
CD&S DATASET: HANDHELD IMAGERY DATASET ACQUIRED UNDER FIELD CONDITIONS FOR CORN DISEASE IDENTIFICATION AND SEVERITY ESTIMATION

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ABSTRACT

Accurate disease identification and its severity estimation is an important consideration for disease management. Deep learning-based solutions for disease management using imagery datasets are being increasingly explored by the research community. However, most reported studies have relied on imagery datasets that were acquired under controlled lab conditions. As a result, such models lacked the ability to identify diseases in the field. Therefore, to train a robust deep learning model for field use, an imagery dataset was created using raw images acquired under field conditions using a handheld sensor and augmented images with varying backgrounds. The Corn Disease and Severity (CD&S) dataset consisted of 511, 524, and 562, field acquired raw images, corresponding to three common foliar corn diseases, namely Northern Leaf Blight (NLB), Gray Leaf Spot (GLS), and Northern Leaf Spot (NLS), respectively. For training disease identification models, half of the imagery data for each disease was annotated using bounding boxes and also used to generate 2343 additional images through augmentation using three different backgrounds. For severity estimation, an additional 515 raw images for NLS were acquired and categorized into severity classes ranging from 1 (resistant) to 5 (susceptible). Overall, the CD&S dataset consisted of 4455 total images comprising of 2112 field images and 2343 augmented images.

Keywords Plant Diseases · Corn Diseases · Disease Identification · Severity Estimation · Deep Learning · Image Classification · Object Detection · Datasets

1 Introduction

Corn is an important crop worldwide and diseases in corn are responsible for reducing crop yield. Northern Leaf Blight (NLB), Gray Leaf Spot (GLS), and Northern Leaf Spot (NLS), are common foliar diseases of corn found in the Midwest, United States. NLB disease is caused by the *Setosphaeria turcica* fungus resulting in long brown cigar shaped lesions. GLS disease is caused by *Cercospora zeae-maydis* and the symptoms include multiple greyish-brown and narrow rectangular lesions. Finally, NLS disease is caused by *Cochliobolus carbonum* resulting in multiple brown spots with circular concentric lesions. The severity of any disease

in corn is dependent on varietal susceptibility, presence of the pathogen, and a favorable environmental condition (<https://cropprotectionnetwork.org/resources/articles/diseases/gray-leaf-spot-of-corn>). Therefore, accurate disease identification and its severity evaluation is required for implementing effective management practices. Traditional approaches for disease identification and severity evaluation relies on manual scouting and expert knowledge. These approaches are time consuming and subjective (Zhang et al., 2014). Therefore, to bring efficiency and objectivity, researchers have started exploring solutions that are based on computer vision methods. After successful application of deep learning-based image classification and object detection models across disciplines, researchers are increasingly investigating their role for disease identification and its severity evaluation by using annotated imagery datasets. However, most datasets such as PlantVillage (Hughes et al., 2015) and Digipathos (Barbedo et al., 2018), consist of images acquired under lab conditions. As a result, models trained on such datasets failed to accurately identify diseases and their severity from images that were acquired under field conditions (Ferentinos, 2018; Lee et al., 2020). Therefore, an annotated corn disease dataset consisting of field acquired raw images and augmented images with three varying backgrounds, was created in order to help develop robust deep learning models for disease identification and its severity estimation in the field. The field acquired raw images from the dataset were recently used (Ahmad et al., 2021).

2 Materials and Methods

2.1 Dataset

The CD&S dataset consists of a total of 4455 raw images and augmented images. A total of 2112 raw images, for three common corn diseases, namely NLB, GLS, and NLS, were acquired under field conditions at Purdue University's Agronomy Center for Research and Education (ACRE) in West Lafayette, Indiana, in July 2020. The images were acquired using a 12-megapixel camera sensor from the iPhone 11 Pro smartphone. The image mode was set to acquire images of size 3000 x 3000 pixels in order to maintain a 1:1 aspect ratio which is commonly used for the training of deep learning-based image classification and object detection models.

In order to prepare the dataset for disease identification, a total of 511, 524, and 562, raw images were first acquired for the NLB, GLS, and NLS diseases, respectively (figure 1). The overall dataset was then split using a 50% - 50% training – testing split ratio. Bounding box annotation were then created for disease lesions within the training images using the LabelImg tool (<https://github.com/tzutalin/labelImg>), in order to train object detection models. The images were annotated using the YOLO .txt format, which resulted in the creation of .txt files for each corresponding image. Each bounding box within an image was represented by five values (label, x-coordinate of center, y-coordinates of center, height of bounding box, width of bounding box), in each line for each annotated disease lesion.

Dataset augmentation is commonly used by increasing the dataset size and adding variations, in order to improve the generalization capability of deep learning models (Chao et al., 2020). Therefore, the NLB, GLS, and NLS training images, that were acquired for disease identification were augmented by varying backgrounds. First, the online background removal tool (<https://www.remove.bg/upload>) was used for removing the field backgrounds and images were resized to 500 x 500 pixels. Background removal resulted in a total of 781 RGBA images of diseased leaves without backgrounds, where A represents the alpha channel for adjusting the transparency of pixels. A Python script was then written to place the RGBA corn disease images with no backgrounds on a white background and a black background, resulting in two additional versions of the training dataset with 781 images each. Overall, a total of 2343 augmented corn disease images were created.

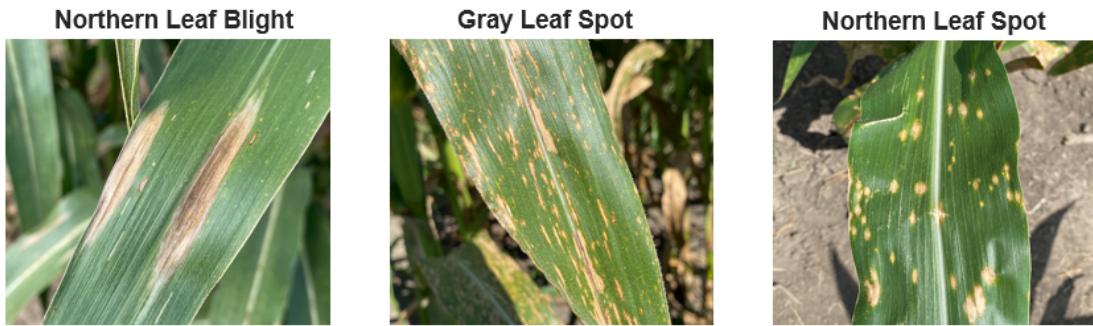


Figure 1: NLB, GLS, and NLS diseases in CD&S Dataset.

For the purpose of training disease severity evaluation models, an additional 515 raw images for the NLS disease were acquired under field conditions. The total 1077 raw NLS disease images were then split into five severity classes ranging from 1 (resistant) to 5 (susceptible) with 108, 330, 297, 231, and 111 images, respectively.

The CD&S dataset was organized into six folders (table 1). Dataset_Original consists of the raw images, for the three diseases, acquired under field conditions. The annotated images with their respective annotation files are present in Dataset_Annotated. The augmented training images with three varying backgrounds, were stored in Dataset_Black_Background, Dataset_White_Background, and Dataset_No_Background. Finally, Dataset_Severity consists of the NLS disease severity images.

Table 1: Folders from CD&S Dataset

Folder Name	File Type	Link
Dataset_Original	JPG files (.jpg)	https://osf.io/s6ru5/
Dataset_Annotated	JPG & Text files (.jpg, .txt)	https://osf.io/s6ru5/
Dataset_Black_Background	JPG files (.jpg)	https://osf.io/s6ru5/
Dataset_White_Background	JPG files (.jpg)	https://osf.io/s6ru5/
Dataset_No_Background	PNG files (.png)	https://osf.io/s6ru5/
Dataset_Severity	JPG files (.jpg)	https://osf.io/s6ru5/

References

- J. Zhang, R. Pu, L. Yuan, J. Wang, W. Huang, G. Yang, Monitoring powdery mildew of winter wheat by using moderate resolution multi-temporal satellite imagery, *PloS one* 9 (2014) e93107.
- D. Hughes, M. Salathé, et al., An open access repository of images on plant health to enable the development of mobile disease diagnostics, *arXiv preprint arXiv:1511.08060* (2015).
- J. G. A. Barbedo, L. V. Koenigkan, B. A. Halfeld-Vieira, R. V. Costa, K. L. Nechet, C. V. Godoy, M. L. Junior, F. R. A. Patrício, V. Talamini, L. G. Chitarra, et al., Annotated plant pathology databases for image-based detection and recognition of diseases, *IEEE Latin America Transactions* 16 (2018) 1749–1757.
- K. P. Ferentinos, Deep learning models for plant disease detection and diagnosis, *Computers and Electronics in Agriculture* 145 (2018) 311–318.
- S. H. Lee, H. Goëau, P. Bonnet, A. Joly, New perspectives on plant disease characterization based on deep learning, *Computers and Electronics in Agriculture* 170 (2020) 105220.
- A. Ahmad, D. Saraswat, A. El Gamal, G. S. Johal, Comparison of deep learning models for corn disease identification, tracking, and severity estimation using images acquired from uav-mounted and handheld sensors, in: 2021 ASABE Annual International Virtual Meeting, American Society of Agricultural and Biological Engineers, 2021, p. 1.
- X. Chao, G. Sun, H. Zhao, M. Li, D. He, Identification of apple tree leaf diseases based on deep learning models, *Symmetry* 12 (2020) 1065.