Domain Adaptive Shake-shake Residual Network for Corn Disease Recognition

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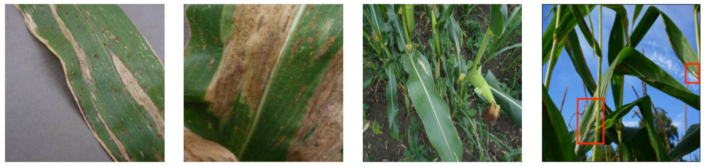
Abstract

Although advanced machine learning models are critical for hand-held camera-based corn disease detection, they are challenged by several key difficulties, e.g., subtle crop disease signatures and limited training samples from heterogeneous multi-source datasets. The paper presents a novel Domain Adaptive shake-shake Residual neural Network approach (DARNet) to simultaneously address these challenges. The proposed DARNet approach has the following characteristics. First, to efficiently capture the weak disease signature information from insufficient training samples, we build into DARNet a novel deep multi-branched residual neural network architecture with shake-shake regularization, where the multi-branched residual architecture is designed for efficient learning of the subtle disease signature, and the shake-shake regularization is designed to overcome the overfitting problem that usually happens in deep feature learning from insufficient dataset. Second, to efficiently learn disease signature information from both indoor and outdoor crop datasets, DARNet is designed to involve some rule-based domain mapping functions and transfer learning procedures to minimize the gaps between the two datasets and to enable transfer learning among two domains. The proposed DARNet is evaluated on two heterogeneous datasets produced from an indoor and an in-field environment respectively. DARNet is trained on both indoor and in-field corn disease datasets, and tested on the in-field dataset. DARNet achieves a high test accuracy of 89.25%, demonstrating that the proposed machine learning approach can efficiently capture the subtle disease signature information from heterogeneous datasets with limited training samples and therefore is promising for developing hand-held camera-based crop disease recognition techniques.

1 Introduction

As one of the most important cereals in the world, corn has an estimated global demand of 852 million metric tonnes (MT) in 2020, ranking the first in all cereals compared with 760 million MT for wheat and 503 million MT for rice [1]. However, corn production is heavily threatened by maize diseases. Efficient and accurate corn disease recognition techniques is critical to maize diseases control for boosting maize production. Traditional corn disease recognition is mainly achieved by visual inspection based on expert domain-knowledge, which is very costly, slow and subjective. The advancement of imaging techniques in hand-hold cameras or smart-phones provides high-resolution colour images, offering new opportunity for developing efficient hand-held camera

AI for Earth Sciences Workshop at NeurIPS 2020.



(a) Indoor (b) Indoor (c) In-field (d) In-field

Figure 1: Image examples of NLB-infected leaves for indoor and in-field datasets. The disease signature appears as the yellow linear patterns on the leaves, which is more visible on (a) and (b), but is very subtle and weak in (c) and (d).

based intelligent crop disease detection system. Recently, some image processing techniques, such as support vector machine (SVM) [2] and neural networks [3, 4], have been developed to support crop disease identification. Nevertheless, advanced artificial intelligence techniques that are tailored to unique characteristics of corn disease application for rapid and accurate corn disease identification from hand-held devices is still lacking.

Although advanced machine learning models are critical for hand-held camera-based corn disease detection, they are challenged by several key difficulties. (1) Corn disease signatures in outdoor images captured by hand-held cameras tend to be some small-sized linear patterns that have weak colour and texture distinctiveness with the general background. The discovery and identification of these weak and subtle disease signature from big outdoor images are very challenging for the machine learning and computer vision techniques. Advanced deep convolutional neural network (CNN) architectures are required to locate interest patterns and to discriminate real disease patterns from the look-alike phenomena. (2) Although a large number of training samples covering most corn disease variations can help the CNN models to better learn the disease signatures, the available outdoor camera images with identified corn disease are very limited, due to the cost and difficulties of on-site sample collection and expert validation. The coupling of the limited training sample issue with the subtle disease signature issue pose more challenges on machine learning algorithms, the success of which depend on significantly on not only their strong discriminative feature extraction capability, but also their overfitting-preventing capability to avoid the capturing of "noise" patterns that do not generalize well. Therefore, advanced robust CNN approach that are less prone to the overfitting problems is highly desired. (3) Although combining multi-source datasets may alleviate the limited training sample issue, the available corn disease datasets have huge variations in terms of cameras, illumination conditions, contexts, disease types, etc. These heterogeneities in multi-source datasets make it difficult for the machine learning algorithms to capture the commonality signature information that generalize across different datasets. Domain adaption and transfer learning approaches are required to be integrated with the advanced CNN approaches for exploiting the signature information from multi-source images.

This study therefore presents an advanced Domain Adaptation shake-shake Residual neural Network approach (DARNet) to simultaneously address the above-mentioned key challenges, i.e., weak and subtle corn disease signature in outdoor image, limited training samples, heterogeneities among multi-source corn disease datasets. The proposed DARNet has the following characteristics. (1) To enable strong feature learning capability for efficient capture of the weak and subtle corn disease signature information, the proposed DARNet is built upon a novel multi-branch residual neural network architecture, where the residual blocks allows deep and subtle feature learning without the vanishing gradient problem, and the multi-branch structure enables stratified accommodation and fusion of signature variations. (2) To alleviate the overfitting problems that frequently happens in weak signature learning from limited training samples, in DARNet, we integrate the multi-branch residual network with the shake-shake regularization, which is an advanced regularization technique that proved being very effective to prevent the overfitting problems in many learning problems [5]. (3) To enable the learning of commonality signature information across multi-source heterogeneous datasets, DARNet is designed to involve some domain adaptive procedures to minimize the gaps between the different datasets and to enable transfer learning among multiple domains. Because of these characteristics of DARNet, it can simultaneously address all three key challenges in corn disease recognition application. Two heterogeneous corn disease datasets, i.e., one indoor and one outdoor, are used to evaluate the proposed approach. DARNet is trained on both indoor and outdoor corn disease datasets, and tested on the outdoor dataset. DARNet achieves a high test accuracy of 89.25%, demonstrating that the proposed machine learning approach can efficiently capture the subtle disease signature information from heterogeneous datasets with limited training samples and therefore is promising for developing hand-held camera-based crop disease recognition techniques.

2 Methodology

2.1 Corn disease datasets

Two multi-source heterogeneous datasets are used in this paper to evaluate the proposed DARNet approach, i.e, the indoor image set and the in-field image set. The characteristics of them are summarized in the Appendix. As we can see, both of them are small-sized datasets with thousand of image samples. Moreover, these two multi-source datasets are very different in many aspects. The indoor image set contains a little more images and disease types than the hand-held in-field image set. The indoor images are taken in the lab with relative stable illumination, angle and scale, while the in-field images have strong variations in terms of the backgrounds, illumination conditions, radiation geometries and image scales. Therefore, it is very challenging for DARNet to capture the commonality disease signature information from the limited samples in the heterogeneous datasets.

Indoor image set The indoor dataset comprises of the corn subset of the new plant diseases dataset [6]. The indoor corn disease dataset contains 2085 images of corn leaves with disease symptoms of northern leaf blight (NLB), 2052 images with gray leaf spot (GLS) and 2324 images of healthy leaves with the size of 256×256, which are taken in the laboratory environment (see Figure 1(a) and (b)).

Hand-held in-field image set The hand-held in-field set is from an image dataset which contains field images of corn annotated with NLB which is a common foliar disease of corn [7]. Images was taken with a Canon EOS Rebel or Sony a6000 camera by hand in summer 2015. The handheld set has a total of 1787 images including 1019 NLB-infected leaves and 768 images of non-infected leaves with two image sizes: 6000×4000 pixels and 5184×3456 pixels. Images with no annotations are labelled as non-infected here. We resize the images to 256×256 pixels (see Figure 1(c) and (d)).

2.2 Domain adaptation residual neural network (DARNet)

The DARNet approach is designed to simultaneously address all three key challenges in corn disease recognition from hand-held camera based images, i.e., subtle disease signature, limited training samples and the heterogeneity in multi-source datasets. In particular, DARNet is built upon a multi-branch residual neural network architecture with the shake-shake regularization to efficiently learn subtle signature without being overfitted to the limited training set. Moreover, DARNet involves some domain adaption procedures to minimize the gaps between the indoor and in-field datasets and to enable transfer learning among two domains.

2.2.1 Shake-shake boosted multi-branch residual neural network architecture

This novel architecture is tailored to address the difficulty in weak and subtle disease signature feature learning, as well as the difficulty to overcome the model overfitting issue in deep feature learning from limited corn disease training samples. Residual blocks with skip connection are designed to enhance deep feature learning and to prevent gradient vanishing. A multi-branch macro-architecture is designed to enable stratified accommodation and fusion of the signature variations. The shake-shake regularization technique, which has proved being very effective to prevent the overfitting problems in many learning problems, is adopted to prevent the model to "over-learn“ the "noise“ and irrelevant patterns that do not generalize well. The first layer of the network is a 3×3 Convolution layer with 16 filters followed by 3 stages, each having a multi-branch residual block. Residual paths have a ReLU-Conv3×3-BN-ReLU-Conv3×3-BN-Mul design, with width doubled when down-sampling to next stage. The network ends with an 8×8 average pooling and a fully connected layer.

2.2.2 Domain adaptation and transfer learning procedures

To learn commonality signature information across multi-source heterogeneous datasets, DARNet is designed to involve some domain adaption and transfer learning procedures to minimize the gaps between the indoor dataset and the in-field dataset and to enable transfer learning among two domains.

Rule-based domain mapping functions. We design some rule-based mapping functions to minimize the gaps between the two domains represented respectively by the indoor and in-field datasets. Given a in-field image, these mapping functions will perform some transformations on it to make it more "indoor-like“. These transformations include an image cropping module that aims to remove the background pixels (e.g., soil, grass, irrelevant body-part in corn that tend to be free of signature patterns) and also to reduce the size of the in-field image. Another colour-matching transformation is also used to deal with the discrepancies caused by different illumination conditions. Several rule-based colour normalization approaches designed based on the prior knowledge concerning the characteristics of the two datasets are used.

Transfer learning. Although rule-based domain mapping functions can reduce some major gaps between the two datasets, there are still discrepancies that are caused by some complex non-linear

Table 1: Test accuracy after a series of image adaptation methods

Experiment design	Overall test accuracy	Accuracy on positive samples
Learning from just the indoor dataset	53.36%	49.75%
Learning from both indoor dataset and transformed in-field dataset	89.25%	82.02%

underlying mechanisms, which are very difficult to be expressed by knowledge-driven rules. We handle these remaining complex discrepancies in a data-driven manner through transfer learning. First, we pretrain the network on the indoor dataset to learn the disease signature information. Then, we finetune the network on the in-field dataset which has been transformed by the rule-based domain mapping functions, such that the finetuned model can capture the remaining discrepancies in the transformed dataset in a data-driven manner. For both dataset, only 80% of the samples are used for training and the rest samples are used for testing. We set the number of epoch as 200, batch size as 64 and learning rate as 0.1 for transfer learning.

3 Results

The second row in Table 1 shows the accuracy achieved by the proposed DARNet approach, which learns the subtle disease signature information jointly from the both the indoor dataset and the in-field dataset. DARnet achieves an overall test accuracy 89.25%, and disease recognition accuracy of 82.02%, meaning that about 82% of diseased hand-held camera images can be correctly identified as diseased. This accuracy is very high to satisfy the operational requirement in different applications, indicating that by simultaneously tackling all the three key challenges in corn disease recognition, the proposed DARNet can effectively learn the weak and subtle corn disease signature information from limited training samples in multi-source heterogeneous datasets, and generalize the learned signature information very well to the "unseen“ hand-held camera images for efficient crop disease recognition. To demonstrate the importance of using multi-source datasets for weak signature learning, we train the proposed multi-branch residual network in DARNet on only the indoor dataset, and test it on the in-field dataset. The overall accuracy is only 53.56%, which is much lower than the DARNet accuracy, demonstrating the importance of information fusion in multiple datasets, and more importantly, the effectiveness of the rule-based domain mapping function and model fine-tuning in DARNet for efficient domain adaption and transfer learning. Figure 2 shows some in-field test images with disease that have been correctly predicted by DARNet, whose recognition accuracy is 82.02%, as reported in Table 1. These images in Figure 2 would have been wrongly predicted as healthy, if DARNet has been finetuned on the raw in-field images, demonstrating the importance and effectiveness of using prior-knowledge based rules for bridging the gaps between the indoor and in-field dataset before performing transfer learning.

(a) (b) (c) (d)

Figure 2: Example of images with disease that are correctly recognized by the DARNet, whose recognition rate is 82.02%, as shown in Table 1. These four images would have been wrongly predicted as being healthy, if the DARNet has been fine-tuned on the raw in-field images without being first transformed by the rule-based domain mapping functions.

4 Conclusion

To simultaneously address three key challenges in hand-held camera based corn disease recognition, i.e., weak and subtle disease signatures, limited training samples and heterogeneity in multi-source datasets, we have designed the DARNet approach to efficiently learn the subtle corn disease signature from insufficient training samples in heterogeneous datasets. First, to efficiently capture the weak disease signature from insufficient training samples, we built into DARNet a novel deep residual network architecture with shake-shake regularization to overcome the overfitting problem. Second, to efficiently learn disease signature from heterogeneous datasets, we integrate into DARNet rule-based domain mapping functions and model finetune procedures to narrow the discrepancy between the two datasets and to enable transfer learning among two domains. We evaluated the proposed DARNet on an indoor corn disease dataset and an outdoor dataset. The results demonstrated that DARNet can efficiently capture the subtle disease signature information from heterogeneous datasets with limited training samples. Therefore, it is promising for developing hand-held camera-based crop disease recognition techniques.

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Appendix

Details of Corn Disease Datasets

Table 2 shows the characteristics of the two corn disease datasets leveraged in this paper.

Table 2: Characteristics of corn disease datasets.

	Indoor dataset	In-field dataset
Number of disease type	2 (GLS & NLB)	1 (NLB)
Image number	2085 for NLB 2052 for GLS 2324 healthy	1019 for NLB 768 healthy
Pros	Clean backgrounds Consistent image scale and angles Even illumination More images and disease types	More representative for in-field use case for farmers.
Cons	Images taken in the lab is far from the true use situation.	Scales, angle and backgrounds variegated