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Deep learning for image-based weed detection in turfgrass

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ABSTRACT

Precision spraying of herbicides can significantly reduce herbicide use. The detection system is the critical component within smart sprayers that is used to detect target weeds and make spraying decisions. In this work, we report several deep convolutional neural network (DCNN) models that are exceptionally accurate at detecting weeds in bermudagrass [*Cynodon dactylon* (L.) Pers.]. VGGNet achieved high F_1 score values (> 0.95) and outperformed GoogLeNet for detection of dollar weed (*Hydrocotyle* spp.), old world diamond-flower (*Hedyotis cormybosa* L. Lam.), and Florida pusley (*Richardia scabra L.*) in actively growing bermudagrass. A single VGGNet model reliably detected these summer annual broadleaf weeds in bermudagrass across different mowing heights and surface conditions. DetectNet was the most successful DCNN architecture for detection of annual bluegrass (*Poa annua* L.) or *Poa annua* growing with various broadleaf weeds in dormant bermudagrass. DetectNet exhibited an excellent performance for detection of weeds while growing in dormant bermudagrass, with F_1 scores > 0.99. Based on the high level of performance, we conclude that DCNN-based weed recognition can be an effective decision system in the machine vision subsystem of a precision herbicide applicator for weed control in bermudagrass turfgrasses.

1. Introduction

Turfgrass landscape is the most intensively managed component of urban landscapes (Balogh and Walker, 1992) and is the predominant form of vegetation cover in athletic, commercial, institutional and residential lawns, golf courses, and parks. Milesi et al. (2005) estimated that the total turfgrass area within in the United States covers 163,812 km^2 (± 35,850 km^2 for upper and lower 95% confidence interval bounds). The National Golf Foundation estimated that there are currently over 15,000 golf courses in the United States with an average of 50–73 ha per golf course (National Golf Foundation, 2018). In a typical city in the United States, it was estimated that 9% of total turfgrass area is golf courses, along with 70% for residential lawns, 10% for city parks and sport facilities, 9% for educational facilities, 2% for churches and cemeteries, and 1% for industrial purposes (Balogh and Walker, 1992).

Weeds are a serious issue in turfgrass management. Weeds compete for environmental resources such as nutrients, sunlight, and water, and reduce turfgrass aesthetics. Many herbicides presently used for turfgrass weed management are suspected of being problematic for the environment. For example, organic arsenical herbicides, such as monosodium methylarsenate (MSMA), may cause groundwater contamination (Mahoney et al., 2015; Yu et al., 2017). As a result, only a single broadcast application of MSMA is permitted in newly constructed golf courses and in all other golf courses, MSMA can only be applied as a spot treatment (MSMA 6 Plus). Weeds generally occur in a non-uniform distribution and spot-spraying is therefore an effective approach to reduce herbicide use. Manual spot-spraying can economically and accurately control weeds, but it is impractical for large turfgrass areas.

Machine vision technology can provide important tools for real-time image processing and weed detection (Behmann et al., 2015; do Santos Ferreira et al., 2017; Yang et al., 2000). It may be used in conjunction with smart sprayers to facilitate precision herbicide application (Berge et al., 2012; Ishak et al., 2009; Yang et al., 2000). Various ground-based weed recognition techniques including artificial neural network (Liakos et al., 2018; Yang et al., 2000), fluorescence imaging (Longchamps et al., 2010), and spectral sensing (Pantazi et al., 2016) have been studied for site-specific weed management in arable crops (Behmann et al., 2015; do Santos Ferreira et al., 2017; Yang et al., 2000). However, in the case of turfgrass systems there are no published studies investigating the feasibility of using machine vision technology for weed detection. In this paper, we present a new approach for weed detection with the ultimate goal of utilizing weed detection for selective

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herbicide application in turfgrasses.

In recent years, deep learning in conjunction with the improvements in computer technology, particularly graphical processing units (GPU) embedded processor (Gu et al., 2018; LeCun et al., 2015), produced remarkable results in various fields of modern science such as image classification and objection detection (Hinton et al., 2012; LeCun et al., 2015; Schmidhuber, 2015). Artificial neural networks are mathematical models that simulate the human brain function with neurons and synapses that interconnect them (LeCun et al., 2015; Schmidhuber, 2015). One way to train artificial neural networks is through supervised learning, in which neural networks are "trained" to model some systems with the dataset containing specific matchings of inputs (actual data labels) and generate outputs (predicted test data labels) (LeCun et al., 2015; Schmidhuber, 2015). DCNN is an advanced form of traditional artificial neural networks (LeCun et al., 2015;Schmidhuber, 2015), with an extraordinary ability to extract complex features from images when provided with a large dataset (Gu et al., 2018; Ghosal et al., 2018; Lee et al., 2017).

In agricultural research, DCNN reliably identified and classified several abiotic (herbicide injury and nutrient deficiency) and biotic (bacterial and fungal diseases) stresses (Ghosal et al., 2018; Mohanty et al., 2016). Lee et al. (2017) documented a DCNN system for plant recognition based on plant leaf features and patterns. Grinblat et al. (2016) presented a DCNN model that accurately identified three legume species based on the morphological patterns of leaf veins. Pattern-based recognition may be the key to detecting weeds within turfgrass. This permits digital cameras as sensors for developing spot-spraying capable precision herbicide applicators. Bermudagrass is a widely used warm-season turfgrass on golf courses, home lawns, and sport facilities (Taliaferro, 1995; Taliaferro et al., 2004). It is also one of the most favored forage grasses in the tropical and sub-tropical regions of the world (Burton et al., 1967; Gaskin et al., 2003; Starks et al., 2006). The objective of this research was to investigate the feasibility of use of DCNN in detecting weeds while growing in bermudagrass turfgrasses.

2. Methods

2.1. Overview

Three DCNN architectures including (i) DetectNet (Tao et al., 2016), (ii) GoogLeNet (Szegedy et al., 2015), and (iii) VGGNet (Simonyan and Zisserman, 2014), were investigated for weed detection capability in bermudagrass. The DCNN architectures used were designed for either image classification or objection detection. GoogLeNet and VGGNet are image classification DCNN (Szegedy et al., 2015; Simonyan and Zisserman, 2014), while DetectNet is an object detection DCNN (Tao et al., 2016). GoogLeNet is implemented with a novel feature in the form of the inception module. GoogLeNet consists of 22 convolutional layers and is designed on small convolutions in order to reduce the number of neurons and parameters (Szegedy et al., 2015). VGGNet used in this work is composed of 16 wt layers. The VGGNet architecture is designed to implement smaller convolutional kernels for limiting the neuron numbers and parameters. It utilizes a stack of convolutional layers with small receptive fields in the first layers rather than a few layers with larger receptive fields (Simonyan and Zisserman, 2014). DetectNet is a fully convolutional network and is designed based on GoogLeNet for optimizing object detection (Tao et al., 2018). The training of DetectNet models require the use of input images and label files that were generated by drawing bounding boxes onto the weeds in the input images using a custom software program compiled with Lazarus (http://www.lazarus-ide.org/). The training of these DCNN models was performed with pre-trained weight files from the ImageNet Database (Deng et al., 2009) and KITTI Dataset (Geiger et al., 2013).

GoogLeNet and VGGNet were evaluated for detection of dollar weed (*Hydrocotyle* spp.), old world diamond-flower (*Hedyotis cormybosa* L. Lam.), and Florida pusley (*Richardia scabra L.*) in actively growing bermudagrass. DetectNet is not used for detecting these summer annual broadleaf weeds because the training of DetectNet models involved the drawing of bounding boxes onto the individual target weeds but these weed species were present in large patches in most training and testing images. In this work, we have also evaluated the feasibility of using DetectNet, GoogLeNet, and VGGNet for detection of annual bluegrass (*Poa annua* L.) or *poa annua* growing with various broadleaf weeds in dormant bermudagrass.

2.2. Image acquisition

Images of *Hydrocotyle* spp., *Hedyotis cormybosa*, and *Richardia scabra* in actively growing bermudagrass were taken from April to September 2018 using a digital camera (DSC-HX1, SONY® Cyber-Shot Digital Still Camera, SONY Corporation, Minato, Tokyo, Japan) at a ratio of 16:9, with a resolution of 1920 × 1080 pixels. The training images were taken at multiple golf courses in Bradenton, FL (27.49 °N, 82.57 °W), Riverview, FL (27.86 °N, 82.32 °W), Sun City, FL (27.71 °N, 82.35 °W), and Tampa, FL (27.95 °N, 82.45 °W). Images taken at multiple athletic fields, golf courses, and institutional lawns in Lakeland, FL (28.03 °N, 81.94 °W) were used in the testing dataset (TD) 1. Images taken at multiple golf courses in Homestead, FL (25.46 °N, 80.47 °W) and Miami, FL (25.76 °N, 80.19 °W) were used in the TD 2. Most images in the TD 2 containing weeds were mixed with other weed species such as spotted spurge (*Euphorbia maculata L.*), crabgrass (*Digitaria* spp.), or tropical signalgrass [*Urochloa subquadripara* (Trin.) R.D. Webster]. Images of *Hydrocotyle* spp., *Hedyotis cormybosa*, and *Richardia scabra* at different growth stages and densities (Fig. 1A), while images of bermudagrass at different mowing heights and surface conditions (Fig. 1B) were used for model training and testing.

Images of *Poa annua* or *Poa annua* growing with various broadleaf weeds in dormant bermudagrass were taken in early February 2018 using the previously described digital camera. Training images were taken at the University of Georgia Griffin Campus in Griffin, GA (33.26 °N, 84.28 °W). Images taken at multiple institutional lawns and golf courses in Peachtree City, GA (33.39 °N, 84.59 °W) and Atlanta, GA (33.74 °N, 84.38 °W) were used in the TD. The training and testing images contained a diversity of broadleaf weed species but the principal broadleaf weed species included common chickweed [Stellaria media (L.) Vill.], dandelion (*Taraxacum officinale F.* H. Wigg.), henbit (Lamium amplexicaule L.), purple deadnettle (*Lamium purpureum* L.), white clover (Trifolium repens L.), and swinecress [*Coronopus didymus* (L.) Sm.]. All training and testing images were acquired at a ground sampling distance of 0.05 cm pixel^{-1}. Images were mostly taken from 9:00 AM to 5:00 PM under varying lighting conditions including clear, cloudy, partly cloudy days, as well as under the shadow of tree canopies.

2.3. Training and testing

Two scenarios for training DCNN models were considered. Either models were trained using a dataset containing a single weed species (single-species neural network) or multiple weed species (multiple-species neural network). When training image classification DCNN for detection of *Hydrocotyle* spp., *Hedyotis cormybosa*, and *Richardia scabra* while growing in bermudagrass, all images were cropped into 9 sub-images with a resolution of 640 × 360 pixels using Irfanview (Version 5.50, Irfan Skijan, Jajce, Bosnia).

For the single-species neural network, the *Hydrocotyle* spp. training dataset contained 6000 negative (images without weeds) and 6000 positive (images with weeds) images, the training dataset of *Hedyotis cormybosa* contained 8500 negative and 7632 positive images, and the training dataset of *Richardia scabra* contained 7000 negative and 6206 positive images. These DCNN models were trained to classify a single weed species with bermudagrass. For each weed species, the validation dataset (VD) contained a total of 500 negative and 500 positive images.

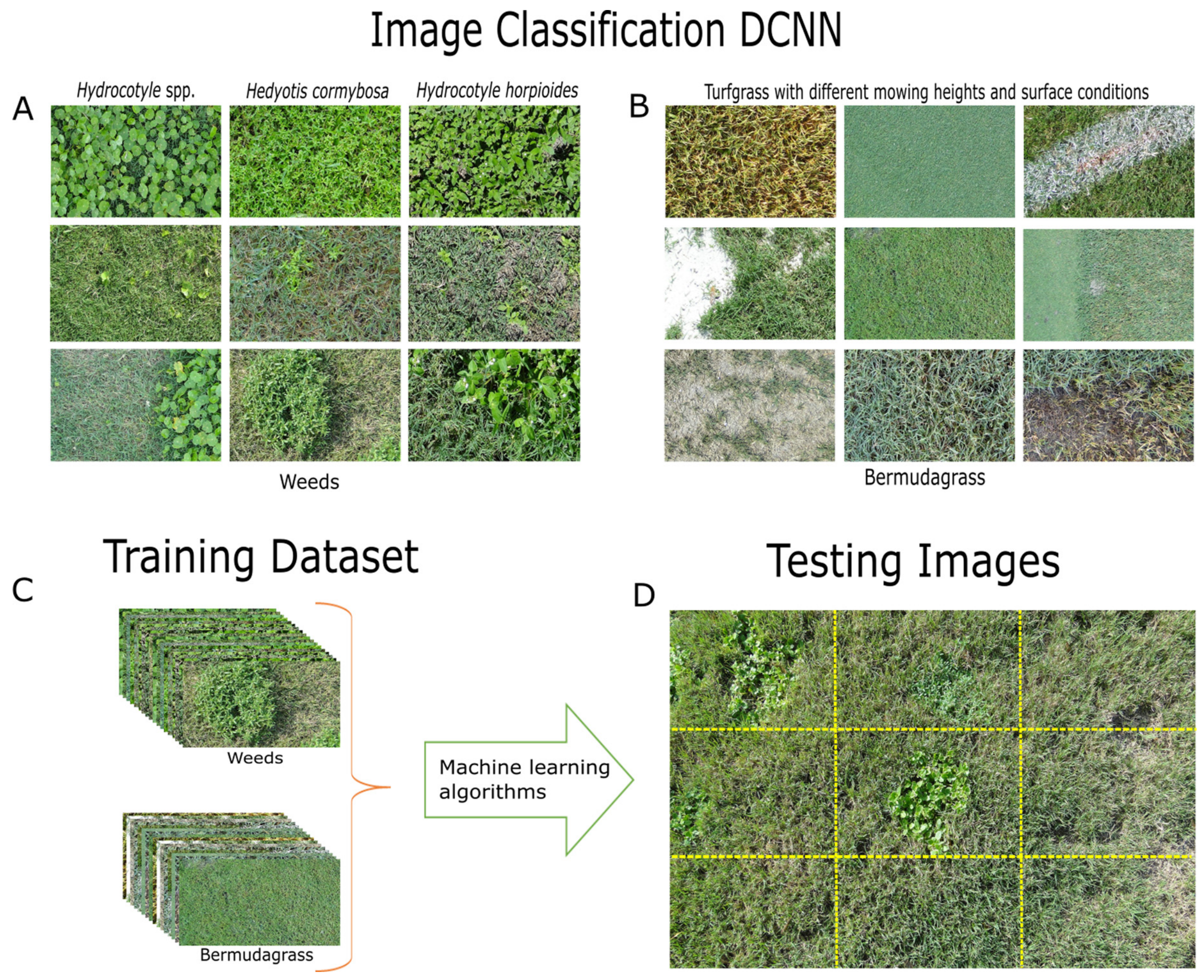

Fig. 1. Schematic of image classification DCNN for detection of *Hydrocotyle* spp., *Hedyotis cormybosa*, and *Richardia scabra* growing in bermudagrass: (A) images of *Hydrocotyle* spp., *Hedyotis cormybosa*, and *Richardia scabra* at different growth stages and weed densities, (B) images of bermudagrass at different turfgrass management regimes, mowing heights, and surface conditions, (C) training dataset containing true negative (images without weeds) and true positive (images with weeds) images, (D) testing images were cropped into 9 sub-images with a resolution of 640 × 360 pixels. Abbreviation: DCNN, deep convolutional neural networks.

Multiple-species neural networks were trained because we were interested in using a single DCNN model to simultaneously discriminate multiple weed species with bermudagrass. Multiple-species neural networks were trained using a total of 36,000 images containing 18,000 negative and 18,000 positive (6000 images for each weed species) images. To enable a fair comparison for the model's performance across weed populations, equal numbers of images were used in the VD, TD 1, and TD 2. Each VD and TD contained 500 negative and 500 positive images with a resolution of 640 × 360 pixels (Fig. 1D).

When training image classification DCNN for detection of *Poa annua* or *Poa annua* growing with various broadleaf weeds in dormant bermudagrass, all images were cropped into 9 sub-images using previously described methods. The training dataset contained 6030 negative and 6000 positive images. The VD or TD contained 500 positive and 500 negative images.

When training DetectNet for detection of weeds while growing in dormant bermudagrass, all images were resized to 1280 × 720 pixels (720p) using Irfanview. The 720p image resolution was used to develop DCNN models for future *in-situ* video input in conjunction with a developed robotic sprayer. A total of 705 images containing *Poa annua* or 1180 images containing *Poa annua* growing with various broadleaf weeds in dormant bermudagrass were used for training DetectNet models. The VD or TD contained 100 images.

Datasets were imported into the NVIDIA Deep Learning GPU Training System (DIGITS) (version 6.0.0, NVIDIA Corporation, Santa Clara, CA). The training of machine learning algorithms and testing processes were implemented in DIGITS using the Convolutional Architecture for Fast Feature Embedding (Caffe) (Jia et al., 2014). The AdaDelta solver type (Zeiler, 2012) was chosen due to its overall increased performance (F_1 scores) compared to other solver types, including AdaGrad (Adaptive Gradient) and SGD (Stochastic Gradient Descent) during preliminary training experiments. To ensure a fair comparison between the results of all DCNN models, we have standardized the following hyper-parameters across all experimental configurations.

- Training epochs: 30
- Solver type: AdaDelta
- Batch size: 2
- Batch accumulation: 5
- Solver type: AdaDelta
- Learning rate policy: Exponential decay
- Base learning rate: 0.1
- Gamma: 0.95

The validation and testing results of image classification or objection detection DCNN models were given in a binary classification confusion matrix under four conditions: a true positive (tp), a false negative (fn), a false positive (fp), or a true negative (tn). Subsequently, we computed the precision (Eq. (1)), recall (Eq. (2)), and F_1 score (Eq. (3)) for all experimental configurations using the results of confusion matrixes.

Precision measures the performances of the neural network at positive detection and was calculated using the following equation (Tao et al., 2016; Hoiem et al., 2012; Sokolova and Lapalme, 2009):

$$\text{Precision} = \frac{\text{tp}}{\text{tp+fp}} \tag{1}$$

Recall measures the effectiveness of the neural network to identify the target weed and was calculated by the following equation (Tao et al., 2016; Hoiem et al., 2012; Sokolova and Lapalme, 2009):

$$\text{Recall} = \frac{\text{tp}}{\text{tp+fn}} \tag{2}$$

In the present research, the high precision value indicates the high successful rate of detection for turfgrass area where weeds do not occur, while the high recall value indicates the high successful rate of detection on target weeds. The F_1 score is the harmonic mean of the precision and recall values and was determined using the following equation (Sokolova and Lapalme, 2009):

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision+Recall}} \tag{3}$$

3. Results

3.1. Detection of summer annual broadleaf weeds growing in bermudagrass

For single-species neural networks, VGGNet consistently performed better than GoogLeNet, as evidenced by higher precision, recall, and F_1 score values (Table 1). For detection of *Hydrocotyle* spp. and *Richardia scabra*, the recall values of GoogLeNet were ≥0.9827 in the VD, TD 1, and TD 2, while the precision values were ≤0.5385 in predicting the correct class label (images with weeds or images without weeds) (Table 1). For detection of *Hedyotis cormybosa*, the recall values of GoogLeNet in the VD, TD 1, and TD 2 were 0.9240, 0.9760, and 0.6475, respectively, while the precision values were 0.5753, 0.5951, and 0.7348, respectively. These results suggested that precision was primarily the limiting factor of GoogLeNet for image classification of weeds while growing in competition with bermudagrass.

For detection of *Hydrocotyle* spp., the F_1 score value of VGGNet was 0.9990, with the recall value of 0.9980 in the VD; and the precision, recall, and F_1 score values were 1.0000 in the TD 1 and TD 2 (Table 1). For detection of *Hedyotis cormybosa*, the F_1 score values of VGGNet were ≥0.9950, with recall values of 1.0000, 0.9980, and 1.0000 in the VD, TD 1, and TD 2, respectively. For detection of *Richardia scabra*, the F_1 score values were ≥0.9579, with the recall values of 1.0000, 1.0000, and 0.9923 in the VD, TD 1, and TD 2, respectively.

For multiple-species neural networks, the VGGNet performed considerably better than GoogLeNet, as evidenced by the F_1 scores in the model validation and testing for all weed species (Table 2). The recall values of GoogLeNet and VGGNet were ≥0.9960. However, VGGNet had higher precision values than GoogLeNet. The precision values of VGGNet were 0.9746, 0.9381, and 0.9124 in the VD for detection of *Hydrocotyle* spp., *Hedyotis cormybosa*, and *Richardia scabra*, respectively, while the precision values of GoogLeNet were 0.5470, 0.6468, and 0.5484, respectively. Similar trends were observed in the TD 1 and TD 2 for all weed species. The precision values of VGGNet were ≥0.9362 in the TD 1 and TD 2 for all weed species, while the precision values of GoogLeNet were ≤0.7200.

3.2. Detection of weeds growing in dormant bermudagrass

The precision, recall, and F_1 score values of DetectNet were consistently higher than GoogLeNet and VGGNet in the VD and TD, for detection of *Poa annua* while growing in dormant bermudagrass (Table 3). Among the image classification DCNN architectures, VGGNet consistently yielded higher F_1 score values than GoogLeNet. The F_1 score values of DetectNet, GoogLeNet, and VGGNet were 0.9978, 0.6667, and 0.9641 in the TD, respectively.

For detection of *Poa annua* growing with various broadleaf weeds in dormant bermudagrass, the recall values of GoogLeNet and VGGNet were 1.0000 in the VD and TD, while precision values were ≤0.5397. In comparison, the precision and recall values of DetectNet were ≥0.9981 in the VD and TD. As a result, the F_1 scores of DetectNet were considerably higher than GoogLeNet and VGGNet. In the TD, the F_1 scores of DetectNet were 0.9990, while the F_1 scores of GoogLeNet and VGGNet were 0.6667 and 0.6868, respectively.

4. Discussion

Both image classification and object detection neural networks can be used in a completed system for the machine vision component of a smart sprayer. The training of image classification DCNN is generally easier than objection detection DCNN because the drawing of bounding boxes is not required. However, the spray outputs of image classification DCNN models are limited to the field of view of the camera's image or sub-image and therefore are not allowed to target the individual weeds. Alternatively, the training of object detection DCNN takes longer time but the spray outputs can target onto the individual weeds using nozzles with narrow spray distribution patterns. In addition, it is likely that the image classification neural networks might be more appropriate at recognizing inconspicuous weed species compared to object detection neural networks. Labeling ground-truth locations within images for individual weeds, particularly weed species with branched stems and small leaves such as spotted spurge (*Euphorbia maculata* L.), is difficult.

Hydrocotyle spp., *Hedyotis cormybosa,* and *Richardia scabra* are the most common summer annual broadleaf weeds found in various turfgrass landscapes in the southern United States. Real-time detection is a

Table 1
Single-species neural network validation and testing result for detection of weeds while growing in bermudagrass.[a]

Single-species neural network	Weed species	VD[b]			TD 1			TD 2		
		Precision	Recall	F_1 score	Precision	Recall	F_1 score	Precision	Recall	F_1 score
GoogLeNet	*Hydrocotyle spp.*	0.5000	1.0000	0.6667	0.5000	1.0000	0.6667	0.4975	1.0000	0.6644
GoogLeNet	*Hedyotis cormybosa*	0.5753	0.9240	0.7091	0.5951	0.9760	0.7394	0.7348	0.6475	0.6884
GoogLeNet	*Richardia scabra*	0.5000	1.0000	0.6667	0.5000	1.0000	0.6667	0.5385	0.9827	0.6958
VGGNet	*Hydrocotyle spp.*	1.0000	0.9980	0.9990	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
VGGNet	*Hedyotis cormybosa*	0.9901	1.0000	0.9950	1.0000	0.9980	0.9990	0.9902	1.0000	0.9950
VGGNet	*Richardia scabra*	0.9823	1.0000	0.9911	0.9191	1.0000	0.9579	0.9904	0.9923	0.9913

Abbreviations: VDvalidation dataset; TD 1testing dataset 1; TD 2testing dataset 2.

[a] The models were trained to detect a single weed species and the training dataset contained a single weed species. The training dataset of *Hydrocotyle* spp. contained 6000 negative and 6000 positive images; the training dataset of *Hedyotis cormybosa* contained 8500 negative and 7632 positive images; and the training dataset of *Richardia scabra* contained 7000 negative and 6206 positive images.

[b] VD, TD 1, or TD 2 contained 500 negative and 500 positive images.

Table 2
Multiple-species neural network validation and testing results for detection of multiple weed species growing in bermudagrass[a].

Multiple-species neural network	Weed species	VD[b]			TD 1			TD 2		
		Precision	Recall	F_1 score	Precision	Recall	F_1 score	Precision	Recall	F_1 score
GoogLeNet	*Hydrocotyle* spp.	0.5470	1.0000	0.7072	0.5754	1.0000	0.7305	0.5331	1.0000	0.6955
	Hedyotis cormybosa	0.6468	1.0000	0.7855	0.7200	0.9720	0.8272	0.5385	0.9827	0.6958
	Richardia scabra	0.5484	0.9980	0.7078	0.6227	1.0000	0.7675	0.5361	1.0000	0.6980
VGGNet	*Hydrocotyle* spp.	0.9746	0.9960	0.9852	0.9452	1.0000	0.9718	0.9362	1.0000	0.9671
	Hedyotis cormybosa	0.9381	1.0000	0.9681	0.9529	0.9720	0.9624	0.9384	0.9981	0.9673
	Richardia scabra	0.9124	1.0000	0.9542	0.9560	1.0000	0.9775	0.9369	1.0000	0.9674

Abbreviations: VD, validation dataset; TD 1, testing dataset 1; TD 2, testing dataset 2.

[a] The models were trained to detect multiple weed species and the training dataset contained a total of 36,000 images including18000 negative images and 18,000 positive images (6000 images for each weed species).

[b] VD, TD 1, or TD 2 contained 500 negative and 500 positive images.

Table 3
Weed detection validation and testing results when using DCNN for detection of weeds growing in dormant bermudagrass.

Turfgrass condition	Deep learning architecture	VD			TD		
		Precision	Recall	F_1 score	Precision	Recall	F_1 score
Poa annua growing in dormant bermudagrass	DetectNet[a]	1.0000	0.9956	0.9978	0.9981	0.9981	0.9978
	GoogLeNet[b]	0.5000	1.0000	0.6667	0.5000	1.0000	0.6667
	VGGNet	0.9360	0.9940	0.9641	0.9360	0.9940	0.9641
Poa annua and various broadleaf weeds growing in dormant bermudagrass	DetectNet	1.0000	0.9981	0.9990	1.0000	0.9981	0.9990
	GoogLeNet	0.5000	1.0000	0.6667	0.5000	1.0000	0.6667
	VGGNet	0.5397	1.0000	0.7010	0.5230	1.0000	0.6868

Abbreviations: DCNN, deep learning convolutional neural network; VD, validation dataset; TD, testing dataset.

[a] For DetectNet models, the training dataset for detection of *Poa annua* in dormant bermudagrass contained 710 images; the training dataset for detection of *Poa annua* and various broadleaf weeds in dormant bermudagrass contained 1180 images; and VD or TD contained 100 images.

[b] For GoogLeNet or VGGNet, the training datasets contained 6030 negative and 6000 positive images; and VD or TD contained 500 negative and 500 positive images.

prerequisite for site-specific management of these weed species. VGGNet performed better than GoogLeNet for detection of these weed species growing in bermudagrass. Compared to bermudagrass, most broadleaf weeds have wider leaf blades that are easily discriminated against bermudagrass leaves. *Hedyotis cormybosa*, however, has noticeably narrower leaf blades compared to the most broadleaf weeds found in turfgrasses. Surprisingly, the VGGNet exhibited high precision and recall values ($>$ 0.99) for detection of *Hedyotis cormybosa* in bermudagrass. GoogLeNet exhibited high recall values but low precision values. The low precision values suggest that GoogLeNet is more likely to misclassify turfgrasses as weeds. This is undesirable, as it could lead to herbicide application on areas where weeds do not occur.

POST broadleaf herbicides, such as 2,4-D, carfentrazone, dicamba, MCPP, metsulfuron-methyl, and simazine are sprayed in bermudagrass to provide broad-spectrum control of various broadleaf weeds (McElroy and Martins, 2013 Reed et al., 2013; Yu and McCullough, 2016; Yu et al., 2015, 2018). For this reason, we evaluated the feasibility of using a single DCNN model to detect multiple weed species growing in bermudagrass. For training purposes, images containing *Hydrocotyle* spp., *Hedyotis cormybosa*, and *Richardia scabra* (with distinct plant morphologies, growth stages, and weed densities) constituted a single category of object to be differentiated from bermudagrass (with different mowing heights and surface conditions) (Fig. 1). When multiple-species neural networks were trained, VGGNet exhibited high F_1 score, precision, and recall, suggesting that a single VGGNet model can reliably detect multiple weed species in bermudagrass.

It is worth mentioning that the bermudagrass images used for model training and testing were taken at various golf course management zones (fairways, tees, putting greens, and roughs), institutional lawns, and sport fields with different mowing heights and surface conditions (Fig. 1B). We hypothesize that the images used for model training and testing at a more specific turfgrass management zone (i.e. taking images at golf course fairways exclusively) can achieve even higher accuracy, which warrant further investigation. Future research should focus on the evaluation with image datasets covering a greater range of weed species.

During winter months, warm-season turfgrasses, such as bermudagrass, are not actively growing and are therefore susceptible to the encroachment of *Poa annua* and various winter annual and perennial broadleaf weeds. Controlling *Poa annua* and various winter annual and perennial broadleaf weeds improves the aesthetic quality of the turfgrass, preserves the turfgrass stands, and reduces the likelihood of an outbreak in the next year. Amicarbazone, atrazine, pronamide, and trifloxysulfuron are broadcast-applied in dormant bermudagrass to control *Poa annua* (McElroy and Martins, 2013; McCullough et al., 2012; Yu et al., 2014, 2015); selective POST broadleaf herbicides such as 2,4-D, dicamba, and MCPP are broadcast-applied in dormant bermudagrass to control various broadleaf weeds (Johnson, 1975; McElroy and Martins, 2013; Reed et al., 2013); and nonselective herbicides such as diquat, glyphosate, and glufosinate are broadcast-applied to control various weed species growing in dormant bermudagrass (Johnson, 1976; McElroy and Martins, 2013; Yu et al., 2018). Precision spraying these herbicides can substantially reduce herbicide input and weed control cost.

Our results showed that *Poa annua* growing in dormant bermudagrass can accurately be detected with DCNN and that DetectNet was the most effective model, while GoogLeNet was the least effective model. For detection of *Poa annua* growing with various broadleaf weeds in dormant bermudagrass, the precision values of DetectNet were 1.0000 in the model training and testing, indicating that all true negatives were correctly identified, while the recall values were 0.9981, indicating that $<$ 1% true positives were incorrectly identified. DetectNet effectively detected *Poa annua* and broadleaf weeds in proximity to each other (Fig. 2b). DetectNet achieved an excellent performance, despite

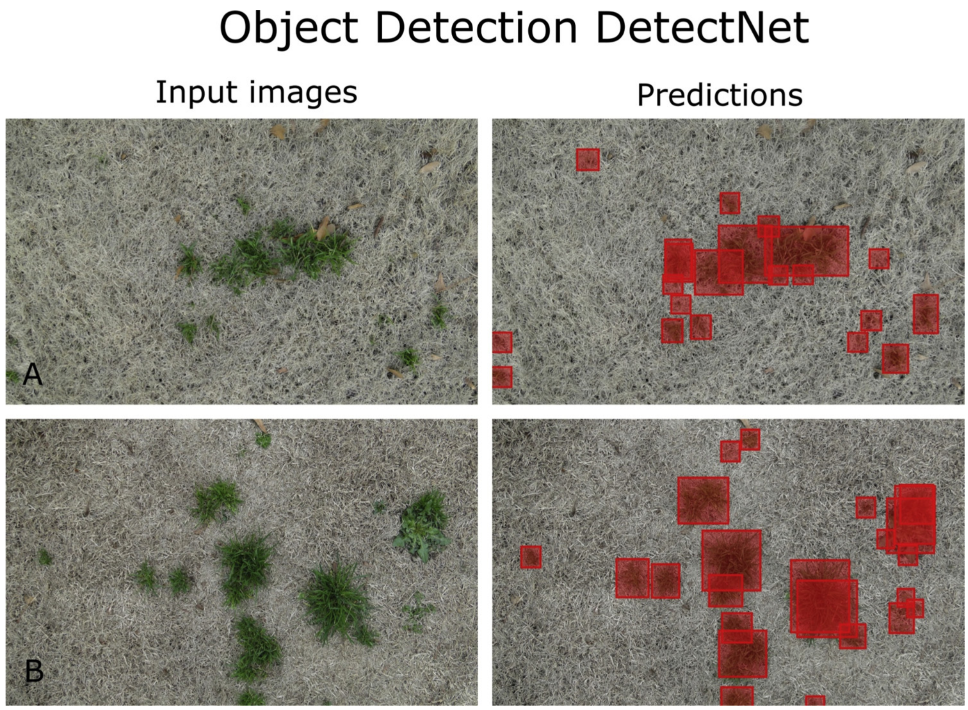

Fig. 2. DetectNet-generated bounding boxes (predictions) generated on the testing images (input images): (A) illustrated the *Poa annua* growing in dormant bermudagrass, and (B) illustrated the *Poa annua* growing with broadleaf weeds in dormant bermudagrass. Abbreviation: DCNN, deep convolutional neural networks.

the training and testing datasets covering *Poa annua* and various broadleaf weeds differed tremendously in plant morphology.

Multiple images used for model testing had very high weed densities (> 100 weeds per image). The DetectNet failed to detect weeds close to the image edge in few testing images containing high weed densities. However, this is unlikely to be an issue in field applications because continuous video inputs would partially eliminate the edge effect. Interestingly, the F_1 scores of VGGNet for detection of *Poa annua* while growing with various broadleaf weeds were significantly lower compared to the exclusive *Poa annua* detection. VGGNet utilized morphological properties and shape parameters of weed leaves as features for image classification and pattern recognition (Behmann et al., 2015; Lee et al., 2017; Simonyan and Zisserman, 2014). The complexity of datasets increased when the training and testing images covering both grassy and broadleaf weeds, which reduced the performance of VGGNet.

Previous research evaluated various classification algorithms but the use of "deep learning" algorithms generally exhibited better weed recognition. For example, Yang et al. (2000) developed a back-propagation artificial neural network to discriminate corn (*Zea mays* L.) and various broadleaf weeds. The authors noted that the neural network achieved 100% accuracy in classifying corn plants, while the accuracy of weed recognition did not exceed 80%. In comparison, do Santos Ferreira et al. (2017) evaluated the use of DCNN to identify various broadleaf and grassy weeds in relation to soil and soybean [*Glycine max* (L.) Merr.] and achieved an average accuracy of > 99%.

5. Conclusions

This work demonstrated the feasibility of using DCNN models for weed detection in bermudagrass turfgrasses. VGGNet consistently outperformed GoogLeNet for detection of *Hydrocotyle* spp., *Hedyotis corymbosa,* and *Richardia scabra* while growing in bermudagrass. A single VGGNet model was effective at detecting multiple broadleaf weed species with different growth stages, weed densities, and plant morphologies in bermudagrass across different mowing heights and surface conditions. DetectNet out-performed GoogLeNet and VGGNet with a high F_1 score (> 0.99) for detection of *Poa annua* or *Poa annua* growing with various broadleaf weeds in dormant bermudagrass.

Based on the high level of performance, the DCNN is highly suitable for the ground-based weed detection and discrimination in bermudagrass. We hypothesize that the use of DCNN models for weed detection is applicable to all cool-season and warm-season turfgrass systems, as well as other agricultural settings such as pastures and rangelands and certain row crops such as corn, rice (*oryza sativa* L.), and wheat (*Triticum aestivum* L.). Further research will be conducted to evaluate weed control in field conditions using the models obtained in the present research for *in-situ* video input in conjunction with a precision herbicide sprayer.

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