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Drought stress impact on the performance of deep convolutional neural networks for weed detection in Bahiagrass

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Abstract

Machine vision-based weed detection relies on features such as plant colour, leaf texture, shape, and patterns. Drought stress in plants can alter leaf colour and morphological features, which may in turn affect the reliability of machine vision-based weed detection. The objective of this research was to evaluate the feasibility of using deep convolutional neural networks for the detection of Florida pusley (*Richardia scabra* L.) growing in drought stressed and unstressed bahiagrass (*Paspalum natatum* Flugge). The object detection neural networks you only look once (YOLO)v3, faster region-based convolutional network (Faster R-CNN), and variable filter net (VFNet) failed to effectively detect Florida pusley growing in drought stressed or unstressed bahiagrass, with F1 scores ≤0.54 in the testing dataset. Nevertheless, the use of the image classification neural networks AlexNet, GoogLeNet, and Visual Geometry Group-Network (VGGNet) was highly effective and achieved high (≥0.97) F1 scores and recall values (≥0.98) in detecting images containing Florida pusley growing in drought stressed or unstressed bahiagrass. Overall, these results demonstrated the effectiveness of using an image classification convolutional neural network for detecting Florida pusley in drought stressed or unstressed bahiagrass. These findings illustrate the broad applicability of these neural networks for weed detection.

KEYWORDS
artificial intelligence, computer vision, deep learning, digital agriculture, weed detection

1 | INTRODUCTION

Bahiagrass (*Paspalum natatum* Flugge), native to South America, is a perennial warm-season species widely grown in the tropical and subtropical regions of the world (Burton, 1989). Apart from being grown as a forage crop in pastures and rangelands (Burton, 1982), bahiagrass is an important turfgrass species for residential lawns and highway rights-of-way (Altpeter & James, 2005; Zhang et al., 2015). In bahiagrass turf, weeds adversely impact turfgrass aesthetics and functionality. In bahiagrass pastures and rangelands, weed infestations can significantly reduce forage quality (Ferrell et al., 2006). Moreover, certain weeds infesting bahiagrass pastures can be toxic to livestock (Evers, 1983). For example, in the southern United States, creeping indigo (*Indigofera spicata* Forssk.), commonly found in bahiagrass, is toxic to horses. Although weeds naturally occur in patches, herbicides are typically broadcast-sprayed across the entire field area for weed control. Manual spot-spraying can reduce herbicide input as it delivers the herbicide only onto weeds; nevertheless, manual spot-spraying in large fields is difficult and impractical.

In recent years, deep learning has emerged as an incredible tool in various scientific applications, such as natural language processing (Collobert et al., 2011), speech recognition (Dahl et al., 2012;

Graves et al., 2013), and computer vision (Jordan & Mitchell, 2015; Krizhevsky et al., 2012; LeCun et al., 2015). The deep convolutional neural networks (DCNNs) are one of the most common deep learning tools used in machine learning applications (LeCun et al., 2015). Compared to other types of neural networks, such as feedforward neural networks, DCNNs require fewer artificial neurons (Jordan & Mitchell, 2015; Krizhevsky et al., 2012; LeCun et al., 2015). Schmidhuber (2015) showed that DCNNs have exceptional image classification and object detection capability. In the 2012 ImageNet competition, DCNNs performed exceptionally in classifying a dataset containing 1.3 million high-resolution images with 1000 classes (Krizhevsky et al., 2012). The availability of graphics processing units (GPU) and the opportunity for training on large datasets have facilitated the use of DCNNs (LeCun et al., 2015).

Several studies have documented the excellent performance of DCNNs for weed detection in various cropping systems (Grinblat et al., 2016; Teimouri et al., 2018; Sharpe et al., 2019, 2020; Yu, Sharpe, et al., 2019a; Yu, Schumann, et al., 2019b; Yu et al., 2020; Wang et al., 2019). For example, dos Santos Ferreira et al. (2017) documented >98% accuracy with a DCNN model for the detection of various broadleaf and grass weeds in relation to soybean (*Glycine max* [L.] Merr.) and soil. Sharpe et al. (2020) reported a DCNN model that reliably detected goosegrass (*Eleusine indica* [L.] Gaertn.) in plastic-mulched strawberry (*Fragaria* × *ananassa* Duch.) and tomato (*Solanum lycopersicum* L.). Yu, Sharpe, et al. (2019a); Yu, Schumann, et al. (2019b) developed neural network models that can reliably detect weeds in bermudagrass (*Cynodon dactylon* [L.] Pers.) and perennial ryegrass (*Lolium perenne* L.). Machine vision-based weed detection is based on numerous characteristics including, but not limited to, plant colour, pattern, and leaf morphological features such as size, shape, and texture (Chaki et al., 2015; Espejo-Garcia et al., 2020). However, leaf morphological features may be affected by environmental factors such as drought, which may affect the performance of machine learning models.

Smart weeding systems rely on machine vision to recognize weeds in digital images (Fennimore et al., 2016; Fennimore & Cutulle, 2019; Su et al., 2019; Wang et al., 2019). In turf systems, several studies have been conducted on weed detection using DCNNs (Xie et al., 2021; Yu et al., 2020). However, the majority of the existing studies were done under non-stress conditions, and it is unclear how stress conditions such as drought might affect the performance of the deep learning models. Drought stress can significantly alter leaf colour and morphological features (Hartfield, 2017; Zhang et al., 2015), which may substantially affect the performance of machine vision models for weed detection, perhaps due to increased complexity for feature extraction. Under severe drought conditions, bahiagrass may become dormant, suspending its growth and becoming physiologically inactive (Huang et al., 2014). Likewise, drought conditions are also expected to affect the morphological features of the Florida pusley being detected, even though it may not be as severe as bahiagrass. Thus, it is imperative to investigate how environmental factors such as drought stress can influence deep learning models.

Both object detection and image classification DCNNs can be utilized as a smart herbicide sprayer's machine vision decision system (Yu, Schumann, et al., 2019b). Object detection neural networks permit the localization of individual weeds, and therefore the nozzles generating narrow spraying outputs can be employed to deliver herbicides onto the weeds. However, training object detection neural networks require labeling individual weeds with bounding boxes and therefore is labor-intensive and time-consuming. Grid cells could be created on the input images, and the developed image classification neural networks can be employed to detect if the grid cells contain 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.

Florida pusley (*Richardia scabra* L.) is an important weed in warm-season turfgrasses such as bahiagrass. Its range in the United States extends from Florida to Virginia in the north and Texas in the west. Dry conditions can be expected during the spring months in Florida, wherein Florida pusley can outcompete bahiagrass and form a mat. Developing a machine vision-based model that can detect this weed in bahiagrass, especially under a range of soil moisture stress conditions, can be useful for in-situ weed detection and precision herbicide applications. To the best of our knowledge, no research has investigated the impact of drought stress on the performance of DCNNs for weed detection in any cropping system. The objective of this research was to evaluate the performance of object detection and image classification DCNNs for the detection of Florida pusley in bahiagrass under a range of drought stress conditions.

2 | MATERIALS AND METHODS

2.1 | Image preparation

The images of Florida pusley in bahiagrass under a range of drought stress conditions were acquired during multiple time periods from March to August 2018 (Table 1). Florida pusley training images were taken at the Gulf Coast Research and Education Center (GCREC) in Balm, Florida (27.71°N, 82.29°W), and at several institutional and residential lawns, sport fields, and roadsides in Riverview, Florida (27.86°N, 82.32°W). The testing images were collected at multiple commercial and residential lawns in Riverview, Florida, and the University of South Florida campus in Tampa, Florida (27.95°N, 82.45°W).

The training and testing images at a ground sampling distance of 0.05 cm pixel^{-1} were acquired at approximately 1.5 m above the ground surface 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 and testing images were captured 90 degrees from the ground surface during the daytime in sunny, cloudy, and partially cloudy outdoor light conditions.

For the purpose of this study, all training and testing images containing Florida pusley growing in bahiagrass were grouped into three categories of drought stress: Severe, moderate, and unstressed (Figure 1). Severe drought stress condition indicates ≤10% visual

TABLE 1 Specifics of the training and testing images used in this study

Dataset type[a]	Turfgrass condition	Image numbers[b]	Image acquisition date	Location
Training	Medium drought stressed	560, 1431, 437, 186	3 March 2018, 12 March 2018, 6 April 2018, 8 April 2018	GCREC, Balm, Florida; Riverview high school, Riverview, Florida
Training	Severe drought stressed	120, 894	9 April 2018, 13 May 2018	GCREC, Balm, Florida; Riverview high school, Riverview, Florida
Training	Unstressed	370, 516, 70	23 July 2018, 24 July 2018, 11 August 2018	GCREC, Balm, Florida
Testing	Medium drought stressed	30, 60	9 March 2018, 7 April 2018	University of South Florida campus, Tampa, Florida
Testing	Severe drought stressed	60	14 March 2018	Commercial and residential turfgrass sites at Riverview, Florida
Testing	Unstressed	50, 50	20 July 2018, 16 August 2018	University of South Florida campus, Tampa, Florida

Abbreviation: GCREC, Gulf Coast Research and Education Center.
[a]Training, validation, and testing datasets consisted of randomly selected training and testing images.
[b]The image numbers correspond to each acquisition date specified in the next column.

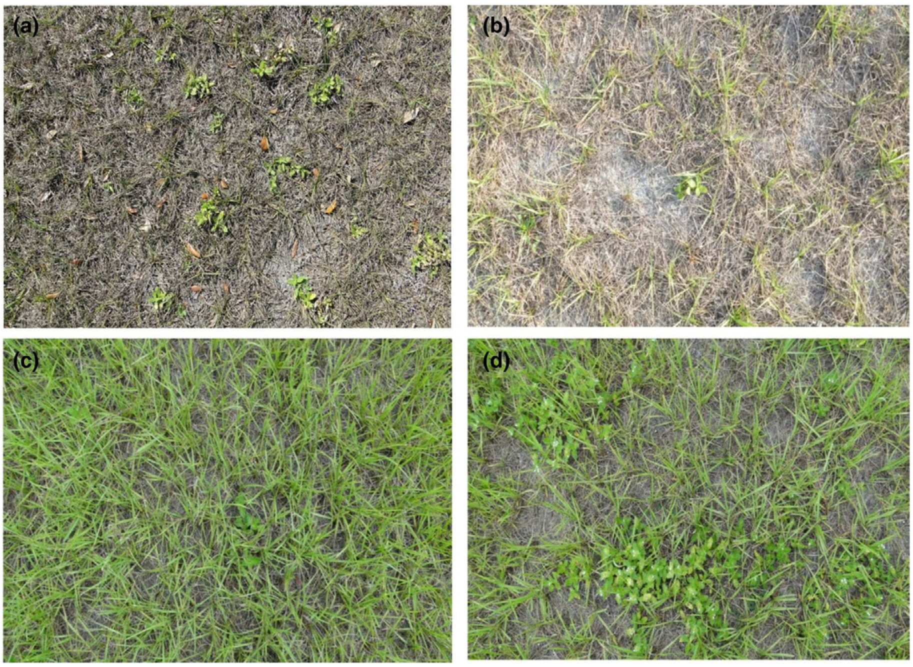

FIGURE 1 Images containing Florida pusley growing in bahiagrass at severe drought stressed (a), medium drought stressed (b), and unstressed (c, d) conditions. The appearance of Florida pusley at the pre-flowering (c) and flowering stages (d).

bahiagrass green foliage coverage in the image area, and bahiagrass is largely in drought-induced dormancy; medium stress represents bahiagrass with substantial visual foliage discoloration/yellowing, yet showed at least 30% visual green foliage coverage in the image area; unstressed condition represents actively growing bahiagrass without any moisture stress or visual symptom of foliage discoloration/yellowing. The images described in Table 1 were randomly selected to create the training, validation, and testing datasets (TDs) for the object detection and image classification neural networks investigated here. Figure 2 outlines the sequence diagram of image processing, training, and testing object detection and image classification neural networks for detecting Florida pusley growing in various stressed bahiagrass.

2.2 | Object detection

Three object detection deep learning architectures, including you only look once (YOLO) version 3 (Redmon & Farhadi, 2018), Faster R-CNN (Ren et al., 2017), and variable filter net (VFNet, Ahmed et al., 2019) were investigated for weed detection. YOLOv3 is a widely used single-stage object detector (Redmon & Farhadi, 2018). YOLOv3 was designed based on YOLO (Redmon et al., 2017) and YOLO Version 2 (Redmon & Farhadi, 2017). The inference time was the top priority when YOLOv3 was designed (Redmon & Farhadi, 2018). Faster R-CNN can achieve a near real-time frame detection speed (Ren et al., 2017). It shares the convolutional features of region proposal network and Fast R-CNN (Ren et al., 2017). VFNet utilizes the application of

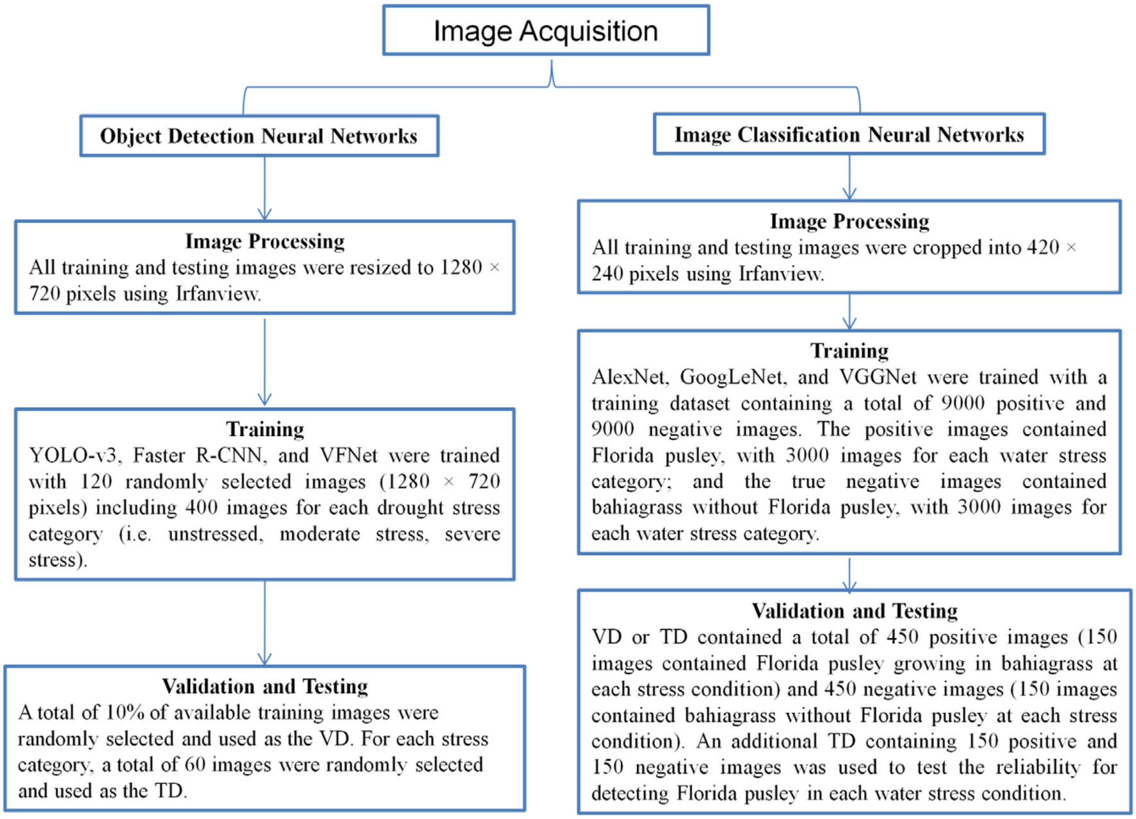

FIGURE 2 Flow diagram illustrates the sequential order of image processing, training, and testing the object detection and image classification neural networks. Faster R-CNN, faster region-based convolutional network; TD, testing dataset; VD, validation dataset; VFnet, variable filter net; VGGNet, Visual Geometry Group-Network; YOLO, you only look once.

variable filter sizes in addition to the audio spectrograms and thus can capture a hierarchy of audio features (Ahmed et al., 2019). VFNet was initially developed for accent recognition (Ahmed et al., 2019), but its feasibility for weed detection was examined in the present research.

All training and testing images were resized to 1280 × 720 pixels using Irfanview (version 5.5, Irfan Skijan, Jaice, Bosnia). A total of 1200 images (400 images for each drought stress category) were randomly selected and used for training the neural networks. During training, a total of 10% of available training images were randomly selected and used as the validation dataset (VD). For each stress category, a total of 60 images were randomly selected and used as the TD.

The areas in the training and testing images containing Florida pusley were annotated (bounding-box annotation) with LabelImg (an open-source software available at https://github.com/tzutalin/labelImg). A total of 5725, 321, and 309 bounding boxes were annotated for training, validation, and testing, respectively. YOLOv3, Fast R-CNN, and VFNet were pre-trained using the Microsoft Common Object in Context (COCO) dataset (Lin et al., 2014). The COCO contains high-quality labelled image datasets and is commonly used to benchmark algorithms to compare the performance of neural networks for object detection. Model training and testing were conducted with the mmDetection based on the Pytorch deep learning framework (an open-source software available at https://pytorch.org/) on a computer equipped with NVIDIA GeForce RTX 2080 Ti GPU. The intersection of union (IoU) between predicted bounding boxes and ground-truth labels with a threshold of 0.5 was employed to determine if the object detected was a true positive (Tao et al., 2016). The neural networks were trained until mean average precision, precision, and recall values ceased to increase or the average loss error ceased to decrease. The hyper-parameters used during training are presented in Table 2.

2.3 | Image classification

The objective of this study was to examine the feasibility of using the image classification neural networks to detect Florida pusley in severe drought stressed, medium drought stressed, and unstressed bahiagrass. Three image classification architectures, including AlexNet (Krizhevsky et al., 2012), GoogleNet (Szegedy et al., 2015), and VGGNet (Simonyan & Zissrman, 2014), were evaluated for weed detection. AlexNet consists of eight layers in which the first five layers are convolutional, and the other three layers are fully connected (Krizhevsky et al., 2012). GoogLeNet consists of a total of 22 convolutional layers with nine inception modules. GoogLeNet learns the convolutional filter entries by stochastic gradient descent (SGD) algorithms (Szegedy et al., 2015). The VGGNet utilized in this study was VGG16, consisting of very small convolution filters with 13 convolutional layers and three fully connected layers (Simonyan & Zisserman, 2014).

TABLE 2 Hyperparameters used for training object detection and image classification neural networks

Neural network	Network type	Base learning rate	Learning rate policy	Gamma	Solver type	Training epochs
YOLO-v3	Object detection	0.001	Step down	2.0	SGD	273
Faster R-CNN	Object detection	0.02	Step down	2.0	SGD	24
VFNet	Object detection	0.01	Step down	2.0	SGD	24
AlexNet	Image classification	0.01	Step down	0.1	SGD	60
GoogleNet	Image classification	0.01	Step down	0.1	SGD	60
VGG	Image classification	0.02	Exponential decay	0.95	AdaDelta	30

Abbreviations: Faster R-CNN, faster region-based convolutional network; SGD, stochastic gradient descent; VFNet, variable filter net; VGG, Visual Geometry Group; YOLO, you only look once.

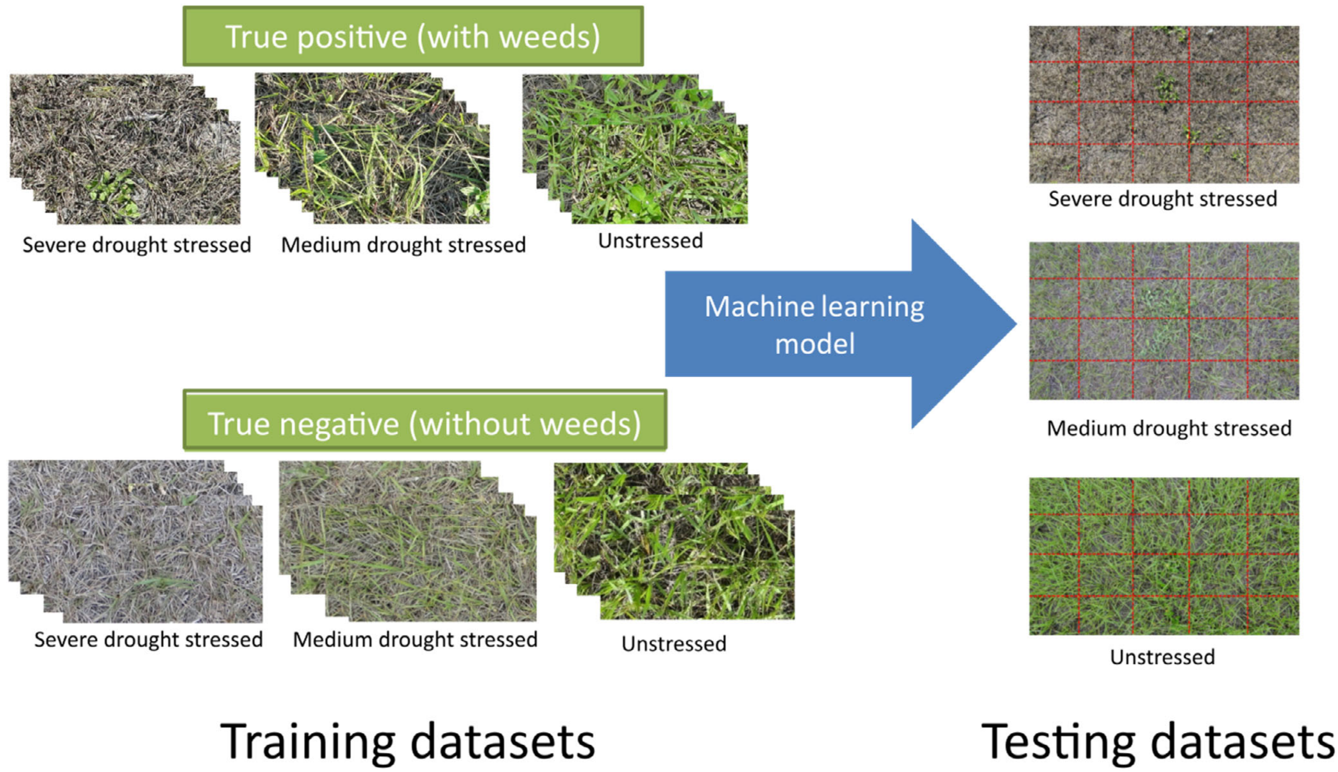

FIGURE 3 The schematic of image classification deep convolutional neural networks (DCNN) used in this study for detection of Florida pusley in bahiagrass under various drought stress conditions: True negative images (images without weeds) included the sub-images of severe drought stressed, medium drought stressed, and unstressed bahiagrass; true positive images included Florida pusley growing in severe drought stressed, medium drought stressed, and unstressed bahiagrass; testing images with Florida pusley growing in severe, medium, and unstressed bahiagrass.

The images containing a single weed species were used for training and testing the image classification neural networks. All images were cropped into 420 × 240 pixels using irfanview. The cropped images were randomly selected and used in the training and TDs. For constituting the training dataset, the true positive images included a total of 9000 images containing Florida pusley, with 3000 images at each of the three water stress conditions (i.e., unstressed, moderate stress, severe stress); and the true negative images included a total of 9000 images containing bahiagrass without weeds, with 3000 images at each of the three water stress conditions.

To evaluate the reliability of using the image classification neural network for the detection of Florida pusley growing in bahiagrass at various water stress conditions, VD or TD contained a total of 450 positive images (150 images contained Florida pusley growing in bahiagrass at each of the three water stress conditions) and 450 negative images (150 images contained bahiagrass without weeds at each of the three water stress conditions). An additional TD containing a total of 150 positive and 150 negative images was used to evaluate the reliability of detecting Florida pusley growing in either severe drought stressed, medium drought stressed, or unstressed bahiagrass.

The training and testing were performed in the NVIDIA Deep Learning GPU Training System (DIGITS) (version 6.1.1, NVIDIA, Santa Clara, CA, USA) using the convolutional architecture for fast feature embedding (Caffe) (Jia et al., 2014). The computer that was used in the training and testing experiments had a GeForece RTX 2080 Ti with 64 GB of memory and Intel® CoreTM i9-10,920X CPU @ 3.50 GHz x 24. Three image classification architectures, including AlexNet, GoogLetNet, and VGGNet, were pre-trained using the ImageNet database (Deng et al., 2009). Previous studies have shown that transfer learning effectively assists weed detection (Espejo-Garcia et al., 2020; Sharpe et al., 2019). These neural networks were selected for training because of their accessibility and effectiveness to train in the DIGITS. For training AlexNet and GoogLeNet, the neural networks were trained with the best combination of hyper-parameters that yielded the highest overall accuracy in the preliminary tests (data not shown). For training VGGNet, the hyper-parameters were selected based on previous reports, resulting in an excellent overall accuracy of weed detection (Yu et al., 2020; Yu, Schumann, et al., 2019b; Yu, Sharpe, et al., 2019a). For all neural networks, various training epochs (10, 20, 30, 50, and 60) were examined in the preliminary work (data not shown), and the training epochs that yielded the highest classification accuracy are presented. The hyper-parameters used for training AlexNet, GoogLeNet, and VGG16 are presented in Table 1. Figure 3 illustrates the method used for training and testing the image classification neural networks.

2.4 | Statistical parameters

For both image classification and object detection neural networks, validation and testing results were arranged in a confusion matrix consisting of four conditions: A true positive (TP), a true negative (TN), a false positive (FP), and a false negative (FN) (Table 3). The performances of the neural networks were measured with precision, recall, and F1 score. These metrics are commonly utilized to evaluate neural networks' effectiveness for weed detection in turfgrass (Yu et al., 2020; Yu, Schumann, et al., 2019b; Yu, Sharpe, et al., 2019a) and other cropping systems (Liu & Bruch, 2020; Sharpe et al., 2019, 2020). Precision measures the accuracy of neural network for positive prediction and was computed using the following equation (Sokolova & Lapalme, 2009):

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}.$$

Recall measures the effectiveness of the neural networks in detecting the target and was computed using the following equation (Sokolova & Lapalme, 2009):

TABLE 3 Confusion matrix used for calculating the statistical parameters

		Actual values	
		Bahiagrass	Weed
Predicated values	Bahiagrass	TN	FP
	Weed	FN	TP

Abbreviations: FN, false negative; FP, false positive; TN, true negative; TP, true positive.

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

F1 score, the harmonic mean of the precision and recall, represents the overall evaluation of the network's positive labels. The F1 score was computed using the following equation (Sokolova & Lapalme, 2009):

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

3 | RESULTS AND DISCUSSION

The evaluated object detection neural networks performed poorly at detecting Florida pusley growing in bahiagrass (Table 4). Because of low precision and recall, the F1 scores of YOLOv3, Faster R-CNN, and VFNet never exceeded 0.56, 0.53, and 0.53, respectively, in the VD. For all stress conditions, the F1 scores of YOLOv3, Faster R-CNN, and VFNet never exceeded 0.54, 0.52, and 0.51, respectively, in the TD. The low precision means that the neural networks are more likely to mistakenly identify bahiagrass as weeds, resulting in herbicide application on the bahiagrass area where weeds do not occur. Low recall indicates that the target weeds are prone to be misidentified, leading to poor herbicide coverage in field applications.

In previous studies, DetecNet achieved high F1 scores in detecting various weeds in dormant bermudagrass (Yu, Sharpe, et al., 2019a) and in detecting dandelion (*Taraxacum officinale* Web.) in actively growing perennial ryegrass (*L. perenne* L.) (Yu, Schumann, et al., 2019b). Sharpe et al. (2019) noted that YOLOv3 effectively detected and discriminated broadleaves, grasses, and sedges (*Cyperus* spp.) growing in the row-middles of plastic-mulched vegetables. In the present study, the training and testing images containing Florida pusley at various growth stages in drought stressed or unstressed bahiagrass have increased computational complexity for feature extraction and thus decreased the precision and recall of the neural networks. Moreover, in the present study, the object detection neural networks were trained using a training dataset that contained severe drought stressed, medium drought stressed, and unstressed bahiagrass. Perhaps, training the object detection neural network using a training dataset containing only a particular water stress condition may increase weed detection performance and warrant further investigation.

It was reported that the annotation method used in the preparation of the training dataset could significantly affect the reliability of object detection neural networks for weed detection (Sharpe et al., 2018, 2020). For instance, Sharpe et al. (2020) reported that annotation methods could affect the accuracy of neural networks for the detection of goosegrass (*E. indica* [L.] Gaertn.) growing in plastic-mulched strawberry and tomato (*S. lycopersicum* L.). The authors reported that YOLOv3-tiny trained with the annotation of individual goosegrass leaf blades demonstrated superior detection accuracy than the neural network trained with annotating the entire goosegrass plant. In the present study, annotation of the training dataset was

TABLE 4 Object detection neural network validation and testing results for detection of Florida pusley in bahiagrass under various water stress conditions[a]

		VD			TD		
Neural network	Turfgrass condition	Precision	Recall	F1 score	Precision	Recall	F1 score
YOLO-v3	Severe drought stressed	0.61	0.51	0.56	0.55	0.46	0.50
	Medium drought stressed				0.50	0.29	0.37
	Unstressed				0.62	0.48	0.54
Faster R-CNN	Severe drought stressed	0.59	0.49	0.53	0.53	0.45	0.49
	Medium drought stressed				0.45	0.37	0.41
	Unstressed				0.57	0.48	0.52
VFNet	Severe drought stressed	0.55	0.51	0.53	0.48	0.39	0.43
	Medium drought stressed				0.37	0.38	0.38
	Unstressed				0.53	0.50	0.51

Abbreviations: Faster R-CNN, faster region-based convolutional network; TD, testing dataset; VD, validation dataset; VFNet, variable filter net; YOLO, you only look once.
[a]The neural networks were trained to detect Florida pusley in bahiagrass at each water stress condition.

TABLE 5 Image classification neural network validation and testing results for detection of Florida pusley in bahiagrass under various water stress conditions[a]

	VD			TD		
Neural network	Precision	Recall	F1 score	Precision	Recall	F1 score
AlexNet	0.99	1.00	0.99	0.99	1.00	0.99
GoogleNet	0.99	1.00	0.99	0.99	1.00	0.99
VGG	0.99	1.00	0.99	0.99	1.00	0.99

Abbreviations: TD, testing dataset; VD, validation dataset; VGG, Visual Geometry Group.
[a]The VD or TD contained a total of 450 positive images (150 images for each of the three stress conditions: severe stress, moderate stress, and no stress) and 450 negative images containing bahiagrass without weeds (the number of negative images for each water stress condition was equal to that of the number of positive images).

performed based on the image area containing Florida pusley plants rather than the individual plants or leaves. This annotation method was adopted because annotating individual leaves in the software used here was impractical. In other research, Xie et al. (2021) constructed and applied a skeleton-based probabilistic map for the detection of nutsedges (*Cyperus* spp.) in bermudagrass turf. They have generated high-fidelity synthetic data to reduce annotation costs. An additional study is needed to evaluate this approach's feasibility for detecting weeds in bahiagrass.

Because of the poor performance of object detection neural networks, we further explored the feasibility of using image classification neural networks for detecting images containing Florida pusley in bahiagrass. Although the training and testing images contained Florida pusely growing in severe drought stressed, medium drought stressed, and unstressed bahiagrass, a single image classification neural network AlexNet, GoogLeNet, and VGGNet achieved high F1 scores (0.99) with high precision (0.99) and recall (1.00) in the VD and TD (Table 5). These results suggest that a single image classification neural network can detect Florida pusley growing in various levels of water stressed turfgrass. For detection of Florida pusley growing in either severe drought stressed, medium drought stressed, or unstressed bahiagrass, the precision and recall values of AlexNet were ≥0.95 and ≥0.98, respectively (Table 6). In previous research, Yu, Schumann, et al. (2019b) reported that the ratio between positive and negative images could affect the performance of deep learning neural networks for weed detection. In the present study, although the number of positive and negative images in the training dataset was selected arbitrarily, the neural networks demonstrated excellent performance for classifying images that did or did not contain weeds.

Previous studies suggest that deep learning-based weed detection methods generally outperform other weed detection techniques (Fennimore et al., 2016; Grinblat et al., 2016; Peteinatos et al., 2014; Sharpe et al., 2018, 2019; Teimouri et al., 2018; Wang et al., 2019). For instance, techniques such as 2D image-processing, relying on the detection of multiple factors including plant size, colour, infrared to red light reflectance ratios, have been used for weed detection in robotic weeding platforms, but such techniques perform well under uniform crop stands, with relatively low weed densities (Fennimore et al., 2016).

Turfgrass may present erratic surface conditions due to drought stress, traffic, dormancy, or varying management practices such as fertilization and mowing. Due to its drought tolerance, Florida pusley (*R. scabra* L.) can thrive in drought-impacted bahiagrass, even though bahiagrass may undergo severe foliage desiccation. The present study results demonstrate that image classification DCNNs can be used to reliably detect Florida pusley growing in varying turfgrass surface conditions. Additionally, in the present study, the training and testing

TABLE 6 Image classification neural network testing results for detection of Florida pusley in bahiagrass at each of the three water stress conditions[a]

Neural network	Turfgrass condition	Precision	Recall	F1 score
AlexNet	Severe drought stressed	0.95	0.99	0.97
	Medium drought stressed	0.99	0.98	0.99
	Unstressed	0.99	0.98	0.98
GoogleNet	Severe drought stressed	0.96	0.99	0.97
	Medium drought stressed	0.99	1.00	0.99
	Unstressed	0.99	1.00	0.99
VGG	Severe drought stressed	0.95	0.99	0.97
	Medium drought stressed	0.98	1.00	0.99
	Unstressed	0.99	0.99	0.99

Abbreviation: VGG, Visual Geometry Group.
[a]The models were trained to detect weeds in bahiagrass at severe drought stressed, medium drought stressed, or unstressed condition. For each water stress condition, the testing datasets contained a total of 150 positive and 150 negative images.

images contained Florida pusley at various growth stages (Figure 1). The results demonstrated that image classification neural networks are effective for detecting the subimages contain various growth stages of Florida pusley with distinct plant morphological features in erratic bahiagrass turf surfaces.

Various herbicides, such as 2,4-D, carfentrazone, dicamba, and mecoprop, are used for postemergence (POST) control of broadleaf weeds in bahiagrass (Akanda et al., 1997; Costa et al., 2010; da Silva et al., 2016). Spraying these herbicides with machine vision-based precision technology can substantially reduce herbicide input and weed control costs. It should be noted that although the evaluated image classification neural networks effectively detected Florida pusley in bahiagrass, reliable weed detection in unstressed turfgrass is more critical. This is because POST herbicides may injure turfgrass when the turfgrass suffers from abiotic and/or biotic stress (Johnson, 1994; Murphy, 1994). Therefore, it is recommended spraying the POST herbicides with the smart sprayer when the turfgrass is not under stress.

4 | CONCLUSIONS

In summary, the present research demonstrated the reliability and effectiveness of using image classification neural networks to detect Florida pusley growing in drought stressed or unstressed bahiagrass. However, object detection neural networks including YOLOv3, Faster R-CNN, and VFNet exhibit low accuracy for detecting Florida pusley in drought stressed or unstressed bahiagrass. This is likely due to the increased complexity of the image background under water stressed conditions. Image classification overcame this limitation and effectively detected Florida pusley regardless of water stress conditions. It is worth noting that this is the first report evaluating the impact of turfgrass growth conditions on the performance of DCNNs for weed detection. The developed networks demonstrated the feasibility for in-situ detection of weeds growing in drought stressed or unstressed bahiagrass, which can be utilized for autonomous weed detection and precision herbicide application under varying soil moisture conditions.

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CONFLICT OF INTEREST

The authors declare they have no conflict of interest.

DATA AVAILABILITY STATEMENT

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

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