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A smart sprayer for weed control in bermudagrass turf based on the herbicide weed control spectrum

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ABSTRACT

Precision application of specific herbicides to susceptible weeds can significantly save herbicide. This is the first study evaluating the performances of precision sprayer for weed control in turf based on the herbicide weed control spectrum in field conditions. The results showed that EfficientNet-v2 and ResNet never fall below 0.992 for discriminating and detecting the grid cells encompassing weeds susceptible to ACCase-inhibiting and synthetic auxin herbicides. MCPA, a synthetic auxin herbicide, is used to evaluate the performance of the developed smart sprayer for precision control of broadleaf weeds in dormant bermudagrass turf. The developed smart sprayer prototype detected and sprayed every grid cell containing broadleaf weeds in field experiments. Compared to the broadcast application, precision spraying of MCPA provided the same level of control of broadleaf weeds. By 18 days after treatment (DAT), the nontreated control had 13 weeds no. m^{-2}, while the plots that received broadcast and precision spraying had 0 and 1 broadleaf weed plant no. m^{-2}, respectively. Precision herbicide application according to the herbicide weed control spectrum (HWCS) with the developed smart sprayer provided the same level of broadleaf weed control and could save more herbicides compared to an approach without discriminating weed species. Overall, these findings clearly indicated that the developed smart sprayer prototype could effectively detect, discriminate, and spray herbicides onto the grid cells containing target weeds based on the HWCS.

1. Introduction

Controlling weeds is one of the most noteworthy challenges for turf management. Weeds compete with turfgrass for sunlight, nutrients, and moisture and could disrupt turf aesthetics and functionality if uncontrolled (Hamuda et al., 2016; Liu and Bruch, 2020; McElroy and Martins, 2013). A common practice of weed control in turf is to broadcast-apply herbicides over the entire turf area, although weeds are almost always present in non-uniform and patchy distributions (Farooq et al., 2019; Jin et al., 2022c). Excessive spraying herbicides may pollute the environment (Pimentel and Burgess, 2014; Zhuang et al., 2023). For example, atrazine, a commonly used photosystem II inhibiting herbicide in warm-season turf, is frequently detected in underground water (Mahoney et al., 2015; McCullough et al., 2016). As a result, in the United States, Environmental Protection Agency recently proposed a series of measures, including prohibiting aerial applications, prohibiting application during rain, when soils are saturated or above field capacity, for all atrazine labels to reduce their chance of runoff from the treated fields (McCullough et al., 2015; Urian et al., 2015). The European Union actively encourages turf managers to employ spot-spraying to reduce the herbicide input (Busey, 2003; Marchand and Robin, 2019). Manual spot-spraying postemergence (POST) herbicides could reduce herbicide input, but it is impractical to be used in large turf fields (Fennimore and Cutulle, 2019).

Computer vision technologies used in precision agriculture could be used to detect and localize weeds in turf (dos Santos Ferreira et al., 2017;

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Fennimore et al., 2016). It can be integrated with a smart sprayer to facilitate precision herbicide application, thereby saving the herbicide usage required to control weeds (Nan et al., 2022; Zhang and Kovacs, 2012). Traditional image processing techniques for discriminating and detecting weeds in arable crops relied on extracting visual characteristics such as color (Jin et al., 2021; Tang et al., 2016), shape (Perez et al., 2000), or textural features (Bakhshipour et al., 2017). However, selecting and analyzing these features is challenging because crops and weeds could be very similar (Hasan et al., 2021; Jin et al., 2022d). Hyperspectral imaging has been investigated for weed detection, but its cost is substantially higher than employing a conventional digital imaging camera (Jiang et al., 2020; Pantazi et al., 2016). Recently, deep learning methods, a subset branch of machine learning, have emerged as an incredible tool in image classification and object detection tasks (He et al., 2020; Shi et al., 2020). A growing number of research studies have investigated the use of deep learning in various scientific fields, such as natural language processing (Collobert and Weston, 2008; Collobert et al., 2011), speech recognition (Hinton et al., 2012; LeCun et al., 2015), and computer vision (Shi et al., 2020; Yu et al., 2021). In agriculture, deep learning methods are generally superior to traditional image processing methods due to their extraordinary feature learning capabilities (Jordan and Mitchell, 2015; Kamilaris and Prenafeta-Boldú, 2018; Liakos et al., 2018).

Several studies have investigated the performances of using deep convolutional neural networks for weed detection in turf (Hasan et al., 2021; Jin et al., 2022b; Yu et al., 2019a). Yu et al. demonstrated that VGGNet is well-performed in classifying several broadleaf and grassy weeds in bermudagrass [*Cynodon dactylon* (L.) Pers.] turf, while DetectNet effectively recognized cutleaf evening-primrose (*Oenothera laciniata* Hill) in bahiagrass (*Paspalum notatum* Flugge) turf (Yu et al., 2019b, 2019c, 2020). In another study, Medrano investigated You Only Look Once (YOLO), including YOLO-v4, YOLO-v4-tiny, and YOLO-v5, and reported that YOLO-v5 exhibited the highest mean average precision (mAP) for detecting dandelion (*Taraxacum officinale* Web.) in bermudagrass turf (Medrano, 2021). Recently, Xie et al. reported the effectiveness of using an improved Mask R–CNN for detecting nutsedges (*Cyperus* spp.) growing in bermudagrass turf (Xie et al., 2021).

Researchers have recently developed several smart sprayer prototypes (Lee et al., 1999; Slaughter et al., 2008). For example, Kargar et al. designed a smart sprayer for controlling weeds in corn (*Zea mays* L.). In this study, image segmentation and feature extraction were utilized to discriminate between corn plants and grassy weeds (Kargar and Shirzadifar, 2013). At that time, the lack of a robust machine vision system to detect and discriminate between crops and weeds was the primary limitation to the commercial development of smart sprayers (Utstumo et al., 2018). Recent advances in deep learning significantly improve weed detection accuracy, and new spraying technologies could considerably reduce the amount of herbicide input for weed control (Liu and Bruch, 2020). Calvert et al. developed a robotic spot-sprayer to manage harrisia cactus (*Cereus martinii* Labour.) in rangeland pastures. The authors used MobileNet-v2 neural network to detect harrisia cactus and achieved an average recall accuracy of 97.2% (Calvert et al., 2021). A few smart weeders such as See & Spray® (Blue River Technology, Sunnyvale, CA, USA) and Weed-it® (Rometron, Steenderen, Netherlands) have recently been commercialized with excellent performances for precision weed control. However, none of these smart sprayers are designed for precision herbicide application on turf (Yu et al., 2020).

Effective weed classification based on the herbicide weed control spectrum (HWCS) enables the smart sprayer to apply herbicides only to the weeds susceptible to the herbicides (Jin et al., 2023). Regardless of recent success, none of the earlier research works designed and developed smart sprayers for precision-spraying herbicides based on the HWCS. In the present research effort, a smart sprayer prototype was designed and developed for precision herbicide application on turf. The trained HWCS neural networks were used in the smart sprayer's machine vision subsystem. Input images were cropped into multiple sub-images to generate grid cell maps. Grid cells containing the susceptible weeds were detected and localized for precision herbicide spraying. The objectives of this research were to (1) design and develop a smart sprayer prototype that can be used to control weeds with a precision spraying technology, and (2) evaluate and compare the performances of the traditional broadcast and precision application based on the HWCS for controlling broadleaf weeds in dormant bermudagrass turf.

2. Materials and methods

2.1. Overview

As shown in Fig. 1, the smart sprayer prototype includes a spraying boom with 10 solenoid valves and nozzles, an herbicide tank, a pump, a digital camera, and a computational unit for weed detection and localization. The sprayer prototype was controlled via embedded controllers with standard communication protocols.

2.2. Smart sprayer hardware

The smart sprayer prototype is powered by batteries and is designed to move intermittently (controlled manually via an Android application). The vehicle has two driving wheels at the front and was equipped with two brushless DC motors.

A spraying boom was built to hold all the solenoid valves and spray nozzles (Fig. 2). The structure utilized was aluminum alloy, and the dimension was 106 cm in length, 36 cm in width, and 3 cm in height. The nozzles covered a spray length of 1 m behind the platform. The height of the boom could be adjusted in order to alter the distance between the nozzles and the ground surface. Ten pairs of solenoid valves and nozzles (with a uniform space of 10 cm between two consecutive pairs) were mounted on the boom. Each nozzle covered a spray width of 10 cm (Fig. 3). The nozzles were BBG-30 (BoyanLtd., Dongguan,

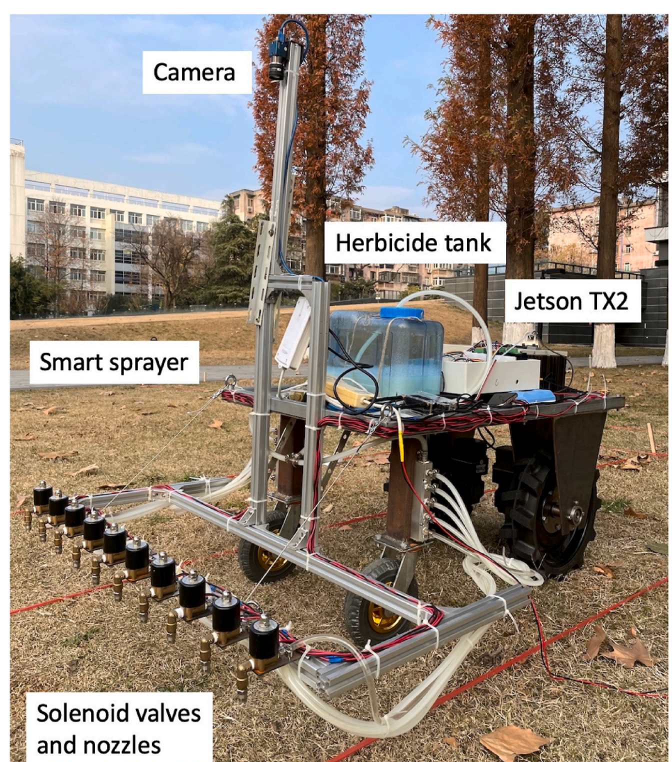

Fig. 1. The main components of the smart sprayer prototype.

Fig. 2. Solenoid valves and spray nozzles.

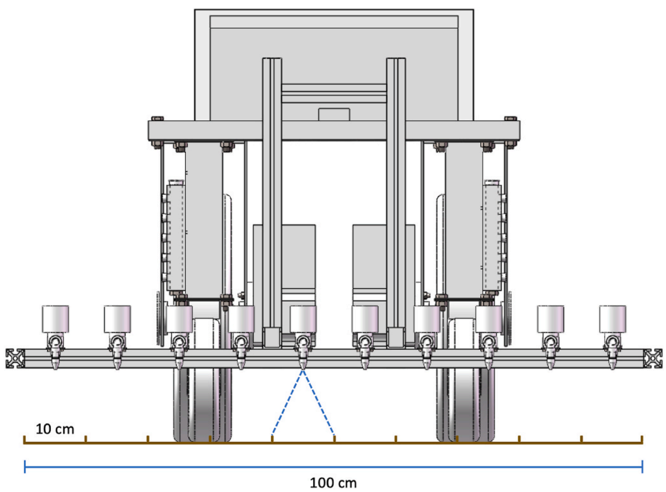

Fig. 3. Spray boom and nozzle arrangement.

Guangdong, China) installed 18 cm above the ground surface at a spray angle of 30°.

The herbicide was stored in a 14 L plastic tank equipped with a 6 L min^{-1} pump and at a constant 6 bar pressure (LS-1426, Leicheng Pump, Ningbo, Zhejiang, China). The solenoid valves (24 V, 2w025-08, Laize Inc., Wenzhou, Zhejiang, China) with <60 ms response time were used to control the nozzles. These hardware units were used to build a smart sprayer with a rapid response time and initiate precision spraying upon receiving trigger signals from the nozzle controllers.

A digital camera (MER-503-36U3M/C, DaHeng Image, Inc., Beijing, China) was used for the image acquisition system. The camera was mounted on the vehicle at 1.2 m above the ground. An NVIDIA Jetson embedded graphical processing unit (GPU) processor (Nvidia Jetson TX2, Santa Clara, CA, USA) was chosen to process images acquired from the camera. The Jetson TX2 has a dual-core central processing unit (CPU) and a GPU including 256 compute unified device architecture (CUDA) cores, making it capable of performing image classification tasks.

2.3. Smart sprayer software

A custom software was established using Python programming language in order to create grid cell maps on the image and control nozzles to spray herbicides precisely onto the grid cells containing the target weeds. The overall workflow of the smart software system is shown in Fig. 4. The software can process the combined steps, including image capture, weed recognition and localization, nozzle control, and communication.

2.3.1. Image acquisition

Since the sprayer was moved intermittently, image acquisition was performed when the sprayer was stopped after moving a constant distance. The developed software captures a resolution of 1920 × 1080 pixels image from the most recent frame of the smart sprayer's camera. The field-of-view (FOV) of the vision system covered a 0.80 × 0.45 m^2 area. Two regions of interest (ROIs) were cropped from the FOV of the vision system for detecting weeds inside the boom box (Fig. 5). Each ROI measured 0.80 m in length by 0.09 m in width based on the overlapping of the FOV of the vision system and the spraying boom in the developed smart sprayer.

2.3.2. Weed detection and localization

The developed software split each ROI into eight identical size grid cells (240 × 216 pixels sub-images), corresponding to eight nozzles on the boom. Although there were ten nozzles on the boom, eight nozzles were used due to the fact that the FOV of the vision system covered the second to the ninth nozzle. To achieve precision spraying, the sprayed area by a single nozzle was equivalent to or slightly larger compared to the physical size of each grid cell. Each grid cell denoted a size of 0.1 m × 0.09 m, which was approximately equal to the scope of the field zone where a single nozzle was covered (a circular area with a diameter of 0.1 m).

A custom software was developed with OpenCV-Python. The software was used to create grid cell maps on the input images. The trained HWCS neural networks were utilized to detect and locate the grid cells

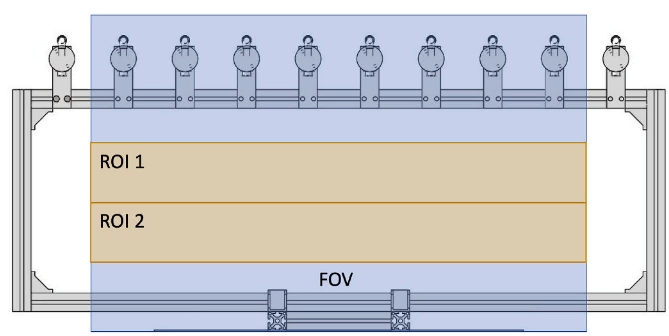

Fig. 5. Geometry location of regions of interest (ROIs) from the field-of-view (FOV) of the machine vision system.

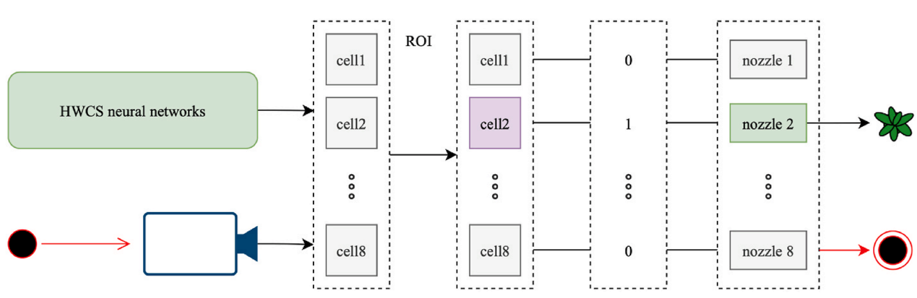

Fig. 4. The schematic diagram of designing the smart sprayer. Abbreviation: HWCS, herbicide weed control spectrum; ROI, region of interest.

containing weeds. The grid cells inside the ROI were identified and labeled as spraying zones if the inference indicated they contained weeds susceptible to herbicides.

2.3.3. Convolutional neural networks and deep learning

Three image classification neural networks, including EfficientNet-v2 (Tan and Le, 2019), ResNet (He et al., 2016), and VGGNet (Simonyan and Zisserman, 2014) were trained according to the HWCS to recognize and classify weeds in dormant bermudagrass turf. EfficientNet utilizes the concept of compound scaling to homogeneously scale the width, depth, and resolution of the network with a set of fixed scaling coefficients. The scaling of dimensions is performed in a principled way (Tan and Le, 2019). As a residual learning method, ResNet employs an identity-based skip connection that could ease the information flow across units and improve accurateness from very deep networks. VGGNet is a classical convolutional neural network architecture composed of 16 wt layers. VGGNet exhibits smaller filters with more depth rather than large filters. EfficientNet-v2 is the state-of-the-art neural network, while ResNet and VGGNet are two of the most classic neural networks. These convolutional neural networks were evaluated for detecting and classifying if the grid cells (sub-images) had weeds susceptible to selective herbicides or merely included dormant bermudagrass turf without weeds.

The training images of various weed species infesting dormant bermudagrass turf were primarily captured in February 2018 utilizing a digital camera (DSC-HX1, SONY®, Cyber-Shot Digital Still Camera, SONY Corporation, Minato, Tokyo, Japan) at the University of Georgia Griffin Campus in Griffin (UGA-Griffin), Georgia, the United States (33.26°N, 84.28°W). The training images primarily included annual bluegrass (*Poa annua* L.) and several broadleaf weed species, including common dandelion (*Taraxacum officinale* F.H. Wigg.), purple deadnettle (*Lamium purpureum* L.), henbit (*Lamium amplexicaule* L.), and white clover (*Trifolium repens* L.). The testing images of various weed species infesting dormant bermudagrass turf were captured in January 2022 with a digital camera (MER-503-36U3M/C, DaHeng Image, Inc., Beijing, China) at Nanjing Forestry University (NFU), Nanjing, Jiangsu, China (32.08°N, 118.82°E). The testing images included annual bluegrass, common dandelion, and white clover. The cameras were configured to take RGB images at an original resolution of 1920 × 1080 pixels. During the image acquisition process, the cameras were set to automatic mode for focus, white balance, and exposure settings. The training and testing images were taken under varying illumination conditions, including sunny and cloudy days.

When training convolutional neural networks for detecting the HWCS in dormant bermudagrass turf, all images were cropped into 40 sub-images (8 columns by 5 rows) with Irfanview (v5.50, Irfan Skijan, Jajce, Bosnia). Each sub-image was 240 by 216 pixels. To establish the training dataset of the HWCS neural networks, 8000 sub-images (4000 images for each class) including weeds susceptible to ACCase-inhibitors (grass weeds growing in dormant bermudagrass turf) or weeds susceptible to auxin herbicides (broadleaf weeds infesting dormant bermudagrass turf) were arbitrarily chosen and utilized as the true positive images; and 4000 sub-images merely had dormant bermudagrass were arbitrarily chosen and utilized as the true negative images.

To establish the HWCS neural networks' validation or testing dataset, 1000 sub-images (500 images for each class) comprising grassy weeds (annual bluegrass) susceptible to ACCase-inhibitors or broadleaf weeds (common dandelion and white clover) susceptible to synthetic auxins were arbitrarily chosen and utilized as the true positive images; and 500 sub-images merely comprising dormant bermudagrass were randomly chosen and utilized as the true negative images.

All neural networks were built and evaluated based on the PyTorch deep learning framework (version 1.8.1) using Python programming language (version 3.7.10). The training and testing of the neural networks were performed on a Nvidia GeForce RTX 2080 Ti GPU with the CUDA toolkit 11.0. Default hyper-parameters were set for training the neural networks to ensure fair comparisons (Table 1).

Precision, recall, and F_1 score values were used as the matrices to evaluate the training and testing results of the HWCS neural networks and compare the performances against each other. These metrics were computed according to the confusion matrices consisting of four categories: true positive (*tp*), false positive (*fp*), true negative (*tn*), and false negative (*fn*).

Precision measures the ratio between the number of *tp* and the sum of *tp* and *fp* (Sokolova and Lapalme, 2009):

$$precision = \frac{tp}{tp + fp} \tag{1}$$

Recall is the true positive rate calculated by dividing *tp* with the sum of *tp* and *fn* (Sokolova and Lapalme, 2009):

$$recall = \frac{tp}{tp + fn} \tag{2}$$

The F_1 score is one of the most widely used metrics for evaluating the overall performance of the neural networks. It was measured by using the following equation (Sokolova and Lapalme, 2009):

$$F_1 = \frac{2 \times precision \times recall}{precision + recall} \tag{3}$$

2.3.4. Nozzle control system

After weed detection and localization, an array of 8 elements containing all the spraying decision flags (0 or 1) was sent to the nozzle controller for triggering the individual nozzles. A binary input command was used for turning off the spray nozzles over the non-target cells; thus, individual nozzles were independently controlled. The communication between the vision unit and the nozzle controller was carried out via a universal serial bus (USB) connection. For the nozzle controllers, a program was established to read and decode the serial data originating from the machine vision sub-system encompassing the grid cells to be sprayed. Finally, the control system sent a 5 V signal to trigger individual 24 V solenoid valves, and then the corresponding nozzles started spraying.

2.4. Weed control evaluation

Field experiments were conducted from January 2022 to February 2022 at two separate dormant bermudagrass turf fields on the campus of NFU to evaluate the precision control of broadleaf weeds with the developed smart sprayer prototype. MCPA (2-methyl-4-chlorophenoxyacetic acid, Taizhou Xianhe Ltd., Gong Ye Jizhong District, Xinghua City, Jiangsu, China), a synthetic auxin herbicide, was used to evaluate the performance of precision control of broadleaf weeds in dormant bermudagrass turf. MCPA at 1.5 kg a.e. ha^{-1} was broadcast-applied using the smart sprayer prototype calibrated to deliver 400 L ha^{-1} spray volume, while the same herbicide treatment solution was used for precision spraying treatment with the smart sprayer prototype.

The experiments were carried out as a randomized complete block with four replications. A nontreated control in each replication was included. The plot measured approximately 3.6 × 4.0 m^2 (0.9 m in width by 1.0 m in length for each replication). Survival weeds were recorded 0,

Table 1
The hyperparameters used for training the HWCS neural networks.

Deep learning architecture	Optimizer	Base learning rate	Learning rate policy	Batch size	Training epochs
EfficientNet-v2	SGD	0. 01	LambdaLR	16	60
ResNet	Adam	0.0001	StepLR	16	60
VGGNet	Adam	0. 0001	StepLR	16	60

Abbreviation: SGD, stochastic gradient descent.

3, 7, 9, 11, 13, 15, and 18 days after treatment (DAT). Data were subjected to analysis of variance in SAS (version 9.4, SAS Institute, Cary, NC, United States). Data were examined for normality and constant variance prior to analysis. For the same rating timing, treatment means were compared with Fisher's Protected LSD test at $P = 0.05$.

3. Results

3.1. Weed detection and localization

No obvious differences were observed between EfficientNet-v2 and ResNet for identifying and classifying the grid cells comprising dormant bermudagrass only, and weeds susceptible to ACCase-inhibiting or synthetic auxin herbicides.

EfficientNet-v2 and ResNet had an F_1 score above 0.995 in the validation datasets for detecting and classifying weeds susceptible to ACCase-inhibitors and synthetic auxin herbicides (Table 2). For all neural networks, weed detection performance was slightly lower in the testing datasets than in the validation datasets. For detecting and classifying weeds susceptible to ACCase-inhibitors and synthetic auxin herbicides, the F_1 scores of VGGNet were 0.982 and 0.985 in the testing dataset. Therefore, by jointly analyzing the validation and testing results, EfficientNet-v2 and ResNet demonstrated superiorities over VGGNet for detecting the HWCS.

Fig. 6 represents the results when the custom software was used to crop the ROIs from the FOV of the vision system and detect the grid cells comprising weeds susceptible to synthetic auxin herbicides in dormant bermudagrass turf. A total of 8 grid cells, corresponding to 8 nozzles on the boom were split from each ROI. The trained HWCS neural network was used to detect weeds within the grid cells. A total of 2 and 3 out of 8 grid cells were shown red (Fig. 6b and c) in ROI 1 and ROI 2, respectively, which represented they contained weeds susceptible to synthetic auxin herbicides; and a total of 6 and 5 grid cells indicated they only contained dormant bermudagrass in ROI 1 and ROI 2, respectively. In this case, nozzles 5 and 6 (from left to right) were turned on for spraying MCPA in ROI 1; while nozzles 4, 5, and 6 (from left to right) were turned on for spraying MCPA in ROI 2.

It should be noted that when the grid cells contained both broadleaf and grassy weeds, the grid cells were labeled as spraying areas regardless of the HWCS. As long as the grid cells comprised the broadleaf weeds, the nozzles were turned on, and the grid cells were sprayed with synthetic auxin herbicides. For instance, as shown in Fig. 6, nozzles 5 and 6 (from left to right) in ROI 1 and nozzle 6 (from left to right) in ROI 2 were turned on for spraying MCPA, although these grid cells contained grassy weeds as well.

3.2. Weed control

Experiments were conducted to compare broadcast and precision spraying using the developed smart sprayer prototype to control broadleaf weeds growing in dormant bermudagrass turf. On the day of herbicide treatments, weed densities in the plots of the nontreated control, precision, and broadcast treatments were 13, 11, and 9 weeds no. m^{-2}, respectively (Table 3). Throughout the experiment, broadcast treatment did not differ from precision spraying for reducing broadleaf weed densities. Broadcast and precision spraying of MCPA using the developed smart sprayer prototype significantly reduced broadleaf weed densities at 9 DAT and thereafter. By 18 DAT, the plots received broadcast, and precision spraying of MCPA with the smart sprayer prototype had 0 and 1 broadleaf weed no. m^{-2}, respectively.

4. Discussion

The machine vision system of a smart sprayer can employ either image classification or object detection neural networks (Zhuang et al., 2021). The object detection neural networks enable the localization of target weeds by drawing bounding boxes around them. However, nozzles generally generate a consistent size of spraying outputs on the ground surface, while the bounding boxes (size of each individual weeds) varies. Precision spraying herbicides for weed control requires the detection and localization of areas infested with weeds and is not necessary to detect and localize individual weed plants. Therefore, in the present study, grid cells with target weeds were identified and localized rather than detecting individual weed plants growing in turf. Precision herbicide application could be achieved with the proposed method as long as the smart sprayer's machine vision subsystem could determine the absence or presence of the target weeds inside the grid cells.

Identifying and classifying weed species according to their susceptibility to herbicides enables spraying specific herbicides for controlling susceptible weeds. In the present research, EfficientNet-v2 and ResNet achieved excellent F_1 scores ($\geq$0.996) in the validation and testing datasets to identify and classify the grid cells containing broadleaf weeds susceptible to MCPA. This finding suggests that creating maps of grid cell on the images and detecting the HWCS is promising to realize precision weed control and can save more herbicides than an approach without discriminating weed species.

MCPA, a synthetic auxin herbicide, controls various broadleaf weed species but exhibits limited herbicidal activity on grassy weeds (Shaner, 2014). In the field experiments, MCPA was used to test the performances of the smart sprayer for precision control of broadleaf weeds in dormant bermudagrass turf. Our results showed that when the grid cells contained the broadleaf weeds, the smart sprayer precisely sprayed MCPA onto the broadleaf weeds. Following the herbicide application, precision spraying of MCPA did not differ from broadcast treatment for reducing weed densities, indicating the feasibility of using the developed smart sprayer for precision weed control based on the HWCS.

It should be noted that when the testing images contained grassy weeds growing close to broadleaf weeds in dormant bermudagrass turf,

Table 2
The performances of the HWCS neural networks for identifying and classifying the grid cells comprising weeds susceptible to ACCase-inhibitors and synthetic auxin herbicides, or dormant bermudagrass without weed infestation (no herbicide).[a]

Deep learning architecture	Herbicides	Validation dataset			Testing dataset		
		Precision	Recall	F_1 score	Precision	Recall	F_1 score
EfficientNet-v2	ACCase-inhibitors	0.998	0.994	0.996	0.992	0.996	0.994
	No herbicide	0.996	1.000	0.998	0.996	1.000	0.998
	Synthetic auxins	0.998	0.998	0.998	1.000	0.992	0.996
ResNet	ACCase-inhibitors	0.994	0.996	0.995	0.986	0.998	0.992
	No herbicide	0.996	0.998	0.997	0.998	0.994	0.996
	Synthetic auxins	0.998	0.994	0.996	1.000	0.992	0.996
VGGNet	ACCase-inhibitors	0.978	0.992	0.985	0.982	0.982	0.982
	No herbicide	0.996	0.996	0.996	0.994	0.996	0.995
	Synthetic auxins	0.996	0.982	0.989	0.986	0.984	0.985

[a] The HWCS neural networks were trained to identify and classify the grid cells comprising weeds susceptible to ACCase-inhibitors, synthetic auxin herbicides, or dormant bermudagrass without weed infestation (no herbicide). Abbreviation: HWCS, herbicide weed control spectrum.

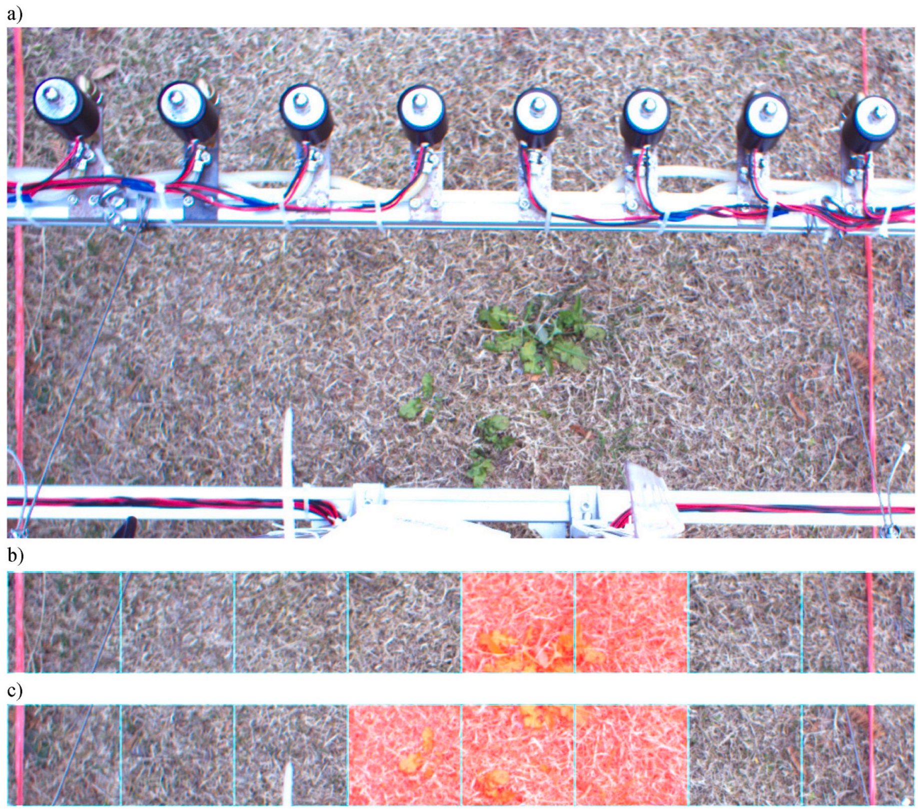

Fig. 6. Weed detection and localization using the developed neural networks. The original image (1920 × 1080 pixels) was captured by vision system (a). The grid cells of ROI 1 and ROI 2 and the neural network inferred the grid cells (240 × 216 pixels) comprising broadleaf weeds (red) and bermudagrass turf only (b, c).

Table 3
Control of broadleaf weeds following broadcast and precision treatment of MCPA with the developed smart sprayer prototype.[a]

	Survived broadleaf weeds (no. m^{-2})[b]							
Treatment	0 d	3 d	7 d	9 d	11 d	13 d	15 d	18 d
Nontreated control	13	13	13	13 a	13 a	13 a	13 a	13 a
Broadcast application	9	9	7	5 b	4 b	3 b	1 b	0 b
Precision spraying	11	11	10	7 b	5 b	4 b	2 b	1 b
$LSD_{0.05}$	4.0	4.0	4.1	3.7	2.9	2.6	2.4	2.2

[a] Treatment means followed by the same letter are not statistically different based on Fisher's Protected LSD test at the 0.05 probability level.

[b] The number of survived broadleaf weeds was recorded on the day of herbicide treatment and at 3, 7, 9, 11, 13, 15, and 18 days after herbicide treatment.

the neural networks did not effectively detect and discriminate the HWCS because the grid cell contained both broadleaf and grassy weeds. Nevertheless, the smart sprayer prototype detected every grid cell containing broadleaf weed plants or broadleaf weeds growing close to grassy weeds. As a result, the smart sprayer prototype sprayed MCPA onto the grid cells comprising grassy weeds as well when the grid cells contained both broadleaf and grassy weeds, as shown in Fig. 6.

In a previous study, Jin et al. developed effective deep convolutional neural networks for identifying and classifying weed species in turf according to the HWCS (Jin et al., 2022a). The authors reported that ShuffleNet-v2 achieved high overall accuracy ($\geq$0.999) in identifying and classifying weeds susceptible to ACCase-inhibiting herbicides or synthetic auxin herbicides. Most synthetic auxins are POST herbicides (e.g., 2,4-D or mecoprop) that can be used to control broadleaf weeds (Reed et al., 2013; Shaner, 2014; Yu and McCullough, 2016) with a few exceptions. For instance, triclopyr and quinclorac are both synthetic auxin herbicides. Triclopyr can suppress bermudagrass, while quinclorac controls crabgrass as well as broadleaf weeds in bermudagrass turf (Grossmann and Kwiatkowski, 2000; Yu and McCullough, 2016). Thus, quinclorac should be used for precision control of broadleaf weeds with the developed smart sprayer prototype when the turf field is infested with crabgrass weeds.

In the present study, only MCPA was used to evaluate the performance of the developed smart sprayer for precision control of broadleaf weeds in dormant bermudagrass turf. While the developed smart sprayer achieved an excellent performance of precision weed control, other POST broadleaf herbicides (e.g., carfentrazone) should be evaluated for precision herbicide application with the developed HWCS neural networks.

5. Conclusions

In summary, the present research investigated the feasibility of utilizing image classification convolutional neural networks to identify and classify weeds growing in dormant bermudagrass turf according to the HWCS. EfficientNet-v2 and ResNet exhibited superiorities over VGGNet for discriminating ACCase-inhibitors or synthetic auxin herbicides. The developed smart sprayer prototype effectively detected and sprayed MCPA onto the grid cells containing broadleaf weeds and resulted in the same level of weed control compared to the broadcast treatment. This is the first research seeking to develop smart sprayer for precision control of weeds according to the HWCS. Although the functionality as a whole has been verified, the developed smart sprayer prototype needs to be further optimized in order to realize precision herbicide application while moving. An additional study is required to examine the performances of precision weed control based on the HWCS using the developed smart sprayer prototype in actively growing turfgrass fields.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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