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An Approach for Weed Detection Using CNNs And Transfer Learning

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Abstract

To prevent yield losses, it is critical to eliminate competition between food crops and weeds at the onset of plant growth. While uniform spraying of herbicides can be economically and environmentally inefficient, site-specific weed management (SSWM) counteracts this by reducing the amount of chemical application with localized spraying of weed species. Past research on weed detection in SSWM has used a large deep convolutional neural network (DCNN) for weed detection. These models are, however, computationally expensive and prone to overfitting on smaller datasets. In this paper, we propose an approach to detecting weeds amongst plant seedlings using transfer learning in a small network. Our approach combines the mobile-sized EfficientNet with transfer learning to achieve up to 95.44% classification accuracy on plant seedlings. Due to the robustness of transfer learning methods, this approach would be beneficial in improving both the classification accuracy and generalizability of current weed detection methods.

1. Introduction

Early season plant growth is essential to agronomic production [1]. The first few weeks of cropping is the most important time to eliminate competition between food crops and weeds for water and nutrients. Research shows that effective weed control at this stage is, in fact, essential to increased yield in some crops [2]. In recent times, effective weed control relies on the use of chemical weed control – such as herbicides with different sites of action – as they can kill from 90 to 99% of targeted weeds [3], [4]. Often, the drawback and most criticized aspect of chemical weed control as a current cropping practice is their apparent harmfulness to the environment. Chemicals like alachlor, ametryn, and atrazine used in commercial pesticide products have been found near (or in) water resources adjacent to cropping areas due to their persistence and low biodegradability [5]–[7]. As a result, there are strong reasons to demand safer cropping systems with minimal environmental consequences.

One such system used to reduce environmental impact, and decrease input costs, is site-specific weed management (SSWM), which falls under a broad spectrum of farming practices that have existed since the 1980s known as Precision Agriculture (PA) [8]. López-Granados [1] posits that SSWM ensures the use of precise weed treatments through a four-step cyclical process consisting of 1) weed monitoring/detection, 2) management planning for action on weeding, 3) execution of the weed control method and 4) evaluation of performance. Therefore, as the foundation of SSWM, the importance of weed detection to the practice, and weed control in general, cannot be understated.

Weed detection relies on several sensing technologies. These can be grouped into two main categories: aerial remote sensing and ground-based tools [9]. While the aerial methods are effective for map-based SSWM in large areas [9], they suffer from several drawbacks such as their inability to detect small variations in reflectivity of seedlings, the need for higher resolution images when weeds are distributed in small patches, the interference in detection caused by the reflectivity of soil background, and the fact that they are largely non-real-time [1], [9], [10]. Hence, ground-based methods are the best for weed detection and control [11], especially with the advancement in computer vision technology such as machine learning and big data.

Machine learning (ML) has achieved remarkable results in image classification tasks using a technique known as deep Convolutional Neural Networks (DCNN) [12]. DCNNs have been successful because they learn to distinguish complex inherent patterns within images often difficult to observe otherwise. DCNNs learn from image data by expanding them into arrays represented by pixel intensities (0 to 255) of each point in the image, and through the process of deconvolution, separating the image into thousands of relevant features which are selected and aggregated into recognizable patterns viable for distinguishing new and unseen images. Past research [13]–[15], [15]–[18] have successfully utilized DCNNs to distinguish various crops in different growth stages using different methods. However, even with their successes in classification accuracy (CA), there are still several issues regarding the generalizability of the methods used [9]. Moreover, further research on weed detection has found that a majority of past studies utilized DCNNs in the much-maligned aerial sensing scenario [19].

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Accordingly, this study aims to use transfer learning with a more efficient CNN model to increase the generalizability of current methods of detecting weeds. The remainder of this study is divided into five sections. In section 2, the background and related works are discussed. This is followed in section 3 by the specific methodology adopted in this paper. In sections 4 and 5, an analysis and discussion of the results are presented. Finally, we conclude the study in section 6 and provide recommendations for future studies.

2. Background

Past research on weed detection has employed various machine learning techniques successfully. Authors such as Pantazi et al [15] and Sørensen et al. [16] used the DCNN to distinguish weeds captured using unmanned aerial vehicles. The authors of [15] used hyperspectral imaging for crop and weed species recognition. Whiles their classifier was able to identify 100% of crops, weed species recognition varied between 31% and 98% in their mixture of Gaussians classifier; and 53% and 94% in their self-organizing maps classifier. In [16], the authors identified weed classes growing among thistles with about 97% CA.

Using ground-based methods, Xinshao and Cheng [17] used the PCANet to classify 91 weed seed types which may be found during the mixing of crop seeds. Their algorithm achieved 91% CA. To take this further, Dyrmann et al. [13] combined several datasets of weed species at early growth stages for classification. They achieved 86.2% CA for 22 species of plant seedlings using a DCNN built from scratch. Similarly, Milioto et al. [14] achieved up to 97.3% accuracy on two test sets using DCNNs.

Apart from the issues discussed earlier with aerial-based methods used in studies such as [14]–[16], the generalizability of the models proposed have also been questioned [9]. Additionally, past research [13], [16], [18] often utilizes larger networks such as the VGGs and DenseNets which are computationally expensive and are prone to overfitting in instances of smaller datasets.

Since, machine learning models, and in extension DCNNs, are often trained and tested with data taken from a single domain where the feature space and probability distribution are the same (or at least similar) [20]. In the case of image datasets, ML models achieve the best result when both the training and the test images consist of the same number of classes, captured under similar conditions using a similar setup. However, ML models like DCNNs require many samples of training data to perform well on a classification task. Unfortunately, high-quality labeled data containing several samples of plant seedlings are generally unavailable to researchers. So, training a large DCNN model with a smaller available dataset could result in overfitting where the model learns all the nuances in the training data and generalizes poorly to new and unseen data.

The problem of overfitting can be combatted by training a DCNN model with a bigger base dataset and repurposing (or transferring) the learned features to a new model for fine-tuning with a smaller target dataset. In effect, train a base model using the base dataset, freeze the first *n* layers of this base model (consisting of generic features), and then re-train the remaining layers with randomly initialized weights using the target dataset (to acquire the target-specific features) [21]. Intuitively, this works because machine learning models have *generic* features near the input while the domain-*specific* features lie much deeper in the model [21]. This approach is known as transfer learning (TL). TL is valuable when data unavailability is a problem (such as the case with plant seedlings) as it allows the domain, tasks, and distributions used in training to be different from those used in testing [20], [21]. TL is motivated by the fact that humans apply previously learned knowledge to solve new problems faster [20]. Hence, in humans and, in this context, machines, learning to identify an apple could make the task of recognizing oranges easier.

To make the task of TL easier, high-level machine learning frameworks such as Keras [22] make available pre-trained models from successful DCNNs such as the VGG, ResNet, Inception, and DenseNet models. The gold standard is to pre-train these models on massive general-purpose image datasets such as ImageNet (http://www.image-net.org/).

Consequently, this paper extends our previous study on DCNN-use for weed detection [23] and investigates further the ability of a mobile-sized CNN, EfficientNet, to deliver comparable results despite being computationally inexpensive as compared to state-of-the-art DCNN models. In the current study, the EfficientNet-B1 pre-trained model is used. The specific approach used is further elaborated in the ensuing section.

3. Methods

3.1. Dataset

The Plant Seedling Dataset was introduced by Giselsson et al. [24] as a ground-based weed or specie spotting database for benchmarking plant seedling classification tasks. The image database is made up of 960 unique plants of 12 different species grown indoors in Styrofoam boxes and captured in 5,539 images over 20 days. Although the issue of overlapping plant leaves has been raised in past literature [9], these are minimal at the onset of plant growth and hence the images were captured in non-overlapping mode. Also, the plants were grown in soil which is covered in gravel further prevents errors in pixel-based segmentation algorithms. Sample images, the number of samples, and names each specie is shown in Figure 1.

Figure 1. Sample images from the plant seedlings dataset (https://vision.eng.au.dk/plant-seedlings-dataset/)

3.2 Data Preparation

We apply the following preprocessing techniques:

- **Image resizing.** Images were resized to 200 x 200 pixels for both transfer learning and training from scratch.

- **Data augmentation.** Since plants do not grow in a single orientation and images could be captured at different angles, image augmentation was performed using horizontal and vertical flips, random rotations of up to 45 degrees, and zooms of up to 10 percent of the original image height and width.

3.3. Model Architecture

This study adopts the *EfficientNet* CNN developed by Tan and Le in 2019 [25]. They are a group of models created through neural architecture search to achieve an optimal network in all dimensions (width, depth, and resolution) that are more efficient and have achieved better accuracy than past models with comparable accuracy. Figure 2 depicts the relative performance of each EfficientNet.

The main building block of EfficientNets is the mobile inverted bottleneck MBConvs introduced in MobileNetV2 [26]. MBConv blocks are made up of layers that expand then compress channels so that fewer channels are skip-connected. They use depthwise and pointwise separable convolutions to reduce the number of trainable parameters by up to a factor of k^2. The authors also employ squeeze-and-excitation (SE) optimization to improve performance by giving weight to channels instead of treating them equally. SE blocks return an output of 1 x 1 x channel. Further, instead of the normal ReLU, the authors rely on a swish activation to avoid information loss. In this study, we replaced the last Dense layer for predicting 1000 ImageNet classes with a new Dense layer consisting of 12 plant seedling classes. All other layers in the model architecture were left as is.

The current study utilizes the EfficientNet-B1 model, a mobile sized CNN with 7.8M trainable parameters. Compared, the VGG16 used in prior research [18] has over 138M trainable parameters, while the ResNet152V2 (the best achieving model from a previous comparative study) has over 60M trainable parameters.

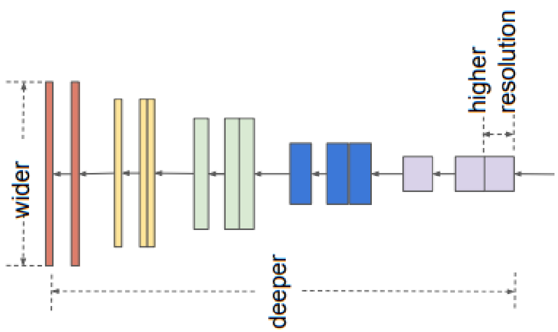
3.4. Model Implementation

The models are implemented using the Keras library with *TensorFlow* backend [22], [27]. The experiments in this study are run on a Dell Inspiron 7577 which houses an NVIDIA GeForce GTX 1060 with Max-Q (6GB GDDR5) with 16GB of RAM.

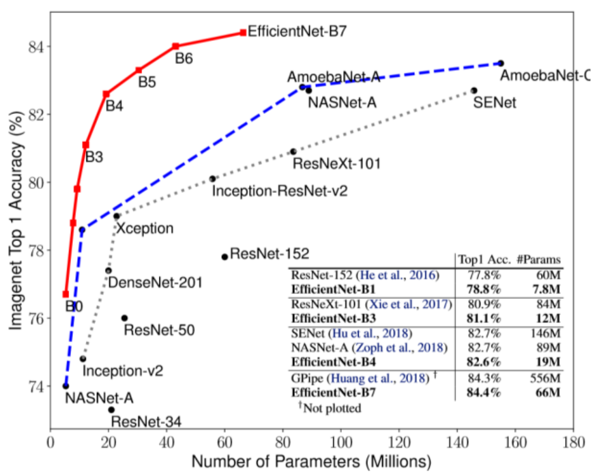
Models are trained for 20 epochs with mini-batch sizes of 32 image instances and an initial learning rate of 0.0001, which is decreased by a factor of 0.5 every 3 epochs where validation accuracy does not improve.

In the first experiment, we train the EfficientNet-B1 model from scratch using randomly initialized weights. In this scenario, only the last prediction layer of the base model is replaced with a fully-connected layer with 12 kernels to distinguish the 12 plant classes.

In further experiments, we employ the EfficientNet-B1 pre-trained on ImageNet weight for transfer learning using a frozen base up to layer 170 (*block5a_expand_conv*). The remaining layers, including a final 12-class fully connected layer, are unfrozen to allow training with new weights.



(a) Compound scaling for optimal EfficientNet



(b) Model Size vs ImageNet accuracy in EfficientNets

Figure 2. (a) Compound scaling method used to achieve uniformly scaled EfficientNet CNNs (b) Current state-of-the-art DCNN model sizes compared to ImageNet accuracy. Source: Tan and Lee (2019) [25]

3.5. Model Evaluation

To ensure robustness in this supervised machine learning task, the data is divided into 90% training and 10% test sets. Further, the original authors of the dataset suggest that a k-fold cross-validation approach be used in benchmarking. This approach is an evaluation method used to divide a dataset into training and validation sets where the dataset *D*, is randomly divided into *k* number of mutually exclusive folds (subsets): S_1, S_2, S_3, …, S_k. The model is then run *k* number of times where *k-1* subsets are used in training and each *k* used as a validation set iteratively. In this study, we use *k=5*.

Model performance evaluation is carried out using the proposed benchmarks suggested by the authors of the dataset. Therefore, as an evaluation metric, we calculated *Accuracy*, as well as, *Precision* (P_C), *Recall* (R_C), and *Mean Weighted Average* f_1*-scores (S)* as shown in equations 1-4 below.

$$P_c = \frac{TP_c}{TP_c + FP_c} \tag{1}$$

$$R_c = \frac{TP_c}{TP_c + FN_c} \tag{2}$$

$$f_{1,c} = 2\frac{P_c \cdot R_c}{TP_c + FN_c} \tag{3}$$

$$avg_{weighted}(f_1) = \sum_{c=1}^{C} \frac{N_c}{N} \cdot f_{1,c} \frac{P_c \cdot R_c}{TP_c + FN_c} \tag{4}$$

TPc, *FPc*, and *FNc* denote True positives, False positives, and False negatives for class *c* respectively. *Pc* is class-specific precision and *Rc* being class-specific recall. *N* denotes the total number of samples and *Nc* the number of samples of class *c* and *C* the total number of classes.

4. Results

We evaluated the EfficientNet-B1 model using the Plant Seedling dataset. The training performance of each network used in this study is shown in Table 1. The results show that when the model used transfer learning, we achieved superior performance as compared to the randomly initialized model. This was realized in the two experiments performed that compared training from scratch to transfer learning. It must be noted that for comparison, we trained the VGG16 network using the same setup due to its performance on a segmented version of this dataset in [18] where it achieved up to 98.57% and 99.48% validation accuracy on balanced and imbalanced classes respectively.

In Table 1, we show a detailed comparison of the validation classification accuracies during training using 5-fold cross-validation. An average of the training regimes (T1 – T5) for each model shows that the EfficientNet-B1 performed better with transfer learning using ImageNet pre-trained weights when part of the model was frozen as compared to training the entire model from scratch. Conversely, the VGG16 performed better in all but one (T2) when using transfer learning with ImageNet weights frozen above *block4_conv2* (12/22 layers) than when trained from scratch.

Table 2 also shows the accuracy, precision, recall, and f_1-scores calculated during the experiments using the 10% test set. This validates the results from the training as transfer learning with the EfficientNet-B1 performed better than all other experiments on the previously unseen test data. Similarly, transfer learning VGG16 outperformed a version of it trained from scratch using random weights initialization.

Table 1. Training performance

Model	#Parameters	Accuracy					$\bar{x}$	S^2
		T1	T2	T3	T4	T5		
VGG16	**138M**	0.9389	0.9308	0.9308	0.9438	0.9348	0.93582	2.502e-05
VGG16: TL		0.9469	0.9228	0.9458	0.9458	0.9358	0.94023	6.154e-05
EfficientNet-B1	**7.8M**	0.9539	0.9448	0.9438	0.9509	0.9438	0.94745	1.726e-05
EfficientNet-B1: TL		**0.9569**	**0.9569**	**0.9519**	**0.9529**	**0.9519**	**0.95407**	**5.441e-06**

Table 2. Average weighted performance measures based on the Test set

Model	Accuracy	Precision	Recall	f1-Score
VGG16	0.93926	0.9395	0.93926	0.93780
VGG16: TL	0.94214	0.94422	0.94214	0.94122
EfficientNet-B1	0.95406	0.95466	0.95406	0.95384
EfficientNet-B1: TL	**0.95444**	**0.95436**	**0.95444**	**0.95406**

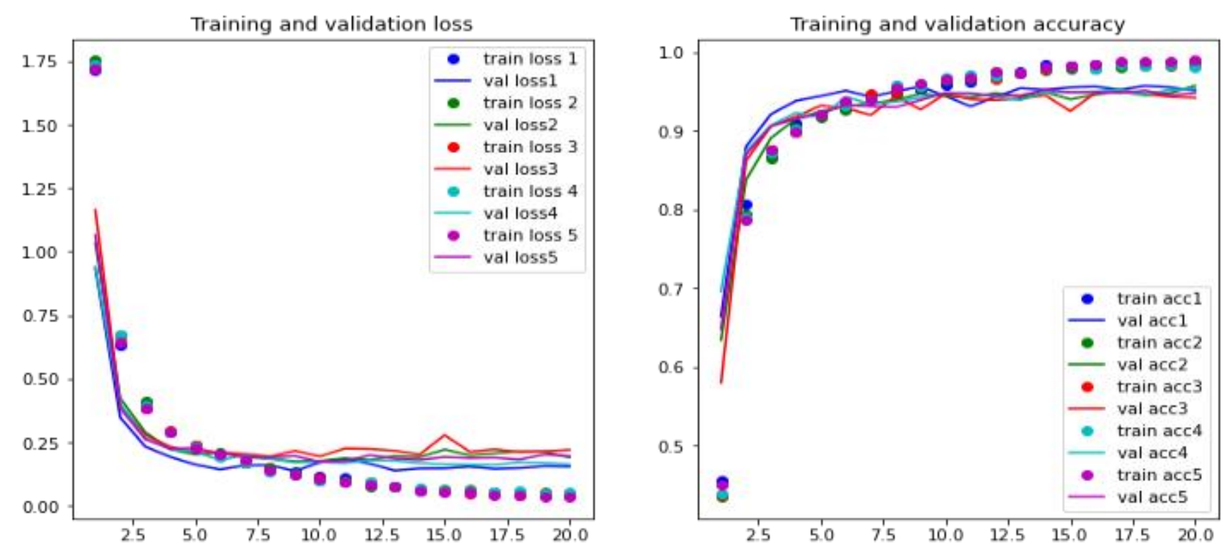
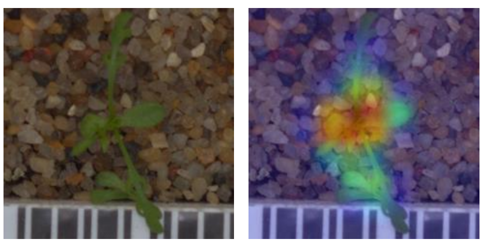


Figure 3. Training and validation loss and accuracy for transfer learning in the EfficientNet-B1

(a) Common wheat identified by the model based on stem

(b) Charlock identified by the model based on leaf



(c) Scentless Mayweed identified by stem and leaves

Figure 4. Grad-CAM maps from the EfficientNet-B1 shows the pre-trained model localizes the stem and leaves as important regions for prediction regardless of the orientation of the image or background information.

5. Discussion

Using a dataset made up of 5,539 images of 12 plant seedling species grown indoors over 20 days in Styrofoam boxes [24], we trained the EfficientNet-B1 model using transfer learning to successfully distinguish food crops and weeds. The results obtained in this study demonstrates the ability of CNNs to classify weeds and food crops. The EfficientNet-B1 model used achieved the best results during transfer learning than when trained from scratch with randomly initialized weights. This mobile-sized model (with a little over 7.8M trainable parameters) achieved 95.40% accuracy on the validation set during training and achieved similar performance (95.44%) on the test set made up of previously unseen images. The model also performed better than the VGG16 (which has over 138M parameters).

Further, Figure 3 which shows the training regime for the network demonstrates that the model peaked between epoch 13 and 16 and hence we could have performed early stopping and halted training and still have achieved high results.

Since pre-trained models are generally trained on large image datasets (in our case ImageNet) it captures a wide array of features that could be relevant to classification tasks such as this one. Therefore, it is safe to assume that using the weights of a pre-trained model could be beneficial to even specialized datasets such as in this research. In theory, the use of a pre-trained model in this study should have been a challenge to the model due to the fundamental differences between the datasets. The ImageNet dataset contains general real-world images hence its features will be made up of varying shapes, colors, and hues compared to this Plant Seedlings dataset which is made up mainly of green plants and brown gravel background. However, when we used the Gradient-weighted Class Activation Map which uses the gradient of a target class on the final convolutional layer to produce a coarse localization map of important regions used in predicting the class [28] to visualize and validate the areas in the images used by the model for prediction, it was realized that the model was indeed looking and identifying seedling based on the correct patterns. Rather than identifying the background information, especially parts of the box that leaked into the image dataset, the model established its predictions on the plant leaves and stems. Figure 4 shows sample classes from the test dataset and the localization maps generated by Grad-CAM.

The performance of this smaller more efficient model using a transfer learning approach, as reported in this study, is higher than previously recorded performance in other studies (Accuracy < 87% or f_1-scores < 0.8) [19]. Due to the attributes of the plant seedling dataset where the images are captured in gravel, the results are more generalizable compared to other studies [18] where similar but already segmented images were used, even if they reported higher performance. Again, because the current study uses images captured on the ground, they will be beneficial to ground-based weed detection equipment used in precision agriculture. This is especially relevant because the image augmentation employed in this study ensured that the equipment could capture and still detect weeds regardless of the orientation of the plant in the field.

6. Conclusion and Future Implications

In this paper, we addressed the problem of generalizability in DCNN models using a more computationally efficient and mobile-sized CNN – EfficientNet-B1. Using transfer learning, the model achieves a classification accuracy of 95.44% with similar high performance in precision, recall, and weighted average f_1-scores on the test set.

The result presented in the study shows that the model outperforms larger state-of-the-art DCNNs and achieves even higher accuracy when pre-trained weights are used. Computer vision equipment used in SSWM should be able to capture images and distinguish between food crops and weeds quickly and efficiently, especially at the onset of plant growth, where a lax weed control could result in up to 100% yield loss. Hence, the results presented in this study are beneficial to the practices of site-specific weed management and precision agriculture as a whole. Based on these results, we conclude that practitioners, equipment producers, and other stakeholders should be able to use pre-trained models in developing new SSWM equipment to minimize environmental impact for sustainability and still maximize production efficiency.

Although we perform supervised transfer learning in this study, which increases the generalizability of the model, future research in this area will benefit from further techniques such as semi-supervised or unsupervised domain adaptation to solve the problem of encountering unlabeled data or data with different input feature space and/or different dimensionality.

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