Leaf Tar Spot Detection Using RGB Images

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Abstract—Tar spot disease is a fungal disease that appears as a series of black circular spots containing spores on corn leaves. Tar spot has proven to be an impactful disease in terms of reducing crop yield. To quantify disease progression, experts usually have to visually phenotype leaves from the plant. This process is very time-consuming and difficult to incorporate into any high-throughput phenotyping system. Deep neural networks could provide quick, automated tar spot detection with sufficient ground truth. However, manually labeling tar spots in images to serve as ground truth is also tedious and time-consuming. In this paper we first describe an approach that uses automated image analysis tools to generate ground truth images that are then used for training a Mask R-CNN. We show that a Mask R-CNN can be used effectively to detect tar spots in close-up images of leaf surfaces. We additionally show that the Mask R-CNN can be used for in-field images of whole leaves to capture the number of tar spots and area of the leaf infected by the disease.

I. INTRODUCTION

Tar spot disease is a fungal disease that appears as a series of black circular spots containing spores on corn leaves [1]. It has proven to be an impactful disease in terms of reducing yield in affected crop fields [2]. Economic damage up to 50% has been documented in Latin America when epidemics are severe early in corn plants’ reproductive phases [3]. Tar spot detection has been done using human visual disease assessments of ‘stromata’, which are black circular structures produced by the tar spot pathogen *Phyllachora maydis*. In general, these stromata start off circular, but can quickly elongate and merge as the disease progresses. To capture disease progression, experts in plant pathology quantify disease intensity using visual methods, such as a manual count of the tar spots. In addition to count, the relative area of the leaf covered in tar spots is a good measure of the disease severity [4]–[6]. This manual analysis can be done using computer-based tools using an image of the leaf, or physically, but either way, the process is very time-consuming.

Despite the alarming nature of tar spot disease, the current capabilities available make it difficult to do any sort of high-throughput phenotyping at the field level. Thus, we aim to automate this process and reduce the required overhead using image processing techniques and deep learning.

Fig. 1: An example of a leaf showing signs of tar spot disease. There are numerous black spots covering the surface of the leaf.

Deep learning is a rapidly growing field that has progressed quickly in the last decade. Neural networks have been shown to be very effective at several computer vision and image processing tasks such as object detection [7] and image segmentation [8], making them an ideal tool to use in detecting tar spots. Neural networks can leverage the parallel processing and computational power of GPUs to process large amounts of image data rapidly, making them ideal for high-throughput phenotyping. However, neural network models require large amounts of training data to achieve optimal performance. As discussed, generating annotated examples of leaf tar spots is a time-consuming process that requires manual labeling from subject matter experts. In this paper, we show that a convolutional neural network (CNN), specifically Mask R-CNN, can be trained using “ground truth” data generated from images using automated image analysis techniques. To be specific, given an RGB image of a leaf of a plant with tar spot, we first designed a traditional image analysis method using techniques such as thresholding and connected components to identify and segment tar spots. The idea here is that we
use an automated approach to generate “ground truth” tar spot masks that we can use for training our neural network. We assume the masks we obtain to be accurate ground truth viable for training. This process involves no manual labeling by expert plant pathologists, so the amount of resources that need to be invested is reduced significantly. Our Mask R-CNN model, trained on these ground truth masks, achieves reasonable performance on our limited expert-labeled dataset and can be used to process in-field images of leaves with tar spot.

II. RELATED WORK
A. Image Based Plant Phenotyping

Manual examination of plants has been fairly effective at evaluating the health and growth of the plant. However, in recent years, with the sheer volume of field crops grown, manual inspection is steadily becoming infeasible, and the accuracy of visual disease assessments is being questioned due to the “human factor” [9]. Using images adds scalability to the analysis conducted, and also introduces a factor of replicability and objectivity when quantifying any plant phenotype.

Image-based plant phenotyping can be categorized into two approaches based on the environment in which the images are acquired [10], [11]. The first is under controlled conditions i.e., the imaging environment is consistent and the plants are grown with minimal unexpected interference. For example, the indoor high-throughput plant phenotyping system proposed in [12] allows plants to be freely moved around to be watered, weighted, and imaged. These environments have been shown to be successful at enabling high precision in trait estimation and growth projection [12]. In [13], leaves are destructively phenotyped to obtain the leaf area measurement from the number of pixels in the segmentation mask and known physical dimensions. In [14], plants in an automated indoor facility are detected using a variety of image processing techniques like color thresholding, k-means, and active contours. While phenotyping in a controlled environment is useful, it cannot be extended to large-scale field studies, which are conducted outdoors.

The other approach to image-based plant phenotyping is estimating plant traits using images collected in an outdoor area. These images tend to have more background variations and are not as uniform. Data collection for outdoor plant phenotyping can be done in several ways. In [15], field images collected using a hand-held device are segmented using histogram thresholding. The resulting segmentation masks are then used to estimate leaf surface area per unit area of land. For the specific task of quantifying tar spot disease progression, in [16], the authors proposed using a combination of regression methods and observable characteristics from overhead images captured by unmanned aerial vehicles (UAVs). Characteristics such as canopy cover and volume were extracted from these images and used to fit regression models like support vector regression to visual estimations of disease severity performed by expert plant pathologists. Another approach [6] used image processing techniques to create a contour-based tar spot detection approach that leads to promising results in tar spot detection and area estimation, but this approach lacks automation.

In the work presented in this paper, we use images collected in an outdoor area. The dataset consists of both close-up images of leaves with tar spot, as well as images of the whole leaf that are better suited for quantifying disease progression in the crop fields. Visual examination of these leaves by experts is difficult and time-consuming, and so we automate the process using image processing and deep learning, which will be discussed in Section III.

B. Object Detection and Image Segmentation

Let us consider object recognition, which is a general term for computer vision tasks that involve identifying objects in digital images. Image classification is the act of labeling an entire image with the class of one of its contained objects i.e., an image of a cat being labeled ‘cat’. Another task, object localization, involves finding the location of the objects in an image and drawing a bounding box around them. Object detection is a combination of these tasks, where all the objects in an image are found and classified (or labeled). An image of three different animals would have three different bounding boxes and class labels.

One approach to object detection using neural networks is the R-CNN [17], or Region-based Convolutional Neural Networks, family of models. The general idea behind these models is shown in Figure 2, consisting of three stages. Given an input image, the first step is to identify class-independent areas of interest i.e., mark possibly interesting bounding boxes. Then the areas within these bounding boxes are passed through a CNN to extract important features. These features are then used to assign the bounding boxes one of the known labels. Initially, this approach consisted of three separate networks (one for each stage). Fast R-CNN [18] is a single model that speeds up the entire learning process by using spatial pyramid pooling networks, or SPPnets [19]. Additional optimization was made when Faster R-CNN [20] was introduced, which used a Region Proposal Network (RPN) to refine region proposals as part of the training process. Effective image segmentation can be achieved by using additional convolutional layers in parallel to generate object masks, as seen with Mask R-CNN [21].

III. OUR APPROACH
A. Generating Ground Truth Tar Spot Images

Most deep learning object detection approaches require labeled data, which is a tedious and time-consuming process of manual work from experts. We instead decided to train our tar spot detection network with labeled data generated using
automated image analysis techniques that exploit properties of a typical tar spot image (e.g., the dark tar spots). To be specific, given an RGB image of a leaf of a plant infected with tar spot, we first designed a traditional image analysis method using techniques such as thresholding and connected components to identify and segment tar spots, a process we call “automatic ground truthing.” The idea here is that we use an automated approach to generate ground truth tar spot masks that we can use for training. We assume the masks we obtain to be accurate ground truth viable for training. This process involves no manual labeling by expert plant pathologists, so the amount of resources that need to be invested is reduced significantly. Note that we have a limited set of ground truth images labeled by plant experts that we will use for testing the performance of our method trained using this ‘automatic ground truthing’ approach.

The block diagram of our automatic ground truthing approach is shown in Figure 3. We convert the RGB image to both the HSV and \( L^*A^*B^* \) color spaces. We then threshold the \( V \) channel in the HSV space and the \( A^* \) channel in the \( L^*A^*B^* \) color space using thresholds determined empirically. This process provides us with two preliminary tar spot masks. We combine these masks using the logical ‘OR’ operation into a single tar spot mask containing information from the \( V \) and \( A^* \) channels. To remove any undesired objects in the mask, we use sequential opening and closing operations [22], [23] with a 3x3 structuring element. This removes noise and fills holes in the mask. The final step is to use connected component labeling [24] on the mask to separate out each instance of a tar spot. These results are then used to train the Mask R-CNN.

B. Mask R-CNN

Mask R-CNN [21] is an extension of the object detection model Faster R-CNN [20]. Faster R-CNN consists of two stages. The first stage is known as a Region Proposal Network (RPN), which proposes potential object bounding boxes. The second stage is essentially a Fast R-CNN [18], since it extracts features from these potential object bounding boxes to assign labels and refine the bounding boxes. Mask R-CNN [21] uses the same two-stage procedure as Faster R-CNN [20]. The first stage consisting of the RPN is kept the same. The second stage, in parallel to learning the classification and refining the bounding boxes, also generates a binary mask output for each region of interest. The novelty here is that the mask output and the classification are done in parallel, as opposed to the classification depending on the mask [21]. Mask R-CNN has proven to be a very good approach for object detection, which can be partially attributed to the impact of multi-task learning [25]. Due to the process of learning the general location of objects (via bounding boxes), types of objects (via class labels), and specific location of objects (via object masks), Mask R-CNN learns more related information and connections between its various inputs. We use a Mask R-CNN for the tar spot detection task due to its high level of performance.

IV. EXPERIMENTAL RESULTS

Our training dataset consists of 500 close-up RGB images with a resolution of 6000 × 4000 pixels, captured by a Nikon D7100 camera. The images are of leaves with tar spot, with 0 – 150 tar spots present in each image. We also have a manually labeled dataset consisting of 100 similar images. These images have been labeled by an expert plant pathologist, and as indicated previously, required a significant amount of time to ensure accuracy. The manually labeled dataset is split into test and validation datasets by a ratio of 4 : 1, meaning we have 20 images to validate our trained model. The validation dataset was also used to empirically select the best thresholds for our “automatic ground truthing” approach. We generate the training ground truth data using our “automatic ground truthing” approach on the 500 images in our training set. We then use a pretrained Mask R-CNN model, trained on ImageNet, and finetune it with the 500 training images until the validation loss no longer decreases. Our model is evaluated on the test set, consisting of 80 images labeled by an expert. As shown in Table I, our trained Mask R-CNN achieves an F1-score of 0.76 on the 80 images in the manual ground truth testing dataset, as well as an average error of 10.4 in counting the number of tar spots (Difference in Count, or DiC). Table I also shows the result of applying our “automatic ground truthing” approach directly on the images of tar spot afflicted leaves. We note that the improvement in performance with using the trained Mask R-CNN over directly applying the “automatic ground truthing” could be attributed to leveraging the general object detection knowledge acquired when the Mask R-CNN was pretrained on ImageNet. An example of the tar spots detected by the Mask R-CNN can be seen in Figure 4.

The other quantitative measurement of performance we are interested in is the average time taken to detect the tar spots in the leaf image. We also report these results in Table I, which show that using the Mask R-CNN leads to a drastic
reduction in the average time taken per image to generate tar spot detections. Additionally, since we are leveraging the parallel processing and computational power of GPUs, it is comparatively easier to scale up and process thousands of leaf images from a field at once. Thus, with this ‘automatic ground truthing’ approach, we show that a deep learning model that facilitates high-throughput phenotyping can be developed.

The Mask R-CNN is trained to work on close-up images of leaves with tar spot, since these are the images where our threshold-based automatic ground truthing approach works optimally, but also are the images that are the easiest to label for the expert. However, to obtain measurements that reflect the extent of the tar spot disease, the more practical approach is to acquire images from further away from the leaf that capture the leaf in its entirety. This ensures some consistency when measuring the relative area of the leaf where the tar spot disease has taken hold. However, by moving further away, the tar spots in the image greatly reduce in size and increase in number. The second column of Figure 5 shows the initial detection performance of our trained model on these types of images.

The larger tar spots are generally still identified, but a drawback of using a CNN-based approach is that smaller details in an image can be lost during the downsampling and feature extraction steps of the CNN. For these images, we make a slight modification to how we input the image to the network. We consider a sliding window of size $600 \times 400$. Its horizontal stride is 75 and its vertical stride is 50. We provide these $600 \times 400$ patches to our Mask R-CNN and detect tar spots for each patch. The output detection masks for each patch are then combined using a voting strategy into a larger $6000 \times 4000$ image that reflects the tar spots detected for the entire image. The third column in Figure 5 shows the results using this approach. Qualitatively, we can see that a greater number of tar spots are detected, and many of the smaller spots missed earlier are now being captured.
Fig. 5: The full images of leaf with tar spot are difficult to analyze, manually or automatically, so there is no manual ground truth. Our trained Mask R-CNN model captures a minimal number of tar spots when used directly, while adding the sliding window approach to the Mask R-CNN enables an increased number of the smaller tar spots to be detected.

It is also important to note that the cost of manual annotation of these images increases exponentially. As can be seen in the examples, the number of tar spots increases tenfold and each one greatly reduces in size. An expert would have to painstakingly examine every pixel in the image to completely capture the extent of the disease.

Even though this approach of using automatically generated ground truth worked reasonably well, there is still room for improvement when dealing with leaves with a high density of tar spots. The tar spots often begin to merge into irregular shapes or are too close to properly distinguish, especially when the whole leaf image is being used. An example of a high tar spot density leaf is shown in Figure 6. Although not every tar spot is detected, the relative relationship between images is maintained, i.e., we detect more tar spots in the leaf image with more tar spots, despite not capturing all of the tar spots. In terms of analysis, we are still generally able to capture the useful trend of increasing disease severity which is important for managing field-based tar spot infections.

V. CONCLUSIONS AND FUTURE WORK

In this paper, we show that a Mask R-CNN is very effective at detecting tar spots in corn leaf images. Since manual annotation is very inefficient, we use image analysis techniques to automatically generate ground truth images for the Mask R-
CNN. With this approach, we are able to achieve reasonable tar spot detection and area estimation performance on close-up images of leaves in an automated manner, greatly reducing the amount of labeled data to leverage vast amounts of unlabeled data and train a neural network for a task. We are also interested in exploring active learning to incorporate expert plant pathologist feedback into the training process of our network.

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