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A comparative evaluation of convolutional neural networks, training image sizes, and deep learning optimizers for weed detection in alfalfa

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Abstract

In this research, the deep-learning optimizers Adagrad, AdaDelta, Adaptive Moment Estimation (Adam), and Stochastic Gradient Descent (SGD) were applied to the deep convolutional neural networks AlexNet, GoogLeNet, VGGNet, and ResNet that were trained to recognize weeds among alfalfa using photographic images taken at 200×200, 400×400, 600×600, and 800×800 pixels. An increase in the image sizes reduced the classification accuracy of all neural networks. The neural networks that were trained with images of 200×200 pixels resulted in better classification accuracy than the other image sizes investigated here. The optimizers AlexNet and GoogLeNet trained with AdaDelta and SGD outperformed the Adagrad and Adam optimizers; VGGNet trained with AdaDelta outperformed Adagrad, Adam, and SGD; and ResNet trained with AdaDelta and Adagrad outperformed the Adam and SGD optimizers. When the neural networks were trained with the best-performing input image size (200×200 pixels) and the best-performing deep learning optimizer, VGGNet was the most effective neural network, with high precision and recall values ($\geq$0.99) when validation and testing datasets were used. Alternatively, ResNet was the least effective neural network in its ability to classify images containing weeds. However, there was no difference among the different neural networks in their ability to differentiate between broadleaf and grass weeds. The neural networks discussed herein may be used for scouting weed infestations in alfalfa and further integrated into the machine vision subsystem of smart sprayers for site-specific weed control.

Introduction

Alfalfa, an important leguminous forage crop, is widely cultivated worldwide (Bai et al. 2018; Li et al. 2021; Mielmann 2013; Radovic et al. 2009). Alfalfa contains a high amount of crude protein and is rich in minerals, particularly calcium, iron, and manganese (Richter et al. 2003), and is thus considered to be a healthy feed for livestock (Salzano et al. 2021). Weeds are a significant challenge in alfalfa production because they compete with alfalfa for nutrients, space, sunlight, and water, and reduce forage yield and nutritive value. Moreover, certain weed species such as perilla mint (*Perilla frutescens* L.) are toxic to livestock (Kerr et al. 1986). A variety of postemergence (POST) herbicides are used for weed control in alfalfa fields. For instance, clethodim and 2,4-DB control a wide range of grasses and broadleaf weeds, respectively, in conventional alfalfa crops (Cudney and Adams 1993; Idris et al. 2019), while glyphosate provides nonselective control of weeds in glyphosate-tolerant alfalfa crops (Wilson and Burgener 2009). These POST-applied herbicides are typically broadcast-applied in alfalfa fields, including where weeds do not occur.

Site-specific weed management, particularly precision herbicide application, can considerably reduce herbicide input and weed control costs (Franco et al. 2017; Sabzi et al. 2018; Yu et al. 2020; Zaman et al. 2011). A major obstacle for autonomous precision herbicide application is the ability to accurately and reliably detect weeds in a real-time manner (Sabzi et al. 2018). Traditional machine vision techniques depend on the ability to recognize and differentiate plant leaf color, spectral information, and feature fusion (Sabzi et al. 2018, 2020); morphological features (Bakhshipour and Jafari 2018; Hamuda et al. 2017; Pulido et al. 2017); and spatial information (Farooq et al. 2019). However, these traditional approaches cannot reliably detect weeds intermingled with crops, especially in the context of a complex environment with high crop and weed densities (Ahmad et al. 2020; Akbarzadeh et al. 2018; Sujaritha et al. 2017; Yu et al. 2019a).

Machine learning techniques have advanced significantly in recent years (Jordan and Mitchell 2015). Deep convolutional neural networks (DCNNs) have been used successfully in various field applications (LeCun et al. 2015; Ni et al. 2019). For example, recent studies have shown that deep learning can be used to diagnose coronavirus disease (Saood and Hatem 2021), to help predict seizure recurrence (Geng et al. 2021), for high-accuracy three-dimensional optical measurement (Yao et al. 2021), to predict the activity of potential drug molecules (Ma et al. 2015), to analyze particle accelerator data (Azhari et al. 2020; Ciodaro et al. 2012), to detect industrial defects in wood veneer finishes (Shi et al. 2020), to achieve efficient classification of green plum detects (Zhou et al. 2020), and to reconstruct brain circuits (Helmstaedter et al. 2013). In addition, DCNNs have demonstrated an exceptional ability to detect objects and classify digital images (Tompson et al. 2014; Wang et al. 2018). Thus, DCNNs show great promise for being employed for weed detection and classification purposes (Wang et al. 2019).

Researchers have recently explored the feasibility of using DCNNs to detect weeds in various cropping systems (Ferentinos 2018; Ghosal et al. 2018; Sharpe et al. 2019b; Singh et al. 2018; Yu et al. 2020). Sharpe et al. (2019b) showed that You Only Look Once (YOLO, version 3; Cornell University, Ithaca, NY [YOLO is a unified, real-time object detection system of software]) can be used as an object detector to discriminate broadleaves, grasses, and sedges in the middle rows of plastic-mulched vegetable crops. Yu et al. (2019a, 2020) reported the feasibility of using DCNNs to detect multiple broadleaf and grass weeds among actively growing or dormant bermudagrass [*Cynodon dactylon* (L.). Pers.] plants. Hennessy et al. (2021) reported the feasibility of using YOLO3-tiny to detect hairy fescue (*Festuca filiformis* Pourr.) and sheep sorrel (*Rumex acetosella* L.) among wild blueberry (*Vaccinium* spp. L.) plants. Hussain et al. (2021) investigated the feasibility of using DCNNs to detect common lambsquarters (*Chenopodium album* L.) in potato (*Solanum tuberosum* L.) fields. However, the feasibility and effectiveness of using DCNNs for weed detection in alfalfa have never been investigated.

Alfalfa hay is typically harvested multiple times per growing season, unlike most other crops. Alfalfa has the capability to regrow following harvest and can rapidly regenerate new stems and leaves. Weed detection in various heights of alfalfa stands might be a significant challenge.

Image classification with DCNNs can be used in the machine vision subsystem of smart sprayers for weed detection and real-time precision treatment (Sharpe et al. 2019b; Wang et al. 2019; Yu et al. 2019a, 2020). He et al. (2015) noted that arbitrary use of fixed-size input images for training a neural network might reduce the classification accuracy. However, a careful review of the literature suggests that almost all previously reported studies that evaluated the feasibility of using DCNNs for weed detection and classification arbitrarily used a particular size of input images (Ferentinos 2018; Sharpe et al. 2019b; Yu et al. 2019a, 2019b, 2020). Limited research has been carried out to investigate the impact of training image sizes on the performance of DCNNs for weed detection and classification through a comparative study.

When training is given to a deep learning model, the algorithm gradually improves to optimize through a large number of samples, with a certain weight of the optimizer (Krizhevsky et al. 2012; Simonyan and Zisserman 2014; Szegedy et al. 2015). Thus, selecting an appropriate optimizer is critical in the training pipeline for deep learning models (Choi et al. 2019). The majority of previous studies have focused on comparing the state-of-the-art deep learning architectures for weed detection (Sharpe et al. 2019a, 2019b; Wang et al. 2019; Yu et al. 2019a, 2019b). However, none of them attempted to improve weed detection accuracies by using deep-learning optimizers through comparative research. Therefore, the objectives of this research were to 1) explore the effects of using various image sizes for training purposes to gauge the performance of DCNNs to detect and classify weeds; 2) compare several DCNNs trained with different deep learning optimizers for weed detection purposes; and 3) determine the feasibility of using DCNNs to detect multiple broadleaf and grass weeds growing in alfalfa.

Materials and Methods

Overview

In this research, the image classification DCNN architectures AlexNet (Krizhevsky et al. 2012), GoogLeNet (Szegedy et al. 2015), VGGNet (Simonyan and Zisserman 2014), and ResNet (He et al. 2016) were evaluated. These neural networks were trained to recognize four different sizes of input images (200×200, 400×400, 600×600, and 800×800 pixels); and three commonly employed deep-learning optimizers, Adagrad (Duchi et al. 2011), AdaDelta (Zeiler 2012), and Stochastic Gradient Descent (SGD; Darken et al. 1992). AlexNet consists of eight layers, including five convolutional layers and three full connection layers (Krizhevsky et al. 2012). GoogLeNet consists of 22 convolutional layers and is designed to work with small convolutions in order to reduce the neuron numbers and parameters (Szegedy et al. 2015). VGGNet used in this research consists of 19 weight layers. VGGNet is designed to implement smaller convolutional kernels to limit neuron numbers and parameters (Simonyan and Zisserman 2014). ResNet is based on the VGG19, which consists of 50 layers and is modified to include a residual unit through a short-circuit mechanism (He et al. 2016). ResNet solves the degradation problem of the deep network through residual learning for training deeper networks (He et al. 2016). All neural networks were pretrained using the ImageNet database (Deng et al. 2009) with specific spatial tensor image sizes of 224×224 pixels, whereas the AlexNet was trained with 227×227 pixels (He et al. 2016; Krizhevsky et al. 2012; Simonyan and Zisserman 2014; Szegedy et al. 2015).

Image Acquisition

Images of various weeds growing in alfalfa fields were acquired multiple times during September and October 2020 using a digital camera (Panasonic® DMC-ZS110; Xiamen, Fujian, China) at a resolution of 4,160×3,120 pixels. The images taken in alfalfa fields in Bengbu, Anhui, China (117.89°N, 117.88°E) were used for the training dataset, validation dataset (VD), and testing dataset (TD). Additional testing images were taken in separate alfalfa fields in Bengbu, Anhui, China (additional testing dataset 1, TD 1) and Yangzhou University Pratacultural Science Experiment Station (32.20°N, 119.23°E) in Yangzhou, Jiangsu, China (additional testing dataset 2, TD 2). The additional testing datasets were used to examine the robustness of the models. The images containing alfalfa (8 to 52 cm height) and various broadleaf and grass weed species were captured from a height of approximately 1.5 m from the ground (0.05 cm pixel^{-1}). Our research team designed a smart sprayer with a camera installed at 1.5 m above the ground (data not shown). Thus, all images were captured at 1.5 m above the ground to mimic the height of the smart sprayer's camera. Images were acquired under various outdoor lighting conditions, including clear/bright, cloudy, and partially cloudy skies. In the present study, weed images were captured in the fall season, and only mature weeds were used for training and testing. An additional investigation is needed to evaluate the feasibility of using neural networks to identify weed growth stages. Variable rates could be sprayed according to the weed growth stages. For example, low and high herbicide rates could be sprayed to control seedling and mature annual weeds, respectively, while maintaining adequate weed control.

Impact of Training Using Various Image Sizes

During training, all collected images were cropped into sub-image datasets with resolutions of 200×200, 400×400, 600×600, or 800×800 pixels using Irfanview (v.5.50; Iran Skijan, Jajce, Bosnia; Figure 1A). The DCNN architectures received training with these image sizes. For each image size, the training dataset contained 3,000 positive images (with weeds) and 3,000 negative images (without weeds; Figure 1B). The VD contained 600 positive and 600 negative images. The TD contained 300 positive and 300 negative images that were randomly selected from the sites where the training images were taken but were not used for training. The TD 1 and TD 2 each contained a total of 700 positive and 700 negative images. The training and testing images contained a variety of broadleaf and grass weed species occurring in the mixture. The dominant broadleaf weed species (Figure 1C) included annual fleabane [*Erigeron annuus* (L.) Pers], common sage (*Salvia plebeia* R. Br.), Canada thistle [*Cirsium arvense* (L.) Scop.], and hemistepta [*Hemistepta lyrata* (Bunge) Bunge]; whereas the major grass weeds (Figure 1C) included crabgrass (*Digitaria* spp.), goosegrass [*Eleusine indica* (L.) Gaertn.], barnyardgrass [*Echinochloa crus-galli* (L.) Beauv], and green foxtail [*Setaria viridis* (L.) Beauv.].

Effect of Optimizers

Next, we investigated the performance of the CDDNs when they received additional training with four common deep-learning optimizers, Adagrad (Duchi et al. 2011), AdaDelta (Zeiler 2012), Adam (Kingma and Ba 2014), and SGD (Darken et al. 1992). The characteristics of the deep-learning optimizers are described below.

Adagrad uses different learning rates for every parameter in the network (Duchi et al. 2011). It updates the learning rate η based on the frequency of the update of each parameter. The performance of Adagrad relies on manually setting a global learning rate. The optimizer AdaDelta is an extension of Adagrad (Zeiler 2012). AdaDelta accumulates the previous gradients over a fixed timeframe and employs Hessian approximation to ensure that the update direction is in the negative gradient. Adam combines the advantages of Adagrad and Root Mean Square Propagation (RMSProp; Kingma and Ba 2014). The method calculates the adaptive learning rate of different parameters by estimating the first and second gradients. It has the following advantages: 1) simple implementation, efficient calculation, and less memory demand; 2) the updating of parameters is not affected by the scaling transformation of gradient; 3) it is suitable for large-scale data and parameter scenarios and is applicable to unstable target functions; and 4) it is suitable for addressing the problem of sparse gradient or large noise gradient. Although Adam is currently the mainstream optimization algorithm, the best results in many fields (e.g., object recognition in computer vision) are still obtained by using SGD (Wilson et al. 2017). SGD refers to mini-batch gradient descent (Qian et al. 2015) and is one of the simplest deep-learning optimizers used to calculate the mini-batch gradient at every iteration. Although SGD is one of the most commonly used optimizers, its disadvantages are obvious. SGD can easily converge to the local optimum and be trapped in a saddle point.

Detection of Broadleaf and Grass Weeds

The deep learning architectures AlexNet, GoogLeNet, VGGNet, and ResNet were trained using input images of 200×200 pixels to detect broadleaf and grass weeds growing among alfalfa plants. The neural networks were trained with a total of 3,000 positive (with broadleaf weeds) and 3,000 negative (with grass weeds) images. The images of VD, TD, TD 1, and TD 2 contained broadleaf or grass weeds. The VD contained 600 positive and 600 negative images, the TD contained 300 positive and 300 negative images, and the TD 1 and TD 2 each contained a total of 700 positive and 700 negative images.

Training and Testing

The training and testing datasets were imported into the NVIDIA Deep Learning GPU Training System (DIGITS v. 6.0.0; NVIDIA Corporation, Santa Clara, CA, USA). The training and testing were performed on a GeForce RTX 2080Ti computer with 64 GB of memory using the Convolutional Architecture for Fast Feature Embedding (CAFFE; Jia et al. 2014). The hyper parameters used for training the neural networks are presented in Table 1. The actual training was carried out using the initial hyper parameters proposed by the original authors (Darken et al. 1992; Duchi et al. 2011; Kingma and Ba 2014; Zeiler 2012).

The testing and validation results of the neural networks were arranged in a confusion matrix with four possible conditions: true positive (*tp*), false positive (*fp*), false negative (*fn*), and true negative (*tn*). Precision, recall, and F_1 scores were computed based on the results of confusion matrices.

Precision measures the accuracy of the neural network at positive detection and was calculated using Equation 1 (Hoiem et al. 2012; Sokolova and Lapalme 2009; Tao et al. 2016):

$$\text{Precision} = \frac{tp}{tp + fp} \quad [1]$$

Recall measures the effectiveness of the neural network in identifying the target and was determined using Equation 2 (Hoiem et al. 2012; Sokolova and Lapalme 2009; Tao et al. 2016):

$$\text{Recall} = \frac{tp}{tp + fn} \quad [2]$$

F_1 score is the harmonic mean of precision and recall. The F_1 score is used for comprehensive evaluation of precision and recall and was calculated using Equation 3 (Tao et al. 2016):

$$F_1\text{score} = \frac{2*\text{precision} * \text{recall}}{\text{precision} + \text{recall}} \quad [3]$$

Results and Discussion

Effect of Training Using Various Image Sizes

The input image size significantly affected the performance of the ability of DCNNs to detect weeds (Table 2). The neural networks

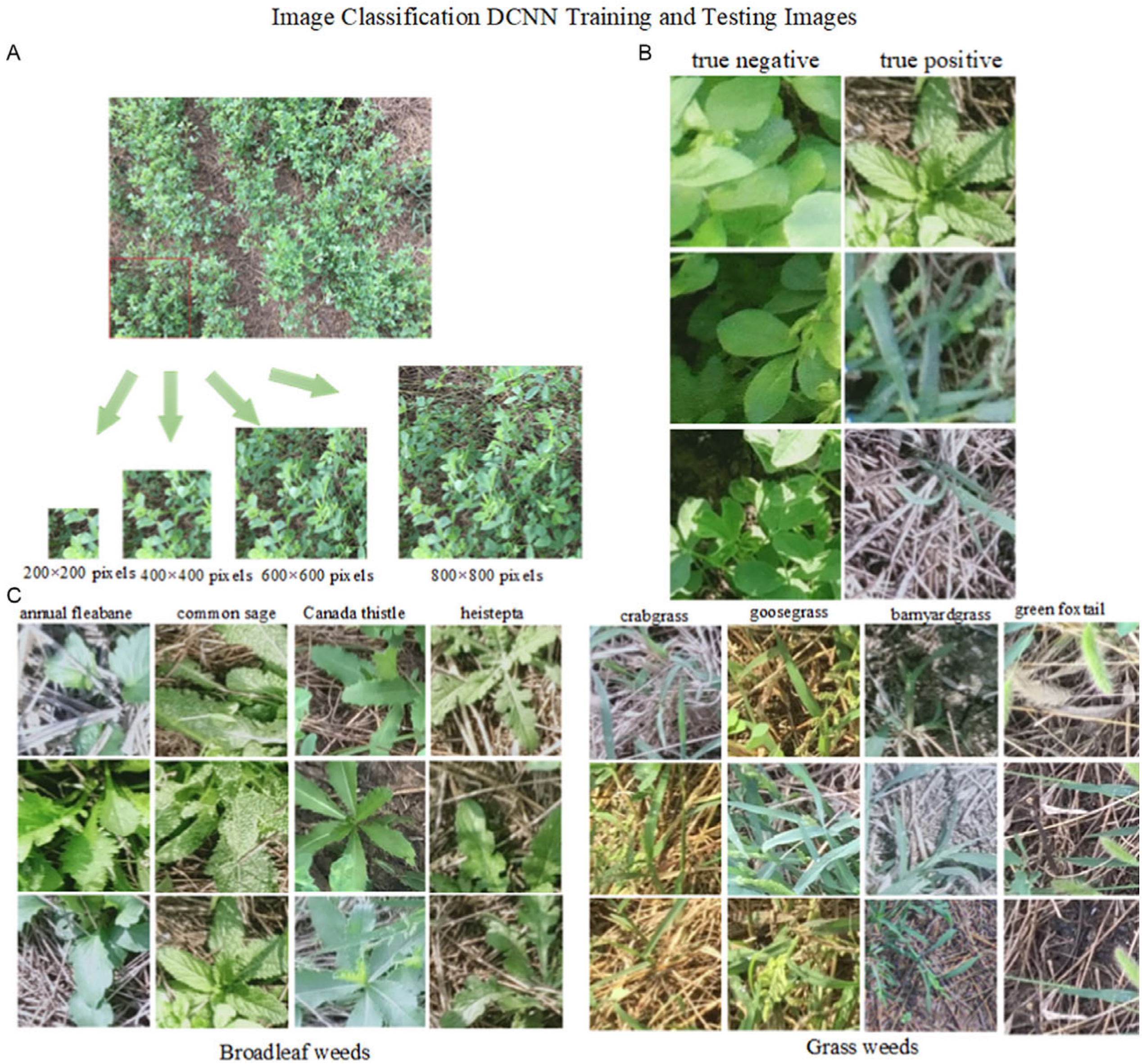

Figure 1. Image classification using deep neural networks in training and testing images. (A) Images were cropped into four different sizes of input images, including 200×200, 400×400, 600×600, and 800×800 pixels; (B) input images were classified into true positive images (including the target weeds) and true negative images (excluding the target weeds); (C) for true positive images, the major broadleaf weeds were annual fleabane, common sage, Canada thistle, and heistepta, while the major grass weeds were crabgrass, goosegrass, barnyardgrass, and green foxtail.

that were trained with the small input images (200×200 pixels) performed better than they did with any other image sizes (400×400, 600×600, and 800×800 pixels) as evidenced by higher precision, recall, and F_1 score values. For all neural networks, the F_1 scores were ≥0.94 for the VD and TD when networks were trained with the small (200×200 pixels) images; however, the F_1 scores were ≤0.95, ≤0.87, and ≤0.82 when the neural networks were trained with the relatively larger input image sizes of 400×400, 600×600, and 800×800 pixels, respectively. Interestingly, an increase in image size resulted in lower F_1 scores for GoogLeNet and VGGNet compared to AlexNet and ResNet. When the neural networks were trained with large input images of 800×800 pixels, the F_1 scores for GoogLeNet and VGGNet were ≤0.59 and ≤0.44, respectively, for VD, TD, TD 1, and TD 2, whereas the F_1 scores of AlexNet and ResNet were ≥0.79 and ≥0.81, respectively.

A significant difference was observed among the ability the neural networks to detect weeds. When the neural networks were trained with input images of 200×200 pixels, AlexNet, GoogLeNet, and VGGNet were highly effective and achieved high F_1 scores (≥0.98), with high recall values (≥0.99) for the VD and TD; however, the F_1 scores of ResNet were ≤0.96 for the VD and TD, primarily due to low precision (≤0.94). The F_1 scores of AlexNet, GoogLeNet, and VGGNet were ≥0.99 for TD 2 but ≤0.98 for TD 1. The lower recall of TD 1 compared with TD 2 images cannot be adequately explained but it might be related to the presence of a greater diversity of weed species and a wider range of alfalfa height. ResNet demonstrated greater image classification accuracy compared to AlexNet, GoogLeNet, and VGGNet when the neural networks were trained with large input images. ResNet also had the highest F_1 scores across all validation and

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Table 1. Hyper parameters used for training the neural networks.[a]

	Training image sizes	Deep learning optimizers	Broadleaf vs. grass weed detection
Training epochs	30	30	30
Solver type	SGD	Adagrad, AdaDelta, Adam and SGD	SGD (AlexNet), SGD (GoogLeNet), AdaDelta (VGGNet), and Adagrad (ResNet)
Batch size	2	2	2
Batch accumulation	5	5	5
Learning rate policy	Step down	Step down	Step down
Base learning rate	0.01	0.01	0.01
Gamma	0.1	0.1	0.1
Step size	33%	33%	33%

[a]The deep convolutional neural networks AlexNet, GoogLeNet, VGGNet, and ResNet were evaluated using various image sizes and various deep-learning optimizers for training purposes. All four neural networks were trained with input images of 200×200 pixels. The images in the validation and testing datasets contained images of both broadleaf and grass weeds.

Table 2. Image classification using deep convolutional neural network architectures under different image sizes in validation and testing datasets for detection of weeds in alfalfa crops.[a,b]

		VD			TD			TD 1			TD 2		
Architecture	Image size	Precision	Recall	F_1 score	Precision	Recall	F_1 score	Precision	Recall	F_1 score	Precision	Recall	F_1 score
AlexNet	200×200	0.98	0.99	0.99	0.98	0.99	0.99	1.00	0.92	0.96	1.00	0.99	0.99
	400×400	0.91	0.95	0.93	0.88	0.96	0.92	0.97	0.96	0.96	0.91	0.98	0.94
	600×600	0.87	0.81	0.84	0.90	0.85	0.87	0.94	0.93	0.93	0.89	0.99	0.93
	800×800	0.93	0.68	0.79	0.93	0.70	0.80	0.98	0.57	0.72	0.88	0.69	0.78
GoogLeNet	200×200	0.98	0.99	0.98	0.99	0.98	0.99	1.00	0.95	0.98	1.00	1.00	1.00
	400×400	0.93	0.95	0.94	0.94	0.97	0.95	0.98	0.93	0.96	0.92	0.94	0.93
	600×600	0.93	0.72	0.81	0.94	0.74	0.83	0.99	0.79	0.88	0.90	0.94	0.92
	800×800	0.98	0.27	0.42	1.00	0.25	0.40	1.00	0.13	0.23	0.89	0.44	0.59
VGGNet	200×200	0.98	0.99	0.98	0.99	1.00	1.00	1.00	0.96	0.98	0.99	1.00	0.99
	400×400	0.90	0.94	0.92	0.92	0.97	0.94	0.96	0.95	0.96	0.99	0.95	0.97
	600×600	0.93	0.52	0.66	0.93	0.51	0.66	0.98	0.88	0.93	0.99	0.66	0.79
	800×800	0.97	0.28	0.43	0.99	0.28	0.44	0.96	0.19	0.32	0.97	0.19	0.31
ResNet	200×200	0.91	0.98	0.94	0.94	0.98	0.96	0.96	0.96	0.96	0.73	1.00	0.85
	400×400	0.78	1.00	0.88	0.86	0.99	0.92	0.78	1.00	0.88	0.63	1.00	0.77
	600×600	0.75	0.99	0.85	0.73	0.99	0.84	0.76	1.00	0.86	0.68	0.99	0.81
	800×800	0.68	0.99	0.81	0.70	1.00	0.82	0.77	0.99	0.87	0.74	0.93	0.83

[a]Abbreviations: VD, validation dataset; TD, testing dataset; TD 1, testing dataset 1; TD 2, testing dataset 2.
[b]The models were trained to detect all types of weeds. The training datasets contained 3,000 positive and 3,000 negative images; the validation dataset contained 600 positive and 600 negative images; the testing results contained 300 positive and 300 negative images; and the TD 1 and TD 2 contained 700 positive and 700 negative images.

testing datasets when the neural networks were trained with images of 800×800 pixels.

In the experiment, the image datasets of the four pixel sizes and the model that had been trained with the 200×200 image datasets demonstrated the greatest ability to recognize weeds. The four networks trained by the four different pixel images and the loss curve is shown in the schematic diagram on the left of Figure 2. Under the training image sizes of 200×200, the model iterated for a total of 30 steps, started to converge within 5 steps, and then tended to stabilize. This size outperformed other cropping sizes, achieved stable convergence in less time, and obtained the lowest loss convergence value and the highest accuracy.

Transfer learning is the process of recycling previously trained neural networks by updating a small part of the original weights using new data (Bengio et al. 2012). The use of transfer learning can reduce the amount of data required for training DCNNs (Espejo-Garcia et al. 2020) and is therefore widely adopted for deep-learning models of training (Geng et al. 2021; Mohanty et al. 2016; Singh et al. 2018; Yu et al. 2019a, 2019b, 2020). In addition, He et al. 2015 noted that the use of fixed-size input images might significantly reduce the recognition accuracy of images or sub-images of arbitrary size. Mishkin et al. (2017) reported a similar finding: that the size of training images could significantly affect the recognition accuracy of DCNNs. As the input image size increases, the number of pixels in the images also increases. Using excessively large images may reduce the abstract level of the information, leading to increased calculation requirements and thereby reduced recognition accuracy; however, the critical information for feature extraction may not be well preserved when excessively small images are used. In addition, the small image size (200× 200pixels) performed best, likely because it is close to the initial spatial tensor image sizes used for pre-training the neural networks. AlexNet was pre-trained with the spatial tensor image size of 227×227 pixels, while GoogLeNet, VGGNet, and ResNet were pre-trained with images of 224×224 pixels (He et al. 2016; Krizhevsky et al. 2012; Simonyan and Zisserman 2014; Szegedy et al. 2015). Therefore, further reducing the image size used for training (i.e., smaller than 200×200 pixels) may not improve weed detection accuracy. Further study is needed to verify this assumption.

In previous research, neural networks exhibited excellent weed detection accuracy, but they were exposed to too many

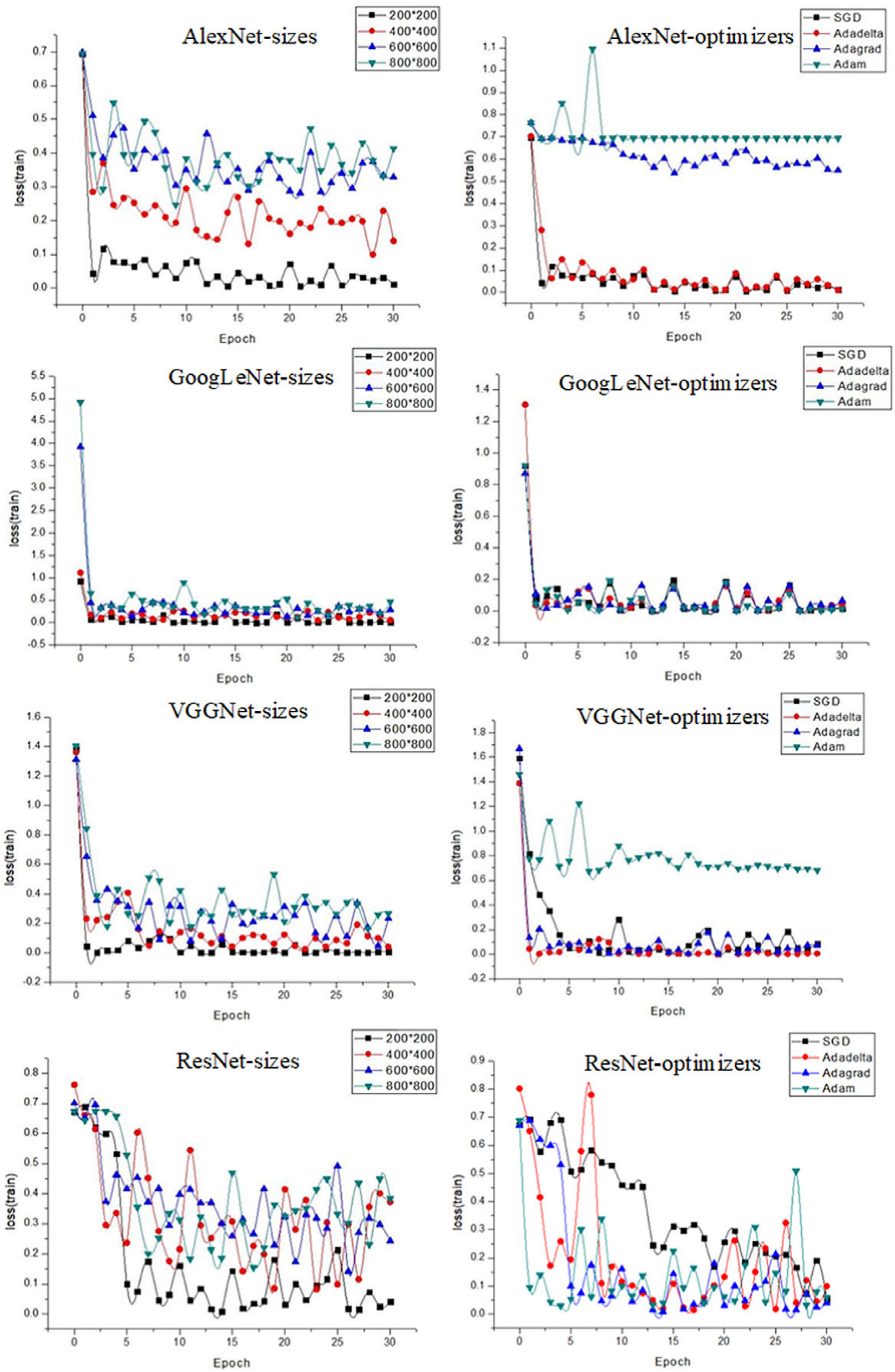

Figure 2. Loss curve of convolutional neural network training.

Table 3. Image classification using deep convolutional neural network architectures under different deep learning optimizers in validation and testing datasets for detection of weeds in alfalfa.[a,b]

		VD			TD			TD1			TD2		
Model	Optimizer	Precision	Recall	F_1 score	Precision	Recall	F_1 score	Precision	Recall	F_1 score	Precision	Recall	F_1 score
AlexNet	AdaDelta	0.98	0.98	0.98	0.98	0.99	0.98	1.00	0.92	0.96	0.99	1.00	1.00
	Adagrad	0.97	0.87	0.91	0.97	0.87	0.92	0.80	0.90	0.85	0.63	0.85	0.73
	Adam	0.98	0.98	0.98	0.98	0.98	0.98	1.00	0.88	0.94	0.54	0.96	0.69
	SGD	0.98	0.99	0.99	0.98	0.99	0.99	1.00	0.92	0.96	1.00	0.99	0.99
GoogLeNet	AdaDelta	0.98	0.99	0.98	0.98	0.98	0.98	1.00	0.94	0.97	0.99	1.00	1.00
	Adagrad	0.98	0.98	0.98	0.98	0.98	0.98	1.00	0.90	0.95	0.93	0.97	0.95
	Adam	0.98	0.98	0.98	0.98	0.98	0.98	1.00	0.86	0.93	0.58	0.96	0.72
	SGD	0.98	0.99	0.98	0.99	0.98	0.99	1.00	0.95	0.98	1.00	1.00	1.00
VGGNet	AdaDelta	0.98	0.99	0.98	0.99	1.00	1.00	1.00	0.96	0.98	0.99	1.00	0.99
	Adagrad	0.98	0.98	0.98	0.98	0.98	0.98	1.00	0.88	0.93	0.72	1.00	0.84
	Adam	0.98	0.98	0.98	0.98	0.98	0.98	1.00	0.86	0.93	0.58	0.94	0.71
	SGD	0.99	0.94	0.96	0.98	0.91	0.94	1.00	0.89	0.94	0.79	1.00	0.89
ResNet	AdaDelta	0.98	0.85	0.91	0.98	0.91	0.94	0.95	0.98	0.96	0.79	0.89	0.84
	Adagrad	0.98	0.92	0.95	0.96	0.92	0.94	0.97	0.95	0.96	0.78	0.90	0.84
	Adam	0.95	0.95	0.95	0.97	0.93	0.95	0.94	0.89	0.92	0.81	0.53	0.64
	SGD	0.89	0.99	0.94	0.90	1.00	0.94	0.80	1.00	0.89	0.66	0.93	0.77

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

[b]The models were trained to detect all types of weeds in images at 200×200 pixels, and the training dataset contained 3,000 positive and 3,000 negative images. The VD contained 600 positive and 600 negative images; the TD contained 300 positive and 300 negative images; and the TD 1 or TD 2 contained 700 positive and 700 negative images.

training images (Ferreira et al. 2017; Yu et al. 2020). For example, Yu et al. (2020) used a dataset of 8,000 positive and 9,000 negative images to train a neural network to detect and classify multiple grass weed species growing among bermudagrass plants; the authors reported that VGGNet outperformed AlexNet and GoogLeNet in their ability to do so. Based on the present study's findings, we suggest that using the most appropriate training image size can substantially enhance the performance of weed detection and thereby reduce the need to train the programs to detect image quantity. Furthermore, using an appropriate image size may also minimize the difference between the neural networks' ability to detect weeds, although this assumption needs to be further verified.

Effect of Optimizers

AdaDelta and SGD optimizers generally outperformed Adagrad and Adam. The F_1 scores of AlexNet trained with AdaDelta and SGD were ≥0.96 with VD, TD, TD 1, and TD 2; whereas F_1 scores were ≤0.92 when AlexNet was trained with Adagrad, and ≤0.98 when it was trained with Adam (Table 3). The F_1 scores of GoogLeNet did not significantly differ between the optimizers when the VD and TD were used. However, the F_1 scores for GoogLeNet were ≥0.97 when TD 1 and TD 2 were used and when it was trained with AdaDelta and SGD, but the scores were ≤0.95 when it was trained with Adagrad and ≤0.93 when it was trained with Adam (Table 3). The F_1 scores for VGGNet were ≥0.98 when VD, TD, TD 1, and TD 2 were used and when it was trained with AdaDelta, but the scores were ≤0.98 when it was trained with Adagrad and Adam (Table 3). ResNet trained with SGD and Adam exhibited significantly lower F_1 scores when TD 1 and TD 2 were used than when it was trained with Adagrad and AdaDelta. These characteristics were evidenced in the loss curve on the right side of Figure 2. For AlexNet, Adagrad and Adam were obviously unsuitable compared to SGD and AdaDelta. SGD converged faster than AdaDelta, and eventually, the two curves tended to be stable. For GoogLeNet, the curves of the four optimizers exhibited little difference and leveled off in the end. For VGGNet, Adam performed worse than the other three optimizers. Among the optimizers, AdaDelta reached convergence faster, and finally, the three curves became stable. For ResNet, the four curves fluctuated greatly and did not tend to be stable when the number of iterations was 30 steps. These findings indicate that the classification accuracy of weed detection can be improved when the neural networks are trained with appropriate optimizers.

To date, hundreds of deep-learning optimizers have been developed (Schmidt et al. 2021). However, the research community commonly relies on benchmarking or even personal and anecdotal experiences to choose an optimizer (Geng et al. 2021; Nagaraju and Chawla 2020). During deep learning, an optimization algorithm is required to reduce losses that occur by updating the weight parameters (Choi et al. 2019; Schmidt et al. 2021). The optimization algorithm can significantly affect the training speed and determine the final performance of the neural network being trained (Choi et al. 2019). Our results confirmed the importance of selecting an appropriate deep-learning optimizer during the period when neural network models are being trained for weed detection purposes. The neural networks evaluated here needed different optimizers to achieve the best performance in weed detection.

To the best of our knowledge, this is the first report to investigate the effect of using optimizers on neural networks for purposes of weed detection. For detection of fruits or plant diseases, recent empirical comparisons revealed the differences between the neural networks when they were trained with different optimizers (Postalcolu 2020; Schmidt et al. 2021). Adam, SGD, and RMSProp were used for training DCNNs for fruit detection and found that Adam and RMSProp outperformed SGD (Postalcolu 2020). In another study, Xception trained with the optimizer Adam achieved higher F_1 scores for classifying plant disease images than other optimizers, including Adagrad, Adamax, SGD, and RMSProp (Saleem et al. 2020). Wilson et al. (2017) reported that adaptive learning-rate methods (e.g., Adagrad, AdaDelta, RMSProp, Adam) generally performed worse than SGD Contrast software (Ithaca, NY: Cornell University) in terms of object recognition character-level language modeling and constituency parsing.

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Table 4. Image classification using deep convolutional neural network architectures in validation and testing datasets to detect broadleaf vs. grass weeds in alfalfa.[a,b]

		VD			TD			TD1			TD2		
Model	Weed species	Precision	Recall	F_1 score	Precision	Recall	F_1 score	Precision	Recall	F_1 score	Precision	Recall	F_1 score
AlexNet	Broadleaves	0.95	0.96	0.96	0.97	0.98	0.97	0.73	0.98	0.84	0.97	0.97	0.97
	Grasses	0.96	0.95	0.96	0.98	0.97	0.97	0.97	0.64	0.77	0.97	0.97	0.97
GoogLeNet	Broadleaves	0.99	0.98	0.99	0.98	0.97	0.98	0.80	0.91	0.85	1.00	0.98	0.99
	Grasses	0.99	0.98	0.98	0.98	0.98	0.98	0.92	0.79	0.85	0.98	0.98	0.98
VGGNet	Broadleaves	0.99	0.99	0.99	1.00	0.98	0.99	0.93	0.85	0.89	0.98	0.99	0.99
	Grasses	0.99	0.99	0.99	0.98	1.00	0.99	0.86	0.94	0.90	0.99	0.98	0.99
ResNet	Broadleaves	0.95	0.59	0.73	0.95	0.53	0.60	0.64	0.49	0.49	0.66	0.45	0.53
	Grasses	0.31	0.87	0.45	0.32	0.89	0.47	0.33	0.48	0.39	0.18	0.35	0.24

[a]Abbreviations: VD, validation dataset; TD, testing dataset; TD 1, testing data set 1; TD 2, testing data set 2.
[b]The models were trained to detect all types of weeds with training images of 200×200 pixels, and the training dataset contained 3,000 positive and 3,000 negative images. The validation dataset contained 600 positive and 600 negative images; the testing results contained 300 positive and 300 negative images; the TD 1 or TD 2 contained 700 positive and 700 negative images.

Figure 3. Classification results of the VGGNet in the testing dataset.

Detection of Broadleaf vs. Grass Weeds

Based on the results presented in the two sections above, AlexNet, GoogLeNet, VGGNet, and ResNet performed best with images of 200×200 pixels in detecting multiple broadleaf and grass weeds and the most effective deep-learning optimizers. No obvious differences were observed among any neural networks in their ability to detect broadleaf plants vs. grasses, as evidenced by the precision, recall, and F_1 score values (Table 4). Among the neural networks we evaluated, VGGNet consistently produced the highest F_1 scores when VD, TD, TD 1, and TD 2 were used (classification results are shown in Figure 3), whereas ResNet consistently produced the lowest F_1 scores in its ability to detect broadleaf and grass weeds. VGGNet achieved high F_1 scores (≥0.99) with high recall (≥0.98) when VD, TD, and TD 2 were used, whereas the F_1 scores of ResNet never exceeded 0.73. GoogLeNet outperformed AlexNet in its ability to detect broadleaf and grass weeds; the F_1 scores of

GoogLeNet were consistently higher than those of AlexNet when VD, TD, TD 1, and TD 2 were used.

Although the neural networks achieved excellent performance in their ability to detect weeds when they were trained with the best-performed image size and optimizer, various factors may affect their performance. In the present study, except for ResNet, the precision and recall values were lower when TD 1 was used than when TD 2 was used. This result might be because the TD 1 photographs were acquired primarily on cloudy days and thus were darker than the TD 2 images. Additional studies are needed to evaluate the training and testing of neural networks with images from a wide range of geographic locations, weed species, weed densities, weed, crop growth stages, and light intensities, and their ability to adapt to more complex situations.

DCNNs detect weeds based on plant morphological features, including leaf pattern and texture (Kamilaris and Prenafeta-Boldu 2018). For this reason, the detection of broadleaf weeds growing in alfalfa fields is hypothetically more difficult than the detection of grasses. However, among all the neural networks tested here, the present study clearly showed no obvious differences in their ability to detect broadleaf and grass weeds. We note that a high image processing speed is vital for real-time weed recognition and precision herbicide application (Yang et al. 2000). The neural networks in this study exhibited fast image processing using the NVIDIA Geforce 2080Ti graphics processing unit in the present study. The image processing speeds were 23 ms, 35 ms, 64 ms, and 68 ms image^{-1} for AlexNet, GoogLeNet, VGGNet, and ResNet, respectively.

Conclusion

This research demonstrated the feasibility of using DCNNs for purposes of weed detection in alfalfa crops. AlexNet, GoogLeNet, VGGNet, and ResNet trained with small input images of 200×200 pixels performed better than when large images of 400×400, 600×600, and 800×800 pixels were used. Furthermore, the choice of a deep-learning optimizer can significantly affect the performance of neural networks. The optimizers AdaDelta and SGD outperformed Adagrad and Adam when they were used with AlexNet and GoogLeNet; AdaDelta outperformed Adagrad, Adam, and SGD when used with VGGNet; and Adagrad and AdaDelta outperformed Adam and SGD when used with ResNet. All neural networks showed no differences in their ability to detect broadleaf and grass weeds. When the neural networks were trained with the best-performing input image size and optimizer, the neural networks were ranked as follows, from the highest to lowest classification accuracy: VGGNet > GoogLeNet > AlexNet > ResNet. Future research will integrate these neural networks into the machine vision subsystem of smart sprayers.

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