 pixels) containing weeds (dallisgrass or white clover) (red) and bermudagrass only.

white clover (Fig. 1). EfficientNetV2 and VGGNet misclassified three and four bermudagrass as purple nutsedge, respectively. Nevertheless, increasing the number of training images containing such weed species probably can reduce the occurrence of this type of misclassification.

All two-classifier neural networks exhibited high F_1 scores in the validation datasets (≥0.990) for discriminating the subimages containing weeds, regardless of species (*spray*) and the subimages containing bermudagrass turfgrass exclusively (*nonspray*) (Table 3). All two-classifier neural networks had slightly reduced precision and recalled values in the testing datasets, but the F_1 scores never fell below 0.960. The EfficientNetV2 two-classifier showed the highest F_1 scores in the validation and testing datasets (≥0.981).

The inference speeds of DenseNet, EfficientNetV2, ResNet, RegNet and VGGNet, in terms of frames per second (FPS), were 51.98, 31.08, 86.24, 36.15 and 12.46, respectively. Because the camera acquires images at a resolution of 1920 × 1080 pixels, the FPS values for the original images were measured using an NVIDIA GeForce RTX 2080 Ti graphic processing unit by inferring the subimages with a batch size value of 40. ResNet demonstrated a significant speed advantage over the other investigated neural networks, whereas the low inference speed of the VGGNet may limit its applications.

3.2 Inference for weed location

The images shown in Figs 2, 3, 4 and 5 contain a single weed species of common dandelion, dallisgrass, purple nutsedge and white clover growing in bermudagrass turf. For each input image, a total of four, 15, 21 and 30 cells of 40 grid cells were marked as red which represented that they contained common dandelion, dallisgrass, purple nutsedge or white clover growing in bermudagrass turf, respectively; and a total of 36, 25, 19 and 10 cells represented that they contained bermudagrass exclusively, respectively.

The images shown in Fig. 6 contain multiple weed species of common dandelion and white clover growing in bermudagrass. A total of 30 cells (26 cells contained common dandelion and four contained white clover) of 40 grid cells were marked as red [Fig. 6 (b)], which represented that they contained weeds, whereas a total of 10 cells represented that they contained merely bermudagrass turf.

As shown in Figs 2–6, when the grid cells contain a single weed species, the present method can be used to identify weed species within the grid cells and locate the grid cells containing weeds. When the grid cells contain multiple weed species, the present method can effectively locate the grid cells containing weeds, but it cannot accurately identify all weed species within the grid cells.

The exact grid cells on the input images containing weeds are located with *x,y* coordinates. Afterward, only the nozzles corresponding to those cells infested with weeds are turned on, thus realizing a smart sensing and spraying system.

4 DISCUSSION

In previous research, image classification neural networks demonstrated excellent performances for detecting images containing weeds growing in turfgrass.[31,33] DenseNet, EfficientNetV2, ResNet and RegNet previously had not been investigated for detecting weeds growing in turfgrass. In the present research, these neural networks exhibited similar performances for detecting weeds growing in turfgrass compared to VGGNet.

The grid cells were created on the input images, and image classification neural networks were employed to detect if the grid cells contained the target weeds. When image classification neural networks are utilized in the machine vision subsystem of the smart sprayers, herbicides need to be delivered using the nozzles that can generate the same or larger spraying outputs to cover the grid cells. By utilizing this strategy, we could realize precision herbicide application so long as we can detect the presence/absence of the target weeds within grid cells.

It should be noted that only four weed species were evaluated in the present study. Although the neural networks achieved high classification rates with multi-classifier neural networks, more positive images of the training dataset comprising a greater diversity of weed species are highly desired. Increasing training image quantities probably can increase the performance of weed discrimination; however, expanding the training and testing images to include more weed species, especially morphologically similar weeds, may reduce classification performance. The inclusion of the neural networks to have a wider variety of weed species with similar morphological features needs to be the next immediate step of this study.

Yu *et al*.[32] trained a neural network for detecting common dandelion, ground ivy (*Glechoma hederacea* L.) and spotted spurge (*Euphorbia maculata* L.) growing in perennial ryegrass using binary classification. The authors found that the ratios of positive and negative images in the training dataset affected the performances of the neural networks for weed detection. Recently, Zhuang *et al*.[51] reported that increasing training image sizes from 200 × 200 pixels to 400 × 400 pixels increased the F_1 scores of DenseNet and ResNet, but generally decreased those of AlexNet and VGGNet for the detection of broadleaf weed seedlings growing in wheat (*Triticum aestivum* L.). However, the authors noted that increasing training image numbers increased classification accuracy, diminishing the differences in training image sizes. Additional research is needed to investigate the impacts of the weed species ratios in the true positive images when training neural networks for weed detection. In addition, the implications of training image sizes and quantities on the performance of neural networks for weed detection in turfgrass might need to be evaluated in order to improve the precision and recall further, and to enhance the overall accuracy of weed detection.

5 CONCLUSION

In summary, the developed multi-classifier neural networks can effectively detect and discriminate between subimages containing multiple weed species growing in turfgrass or containing turfgrass exclusively. The developed two-classifier neural networks can effectively detect and discriminate between subimages containing weeds (regardless of weed species) and those containing turfgrass only. This is the first study attempting to locate weeds using image classification neural networks. The developed multi-classifier neural networks used in conjunction with the proposed method can effectively identify and locate the grid cells containing common dandelion, dallisgrass, purple nutsedge or white clover growing in turfgrass. The developed two-classifier neural networks can effectively identify and locate the grid cells containing weeds growing in turfgrass, regardless of weed species. The proposed method for classifying, detecting and localizing weeds can be used in a machine vision subsystem with an automatic herbicide sprayer to create a smart sensing and spraying system.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

REFERENCES

1 McElroy J and Martins D, Use of herbicides on turfgrass. *Planta Daninha* **31**:455–467 (2013).
2 Dai X, Xu Y, Zheng J and Song H, Analysis of the variability of pesticide concentration downstream of inline mixers for direct nozzle injection systems. *Biosyst Eng* **180**:59–69 (2019).
3 Pimentel D and Burgess M, Environmental and economic costs of the application of pesticides primarily in the United States, in *Integrated Pest Management*. Springer, Dordrecht, Netherlands, pp. 47–71 (2014).
4 McCullough PE, Yu J and de Barreda DG, Seashore paspalum (*Paspalum vaginatum*) tolerance to pronamide applications for annual bluegrass control. *Weed Technol* **26**:289–293 (2012).
5 Yu J and McCullough PE, Efficacy and fate of atrazine and simazine in doveweed (*Murdannia nudiflora*). *Weed Sci* **64**:379–388 (2016).
6 Wang A, Hu X, Wan Y, Mahai G, Jiang Y and Huo W, A nationwide study of the occurrence and distribution of atrazine and its degradates in tap water and groundwater in China: assessment of human exposure potential. *Chemosphere* **252**:126533 (2020).
7 Henry G, Burton J, Richardson R and Yelverton F, Absorption and translocation of foramsulfuron in dallisgrass (*Paspalum dilatatum*) following preapplication of MSMA. *Weed Sci* **56**:785–788 (2008).
8 Matteson AR, Gannon TW, Jeffries MD, Haines S, Lewis DF and Polizzotto ML, Arsenic retention in foliage and soil after monosodium methyl arsenate (MSMA) application to turfgrass. *J Environ Qual* **43**:379–388 (2014).
9 Yu J, McCullough PE and Czarnota MA, Selectivity and fate of monosodium methylarsenate in bermudagrass, centipedegrass, and seashore paspalum. *Crop Sci* **57**:322–330 (2017).
10 Bergtold JS, Ramsey S, Maddy L and Williams JR, A review of economic considerations for cover crops as a conservation practice. *Renewable Agric Food Syst* **34**:62–76 (2019).
11 Risal A, Parajuli PB, Dash P, Ouyang Y and Linhoss A, Sensitivity of hydrology and water quality to variation in land use and land cover data. *Agric Water Manage* **241**:106366 (2020).
12 Fennimore SA, Slaughter DC, Siemens MC, Leon RG and Saber MN, Technology for automation of weed control in specialty crops. *Weed Technol* **30**:823–837 (2016).
13 Fennimore SA and Cutulle M, Robotic weeders can improve weed control options for specialty crops. *Pest Manage Sci* **75**:1767–1774 (2019).
14 Su W-H, Slaughter DC and Fennimore SA, Non-destructive evaluation of photostability of crop signaling compounds and dose effects on celery vigor for precision plant identification using computer vision. *Comput Electron Agric* **168**:105155 (2020).
15 Peteinatos GG, Weis M, Andújar D, Rueda Ayala V and Gerhards R, Potential use of ground-based sensor technologies for weed detection. *Pest Manage Sci* **70**:190–199 (2014).
16 Wendel A and Underwood J, Self-supervised weed detection in vegetable crops using ground based hyperspectral imaging, in *2016 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, Stockholm, Sweden, pp. 5128–5135 (2016).
17 Jiang H, Jiang X, Ru Y, Wang J, Xu L and Zhou H, Application of hyperspectral imaging for detecting and visualizing leaf lard adulteration in minced pork. *Infrared Phys Technol* **110**:103467 (2020).
18 Wang A, Zhang W and Wei X, A review on weed detection using ground-based machine vision and image processing techniques. *Comput Electron Agric* **158**:226–240 (2019).
19 Osorio K, Puerto A, Pedraza C, Jamaica D and Rodríguez L, A deep learning approach for weed detection in lettuce crops using multispectral images. *AgriEngineering* **2**:471–488 (2020).
20 LeCun Y, Bengio Y and Hinton G, Deep learning. *Nature* **521**:436–444 (2015).
21 Shi J, Li Z, Zhu T, Wang D and Ni C, Defect detection of industry wood veneer based on NAS and multi-channel mask R-CNN. *Sensors* **20**:4398 (2020).
22 Liakos KG, Busato P, Moshou D, Pearson S and Bochtis D, Machine learning in agriculture: a review. *Sensors* **18**:2674 (2018).
23 Hasan AM, Sohel F, Diepeveen D, Laga H and Jones MG, A survey of deep learning techniques for weed detection from images. *Comput Electron Agric* **184**:106067 (2021).
24 Ahmad A, Saraswat D, Aggarwal V, Etienne A and Hancock B, Performance of deep learning models for classifying and detecting common weeds in corn and soybean production systems. *Comput Electron Agric* **184**:106081 (2021).
25 dos Santos FA, Matte Freitas D, Gonçalves da Silva G, Pistori H and Theophilo Folhes M, Weed detection in soybean crops using ConvNets. *Comput Electron Agric* **143**:314–324 (2017).
26 Sharpe SM, Schumann AW and Boyd NS, Detection of Carolina geranium (*Geranium carolinianum*) growing in competition with strawberry using convolutional neural networks. *Weed Sci* **67**:239–245 (2019).
27 Sharpe SM, Schumann AW, Yu J and Boyd NS, Vegetation detection and discrimination within vegetable plasticulture row-middles using a convolutional neural network. *Precis Agric* **21**:264–277 (2020).
28 Sharpe SM, Schumann AW and Boyd NS, Goosegrass detection in strawberry and tomato using a convolutional neural network. *Sci Rep* **10**:1–8 (2020).
29 Veeranampalayam Sivakumar AN, Li J, Scott S, Psota E, Jhala JA and Luck JD, Comparison of object detection and patch-based classification deep learning models on mid-to late-season weed detection in UAV imagery. *Remote Sens (Basel)* **12**:2136 (2020).
30 Jin X, Sun Y, Che J, Bagavathiannan M, Yu J and Chen Y, A novel deep learning-based method for detection of weeds in vegetables. *Pest Manage Sci* **78**:1861–1869 (2022).
31 Yu J, Sharpe SM, Schumann AW and Boyd NS, Deep learning for image-based weed detection in turfgrass. *Eur J Agron* **104**:78–84 (2019).
32 Yu J, Schumann AW, Cao Z, Sharpe SM and Boyd NS, Weed detection in perennial ryegrass with deep learning convolutional neural network. *Front Plant Sci* **10**:1422–1422 (2019).
33 Yu J, Schumann AW, Sharpe SM, Li X and Boyd NS, Detection of grassy weeds in bermudagrass with deep convolutional neural networks. *Weed Sci* **68**:545–552 (2020).
34 Xie S, Hu C, Bagavathiannan M and Song D, Toward Robotic Weed Control: Detection of Nutsedge Weed in Bermudagrass Turf Using Inaccurate and Insufficient Training Data. *arXiv preprint arXiv:210608897* (2021).
35 Medrano R, *Feasibility of Real-Time Weed Detection in Turfgrass on an Edge Device*. The California State University, USA (2021).
36 Yu J, Sharpe SM, Schumann AW and Boyd NS, Detection of broadleaf weeds growing in turfgrass with convolutional neural networks. *Pest Manage Sci* **75**:2211–2218 (2019).
37 Chandran RS, Integrated turfgrass weed management, in *Handbook of Sustainable Weed Management*. CRC Press, Boca Raton, FL, USA, pp. 819–840 (2006).
38 McCarty LB and Murphy TR, Control of turf grass weeds, in *Turf Weeds and Their Control*, Vol. **1**. Madison, WI, USA, pp. 209–248 (1994).
39 Yu J and McCullough PE, Triclopyr reduces foliar bleaching from mesotrione and enhances efficacy for smooth crabgrass control by altering uptake and translocation. *Weed Technol* **30**:516–523 (2016).
40 Reed TV, Yu J and McCullough PE, Aminocyclopyrachlor efficacy for controlling Virginia buttonweed (*Diodia virginiana*) and smooth crabgrass (*Digitaria ischaemum*) in tall fescue. *Weed Technol* **27**:488–491 (2013).
41 Takano HK, Ovejero RFL, Belchior GG, Maymone GPL and Dayan FE, ACCase-inhibiting herbicides: mechanism of action, resistance evolution and stewardship. *Sci Agric* **78**:1 (2020).
42 Peppers JM, Gonçalves CG and McElroy JS, Rate response of select grass weeds to pinoxaden. *Weed Technol* **34**:818–823 (2020).
43 Blum RR, Isgrigg J and Yelverton FH, Purple (*Cyperus rotundus*) and yellow nutsedge (C. *esculentus*) control in bermudagrass (*Cynodon dactylon*) turf. *Weed Technol* **14**:357–365 (2000).
44 Huang G, Liu Z, Van Der Maaten L and Weinberger KQ, Densely connected convolutional networks, in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. Honolulu, HI, USA, pp. 4700–4708 (2017).
45 Tan M and Le Q, Efficientnet: rethinking model scaling for convolutional neural networks, in *International Conference on Machine Learning*. PMLR, London, UK, pp. 6105–6114 (2019).
46 He K, Zhang X, Ren S and Sun J, Deep residual learning for image recognition, in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. Chengdu, China, pp. 770–778 (2016).
47 Schneider N, Piewak F, Stiller C and Franke U, RegNet: Multimodal sensor registration using deep neural networks, in *2017 IEEE Intelligent Vehicles Symposium (IV)*. IEEE, Los Angeles, CA, USA, pp. 1803–1810 (2017).

48 Simonyan K and Zisserman A, Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:14091556* (2014).
49 Sokolova M and Lapalme G, A systematic analysis of performance measures for classification tasks. *Inform Process Manage* **45**:427–437 (2009).
50 Tian L, Reid JF and Hummel JW, Development of a precision sprayer for site-specific weed management. *Trans ASABE* **42**:893–900 (1999).
51 Zhuang J, Li X, Bagavathiannan M, Jin X, Yang J and Meng W, Evaluation of different deep convolutional neural networks for detection of broadleaf weed seedlings in wheat. *Pest Manage Sci* **78**:521–529 (2021).

