PlantDoc: A Dataset for Visual Plant Disease Detection

Davinder Singh*, Naman Jain*, Pranjali Jain*, Pratik Kayal*
Sudhakar Kumawat, Nipun Batra
Indian Institute of Technology Gandhinagar, Gujarat, India 382 355
{davinder.singh,naman.j,pranjali.jain,pratik.kayal,sudhakar.kumawat,nipun.batra}@iitgn.ac.in

ABSTRACT

India loses 35% of the annual crop yield due to plant diseases. Early detection of plant diseases remains difficult due to the lack of lab infrastructure and expertise. In this paper, we explore the possibility of computer vision approaches for scalable and early plant disease detection. The lack of availability of sufficiently large-scale non-lab data set remains a major challenge for enabling vision based plant disease detection. Against this background, we present PlantDoc: a dataset for visual plant disease detection. Our dataset contains 2,598 data points in total across 13 plant species and up to 17 classes of diseases, involving approximately 300 human hours of effort in annotating internet scraped images. To show the efficacy of our dataset, we learn 3 models for the task of plant disease classification. Our results show that modelling using our dataset can increase the classification accuracy by up to 31%. We believe that our dataset can help reduce the entry barrier of computer vision techniques in plant disease detection.
Work accepted as a SHORT paper and for presentation at the ACM India Joint International Conference on Data Sciences and Management of Data (CoDS-COMAD) 2020 (7th ACM iKDD CoDS and 25th COMAD) to be held in Hyderabad, India, on January 5-7, 2020.

1 INTRODUCTION

Annually the Earth's population increases by about 1.6%, and so does the demand for plant products of every kind [11]. The protection of crops against plant diseases has a vital role to play in meeting the growing demand for food quality and quantity [14]. In terms of economic value, plant diseases alone cost the global economy around US$220 billion annually [1]. According to the Indian Council of Agricultural Research, more than 35% of crop production is lost every year due to Pests and Disease [10]. Food security is threatened by an alarming increase in the number of outbreaks of pests and plant diseases. These diseases jeopardize food security and have broad economic, social, and environmental impacts [4]. Timely disease detection in plants remains a challenging taskfor farmers.

In this work, we explore the possibility of using computer vision for scalable and cost-effective plant disease detection. While training large neural networks can be very time consuming, the trained models can classify images very quickly, which makes them also suitable for consumer applications on smartphones. Image processing for detecting plant diseases opens up new avenues to combine the knowledge of deep learning approaches with real-world problems in agriculture, and hence, facilitates advancements in agricultural knowledge, the yield of crops, and disease control. Majority of existing vision-based solutions require high-resolution images with a plain background. We focus on images in natural environmental conditions with non-trivial background noise and provide the best possible query resolution for crops and plants. Against this background, we highlight our two main contributions: i) development of PlantDoc: a dataset of 2,598 images across 13 plant species and 27 classes(17-10, disease-healthy) ii) benchmarking the curated data set and showing its utility in disease detection in non-controlled environments. To the best of our knowledge, this is the first such dataset containing data from non-controlled settings.

*Equal Contribution.

2 RELATED WORK

The related work can be broadly categorized into: i) techniques for plant disease detection; and ii) datasets advancing research in plant disease detection.

2.1 Techniques for plant disease detection

Prior work by Patil et al. [12] extracted shape features for disease detection in sugarcane leaves obtaining a final average accuracy of 98.60%. In a similar work, Patil et al. [3] used texture features for disease detection on maize leaves. Recent work [6] has looked into neural networks for the identification of three different legume species based on the morphological patterns of leaves veins. These works are limited to a particular crop, which is a significant limitation.

2.2 Datasets for plant disease detection

The PlantVillage dataset(PVD) [9] is the only public dataset for plant disease detection to the best of our knowledge. The data set curators created an automated system using GoogleNet [15] and AlexNet [8] for disease detection, achieving an accuracy of 99.35%. However, the images in PlantVillage dataset are taken in laboratory setups and not in the real conditions of cultivation fields, due to which their efficacy in real world is likely to be poor. In contrast, we curate real-life images of healthy and diseased plants to create a publicly available dataset.

3 THE PLANTDOC DATASET

The PlantVillage dataset contains images taken under controlled settings. This dataset limits the effectiveness of detecting diseases because, in reality, plant images may contain multiple leaves with different types of background conditions with varying lighting conditions (shown in Figure 1). This fact motivated us to create a new dataset that can handle the intricacies of real life. We collected about 20,900 images by using scientific and common names of 38 classes of plants and crops from sites like Google Images and Ecosia [5]. Four annotators filtered the images by selecting images based on their metadata on the website and guidelines mentioned on APSNet [2]. APS compiled a list of peer-reviewed literature

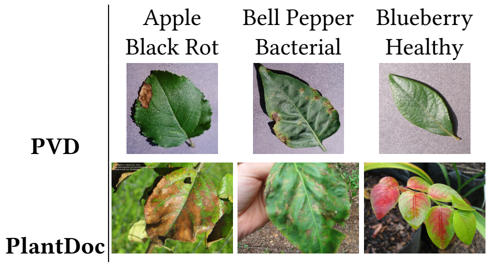

Figure 1: Samples from various classes in the PlantDoc Dataset show the gap between lab-controlled and real-life images

corresponding to each plant disease. Some of the most important factors for classification were the color, area and density of the diseased part and shape of the species. Every image was checked by two individuals according to the guidelines to reduce labeling errors. Finally, to have sufficient training samples, we removed the classes with less than 50 images. Finally, we got a total of 27 classes spanning over 13 species with 2,598 images.

Object Detection-PlantDoc Dataset: We used the `LabelImg` tool [16] to make the bounding boxes around the leaves in all the images. In real scenarios, the image may have multiple leaves or a combination of diseased and healthy leaves. We labeled all the leaves in the image explicitly with their particular classes.

Cropped-PlantDoc Dataset: To show the differences between our dataset and PlantVillage, we built another dataset called the *Cropped-PlantDoc (C-PD)* by cropping the images using bounding box information. Similar to PlantVillage, cropped images contains only the leaf but these images are of low-quality, have small-size and varying backgrounds. The total number of leaf images after cropping 2,598 images turns out to be 9,216 i.e. 9,216 bounding boxes.

4 BENCHMARKING PLANTDOC DATASET

We now discuss two benchmark set of experiments on our dataset: i) plant image classification; and ii) detecting leaf within an image.

PreTrained Weights	Training Set (Set %)	Test Set (Set %)	Accuracy	F1-Score
ImageNet	PlantDoc (80)	PlantDoc (20)	13.74	0.12
ImageNet	PVD	PlantDoc (100)	15.08	0.15
ImageNet+PVD	PlantDoc (80)	PlantDoc (20)	**29.73**	**0.28**

Table 1: Transfer Learning doubled the accuracy after fine-tuning on Uncropped PlantDoc dataset

Our main goal was to construct a model which can detect a leaf in an image and then classify it into the particular classes. We evaluated the performance of VGG16 [13] using different training sets on PlantDoc to understand classification accuracy on the uncropped PlantDoc dataset.

The aim of our next experiments is to evaluate the performance of Faster R-CNN with InceptionResnetV2 model and MobileNet model on our PlantDoc Dataset. We split our dataset into 2,360-238 based on training-testing. We took the pre-trained weights and fine-tuned on training set of PlantDoc.

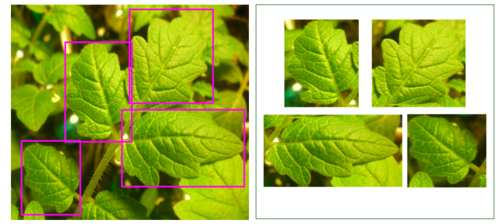

Figure 2: An Image with bounding boxes and its cropped leaves

Model	PreTrained Weights	Training Set (Set %)	Test Set (Set %)	Accuracy	F1-Score
VGG16	ImageNet	C-PD (80)	C-PD(20)	44.52	0.44
VGG16	ImageNet	PVD	C-PD (100)	19.73	0.18
VGG16	ImageNet+PVD	C-PD (80)	C-PD (20)	60.41	0.60
InceptionV3	ImageNet	C-PD (80)	C-PD (20)	46.67	0.46
InceptionV3	ImageNet	PVD	C-PD (100)	30.78	0.28
InceptionV3	ImageNet+PVD	C-PD (80)	C-PD (20)	62.06	0.61
InceptionResNet V2	ImageNet	C-PD (80)	C-PD (20)	49.04	0.49
InceptionResNet V2	ImageNet	PVD	C-PD (100)	39.87	0.38
InceptionResNet V2	ImageNet+PVD	C-PD (80)	C-PD (20)	**70.53**	**0.70**

Table 2: Training on controlled dataset (PlantVillage - PVD) gives poor performance on real world images.

Model	PreTrained Weights	mAP (at 50% iou)
MobileNet	COCO	32.8
MobileNet	COCO+PVD	22.4
Faster-rcnn-inception-resnet	iNaturalist	36.1
Faster-rcnn-inception-resnet	COCO	**38.9**

Table 3: Leaf detection mAP (iou refers to intersection over union)

5 RESULTS AND DISCUSSION

The results shows that real case scenarios have low accuracy when processed initially with ImageNet or PlantVillage. Also, Table 1 and Table 2 clearly shows low accuracy achieved by training on PlantVillage and testing on PlantDoc. Model fails to produce accurate results due to background noise, images with leaf from multiple classes in a dataset and low-resolution leaf images.

6 APPLICATION BUILDING

We have build application that utilizes MobileNets Object Detection Network [7] due to its efficiency and competitive accuracy. The application predicts the bounding boxes and classes in real time in a mobile CPU.

7 CONCLUSIONS AND FUTURE WORK

One of the main contributions of our work is to propose an entirely new dataset for plant disease detection called PlantDoc. Our benchmark experiments show the lack of efficacy of models learnt on controlled datasets, thereby, showing the significance of real-world datasets such as ours. Applying image segmentation techniques to extract leaf out of the images can potentially enhance the utility of the dataset. We believe that this dataset is an important first step towards computer vision enabled scalable plant disease detection.

REFERENCES

[1] GN Agrios. 2005. Plant pathology 5th Edition: Elsevier Academic Press. *Burlington, Ma. USA* (2005), 79–103.

[2] APSNet. 2019. Resources for Plant Diseases. https://www.apsnet.org/edcenter/resources/commonnames/Pages/default.aspx

[3] Sanjay B Patil, K Shrikant, and Bodhe . 2011. Betel Leaf Area Measurement Using Image Processing. *International Journal on Computer Science and Engineering (IJCSE)* 3 (01 2011).

[4] Messe Düsseldorf. [n. d.]. SAVE FOOD. ([n. d.]). https://www.messe-duesseldorf.com/cgi-bin/md_home/lib/pub/tt.cgi/SAVE_FOOD.html?oid=121&lang=2&ticket=g_u_e_s_t

[5] Ecosia. 2019. Search Engine. https://www.ecosia.org/?c=en

[6] Guillermo L Grinblat, Lucas C Uzal, Mónica G Larese, and Pablo M Granitto. 2016. Deep learning for plant identification using vein morphological patterns. *Computers and Electronics in Agriculture* 127 (2016), 418–424.

[7] Andrew G. Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, and Hartwig Adam. 2017. MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications. *CoRR* abs/1704.04861 (2017). arXiv:1704.04861 http://arxiv.org/abs/1704.04861

[8] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. 2012. Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*. 1097–1105.

[9] Sharada P Mohanty, David P Hughes, and Marcel Salathé. 2016. Using deep learning for image-based plant disease detection. *Frontiers in plant science* 7 (2016), 1419.

[10] T Mohapatra. 2018. ICAR News July-September 2018. Published in monthly newsletter, https://www.icar.org.in/sites/default/files/ICARNewsJulySeptember2018.pdf.

[11] E-C Oerke, H-W Dehne, Fritz Schönbeck, and Adolf Weber. 2012. *Crop production and crop protection: estimated losses in major food and cash crops*. Elsevier.

[12] Sanjay B Patil and Shrikant K Bodhe. 2011. Leaf disease severity measurement using image processing. *International Journal of Engineering and Technology* 3, 5 (2011), 297–301.

[13] Karen Simonyan and Andrew Zisserman. 2014. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556* (2014).

[14] Richard N Strange and Peter R Scott. 2005. Plant disease: a threat to global food security. *Annu. Rev. Phytopathol.* 43 (2005), 83–116.

[15] Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. 2015. Going deeper with convolutions. In *Proceedings of the IEEE conference on computer vision and pattern recognition*. 1–9.

[16] Tzutalin. 2015. LabelImg. Free Software: MIT License. https://github.com/tzutalin/labelImg