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Adaptive Thresholding of CNN Features for Maize Leaf Disease Classification and Severity Estimation

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Abstract: Convolutional neural networks (CNNs) are the gold standard in the machine learning (ML) community. As a result, most of the recent studies have relied on CNNs, which have achieved higher accuracies compared with traditional machine learning approaches. From prior research, we learned that multi-class image classification models can solve leaf disease identification problems, and multi-label image classification models can solve leaf disease quantification problems (severity analysis). Historically, maize leaf disease severity analysis or quantification has always relied on domain knowledge—that is, experts evaluate the images and train the CNN models based on their knowledge. Here, we propose a unique system that achieves the same objective while excluding input from specialists. This avoids bias and does not rely on a "human in the loop model" for disease quantification. The advantages of the proposed system are many. Notably, the conventional system of maize leaf disease quantification is labor intensive, time-consuming and prone to errors since it lacks standardized diagnosis guidelines. In this work, we present an approach to quantify maize leaf disease based on adaptive thresholding. The experimental work of our study is in three parts. First, we train a wide variety of well-known deep learning models for maize leaf disease classification, then we compare the performance of the deep learning models and finally extract the class activation heatmaps from the prediction layers of the CNN models. Second, we develop an adaptive thresholding technique that automatically extracts the regions of interest from the class activation maps without any prior knowledge. Lastly, we use these regions of interest to estimate image leaf disease severity. Experimental results show that transfer learning approaches can classify maize leaf diseases with up to 99% accuracy. With a high quantification accuracy, our proposed adaptive thresholding method for CNN class activation maps can be a valuable contribution to quantifying maize leaf diseases without relying on domain knowledge.

Keywords: CNN; transfer learning; class activation heatmap; adaptive thresholding

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1. Introduction

Crop diseases remain a global challenge to food security. According to [1], 20 to 40% of global crop production is lost to pests and diseases annually. Accordingly, the application of machine learning and deep learning models for identifying and quantifying crop diseases has emerged as one of the important themes of the 21st century, especially in precision agriculture [2]. This follows multiple efforts to automate disease monitoring in agriculture, for example [3,4]. Most deep learning models in the literature have achieved tremendous success in general image classification tasks. Therefore, it is natural to leverage the advances made in this field to meet the demands of precision agriculture [5]. Central to this is the selection of leaf image features that contain sufficient data for training the models, or the use of specialized deep learning models to extract features on the fly using a combination of various convolution and pooling layers. In most cases, deep learning in this work rely on multiple deep convolutional layers to obtain high performance on our dataset. Additionally, when shallow CNN was used together with regularization, we obtained a slight improvement in performance (96% accuracy). Our method of extracting the ROI specifies an adaptive threshold for each CUT based on the average intensity values of the reference cells in the 2D sliding window. Problems caused by busy backgrounds and specular lighting are well-known in the literature, but in this study, we report no impact of such factors on the performance of our algorithm. This work analysed the performance of several CNN architectures: Inception V3, DenseNet 121, DenseNet 201, MobileNet, VGG16, EfficientNetB0, LeNet, ResNet50 and our proposed shallow CNN.

In the future, the current findings of this work can be extended to: (i) Disease classification problems in other crops where yield is largely affected by crop disease, thus affecting the livelihoods of farmers, such as beans, bananas and cassava. (ii) Develop new algorithms for simultaneous multi-label leaf disease classification and quantification. Developing a robust method for quantifying leaf diseases with multiple symptoms is the next logical step. (iii) Validate the proposed CNN model on standard image processing datasets such as ImageNet and CiFar.

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Abbreviations

The following abbreviations are used in this manuscript:

CAM	Class Activation Map
CNN	Convolutional Neural Network
CUT	Cell Under Test
DL	Deep Learning
ML	Machine Learning
ROI	Region of Interest
SVM	Support Vector Machine

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