

Template for Technical Reports

DL-IC 2018 Project

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Abstract

The ABSTRACT should be self contained and explain what the paper is about. Usually abstracts are no longer than 300 words. You should state what are the main contributions of your work and tempt the reader to continue to read your paper. A good abstract briefly describes your problem, approach, and key results. This document is based on the CVPR submission template, and it has been adapted to submit a technical report of a project of the Deep Learning and Image Classification course.

1. Introduction

The advances of science and technology in history have given the possibility to produce enough food to meet the demand of more than 7 billion people. However, food provisioning is threatened by a number of factors such as climate change [1], the decline in pollinators [5], plant diseases [11], and others. Thus, these factors cause direct impacts on the population, such as economic, health, and livelihood impacts [14]. Plant diseases are not only a threat to food security at the global scale, but can also have disastrous consequences for smallholder farmers whose livelihoods depend on healthy crops. In the developing world, more than 80 percent of the agricultural production is generated by smallholder farmers [15], and reports of yield loss of more than 50% due to pests and diseases are common [3]. Furthermore, the largest fraction of hungry people (50%) live in smallholder farming households [9], making smallholder farmers a group that is particularly vulnerable to pathogen-derived disruptions in food supply. Various efforts have been developed to prevent crop loss due to diseases based on pesticide usage. Independent of the approach, identifying a disease correctly when it first appears is a crucial step for effective and efficient disease management [7].

Historically, disease identification has been supported

by agricultural extension organizations or other institutions, such as local plant clinics that have provided expertise support directly on the field. In recently times, these efforts have been additionally supported by leveraging the increasing of Internet penetration worldwide with on-line diagnoses and the tools based on mobile phones, taking advantage of the rapid uptake of mobile phones technology in all parts of the world [6]. These factors, together with advances in computer vision and machine learning, lead to a situation where disease diagnosis based on automated image classification, if technically feasible, can be made available at an unprecedented scale and cost-effectiveness.

On this line, our work focuses first on a Deep Learning approach to disease identification task of 10 tomato plant classes (1 healthy and 9 diseases) using PlantVillage dataset (leaves images) [10] and secondly on the targeted sensitivity analysis of the dataset which has been, in fact, used in state-of-the-art related works [2, 12]. The rationale behind choosing a particular specie of plants (i.e., tomato plants) is that farmers do know what their plantations is about, hence we exploit this fact as prior knowledge. Furthermore, Tomato crops are highly affected by diseases, which decrease the yield and cause dramatic losses in agriculture economy [?].

As first step we reproduce the experiments of [2] improving their performance results. Then, we show how the learned models respond to input images by using two visualization techniques: GradCam [13] and Occlusion [17]. Finally, on that basis, we conduct a sensitivity analysis of the dataset by building ad hoc variations of it. These variations, together with models visualization, give insights on actual robustness of the dataset. Indeed, the experiments are pursued keeping in mind realistic deployment environments in which the prediction phase will be performed (i.e., images taken from plantations, greenhouses, and so on). On this assumption we show that the dataset has some not negligible limitations. In light of this we propose a reasonable image augmentation choice that lets the dataset be more robust to various deployment

environments.

2. Related work

Several works have been proposed in the literature to plant diseases identification. The classical approach given by the expertise support directly on the field has offered diverse solutions such as: hyperspectral proximal sensing techniques to evaluate plant stress to environmental conditions [?], optical technologies like thermal and fluorescence imaging methods for estimating plant stress produced mainly by increased gases, radiation, water status, and insect attack, among others [?], chemical elements were applied to leaves in order to estimate their defense capabilities against pathogens [?]. Previous methods show outstanding performance, nonetheless they do not provide yet a scalable and cost-effective solution [?].

After analysis of their work and investigation presented by the authors of [?, ?], it was decided to employ the image processing approach among other laboratory-based approaches. Several handcrafted feature-based methods have been widely applied specifically for image processing. These methods are usually combined with classifiers from machine learning (e.g., Support Vector Machines (SVMs) [4], K-Nearest Neighbors [?], Random Forests [?], and so on). Some of the best-known handcrafted feature methods which have been proposed for plant diseases identification are: the Histogram of Oriented Gradients (HOG) [?] and Scale-Invariant Feature Transform (SIFT) [?]; YcbCr, HSI, and CIElB colour models [?] effective against noise from different sources; shape feature method to determine leaf and lesioning area [?]; texture feature such as inertia homogeneity, and correlation obtained by calculating the gray level co-occurrence matrix (GLCM) [?]. In [?], GLCM features have been extracted from a dataset of 800 tomato leaf images and classified distinguishing healthy from infected using SVMs with 99.83% accuracy. Combination of more features provides a robust feature set for image improvement and better classification accuracy. In [?], the authors have presented a survey of well-known conventional methods for handcrafted feature extraction.

The main drawback of these methods regard feature engineering, that is a complex and time-consuming process which needs to be revisited every time according to the problem at hand. Thus, the performance of classifiers depend heavily on the underlying features. For these reason, deep learning has allowed researchers to consider and design systems as a unified and automated process with no *handcrafted* features [8]. In particular, Convolutional Neural Networks (CNNs), first introduced in [16], have showed, in fact, how to bind together feature extraction to classification in image recognition task by means of LeNet architecture. Tremendous achievements have been made by CNNs in the past few years on image classification of, for

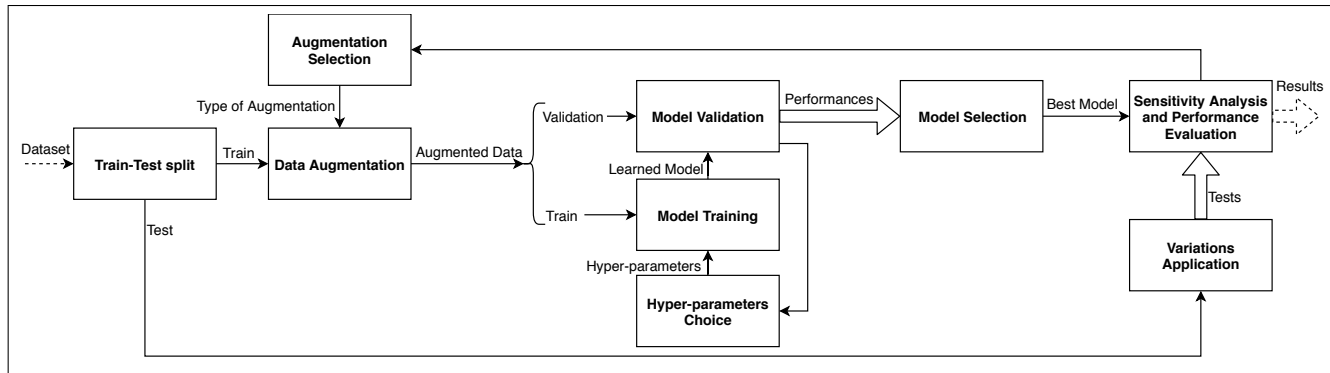
instance, ImageNet dataset [?].

The principles of CNNs have spread also to plant diseases identification. The authors of [?], have proposed a comparison between shallow models with combined handcrafted features and deep models for the identification of 9 tomato plant diseases. They have analyzed different models using PlantVillage dataset containing 14,828 images of cropped leaves put on a table. The best shallow model has achieved 95.47% accuracy using Random Forests, while the best deep model has achieved 99.19% accuracy using GoogLeNet architecture (pre-trained on ImageNet). Furthermore, they have used Occlusion [?] as model visualization method and on its basis they claim that backgrounds in images do not influence the prediction of their best model. In other related works and in ours we will argue that this is not always true.

The work proposed in [?] have focused on developing deep models for the identification of 38 classes (i.e., crop and disease information) using PlantVillage dataset (54,306 images of leaves). They have compared several models having various hyper-parameters and dataset variations (RGB, gray-scale, segmented). Their best result, 99.34% accuracy, has been achieved by GoogLeNet (pre-trained on ImageNet) employing RGB images. They noticed that their best model, when tested on a set of images (derived from trusted Internet sources) taken under conditions different from the images employed for training, determines a substantial accuracy reduction, to just above 31%. According to the authors, this limitation is caused by homogeneous background in the images.

A more robust approach has been pursued in [?] where the authors proposed a robust deep-learning-based detector for real-time tomato diseases and pests recognition. They have built their own dataset of 5,000 images taken under different conditions and scenarios divided in 9 classes (and the backgrounds class). Then, with the support of experts, they manually annotated the areas of every image containing the disease or pest with a bounding box and class. Finally, they have analyzed several models for object detection and achieving outstanding performances. Interestingly, they criticize PlantVillage dataset since the images it contains have been previously cropped in the field and captured by a camera in the laboratory causing image recognition and object detection on realistic environments images unfeasible. Instead, their work aims at dealing with background variations mainly caused by the surrounding areas of plants or the place itself (i.e., images taken from plantations, greenhouses, and so on).

According to the complains that have been made about PlantVillage dataset, our work provides a reasonable heuristic solution to overcome its limitations for what backgrounds are concerned within the image classification task.



[1] A. P. Tai, M. V. Martin, and C. L. Heald. Threat to future global food security from climate change and ozone

- air pollution. *Nat. Clim. Change*, 4(9):817–821, 2014. <https://doi.org/10.1038/nclimate2317>. 1
- [2] M. Brahimi, B. Kamel, and A. Moussaoui. Deep Learning for Tomato Diseases: Classification and Symptoms Visualization. *Applied Artificial Intelligence*, 31(4):299–315, Apr. 2017. <https://doi.org/10.1080/08839514.2017.1315516>. 1
- [3] C. A. Harvey et al. Extreme vulnerability of smallholder farmers to agricultural risks and climate change in Madagascar. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 369(1639):20130089–20130089, Feb. 2014. <https://doi.org/10.1098/rstb.2013.0089>. 1
- [4] C. Cortes and V. Vapnik. Support-vector networks. *Machine Learning*, 20(3):273–297, Sep. 1995. <https://doi.org/10.1007/BF00994018>. 2
- [5] Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services Fourth session. *Report of the Plenary of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services on the work of its fourth session*, Kuala Lumpur, 2016. <https://www.ipbes.net/event/ipbes-4-plenary>. 1
- [6] International Telecommunication Union (ITU). *ICT Facts and Figures – the World in 2015*, Geneva, 2015. <https://www.itu.int/en/ITU-D/Statistics/Documents/facts/ICTFactsFigures2015.pdf>. 1
- [7] L. E. Ehler. Integrated pest management (IPM): definition, historical development and implementation, and the other IPM. *Pest Management Science*, 62(9):787–789, 2006. <https://doi.org/10.1002/ps.1247>. 1
- [8] Y. LeCun, Y. Bengio, and G. Hinton. Deep Learning. *Nature*, 521:436–444, 2015. <https://doi.org/10.1038/nature14539>. 2
- [9] P. A. Sanchez and M. S. Swaminathan. Cutting World Hunger in Half. *Science*, 307(5708):357–359, Jan. 2005. <https://doi.org/10.1126/science.1109057>. 1
- [10] PlantVillage. PlantVillage Dataset. <https://github.com/spMohanty/PlantVillage-Dataset>. 1
- [11] R. N. Strange and P. R. Scott. Plant Disease: A Threat to Global Food Security. *Annual Review of Phytopathology*, 43(1):83–116, Sep. 2005. <https://doi.org/10.1146/annurev.phyto.43.113004.133839>. 1
- [12] S. P. Mohanty, D. P. Hughes, and M. Salathé. Using Deep Learning for Image-Based Plant Disease Detection. *Frontiers in Plant Science*, 7:1419, Sep. 2016. <https://doi.org/10.3389/fpls.2016.01419>. 1
- [13] R. R. Selvaraju, A. Das, R. Vedantam, M. Cogswell, D. Parikh, and D. Batra. Grad-cam: Visual explanations from deep networks via gradient-based localization. *CoRR*, abs/1610.02391, 2016. <http://arxiv.org/abs/1610.02391>. 1
- [14] T. Bouley, M. Gilbert, Whung Pai-Yei, F. L. Gall, C. Plante. *Reducing Climate-Sensitive Risks*, volume 1 of *Agriculture and environmental services discussion paper*. World Bank Group, Washington, DC, 2014. <http://documents.worldbank.org/curated/en/486511468167944431/Reducing-climate-sensitive-disease-risks>. 1
- [15] UNEP, International Fund for Agricultural Development (IFAD). *Smallholders, Food Security, and the Environment*, Rome, 2013. <https://www.ifad.org/documents/10180/666cac24-14b6-43c2-876d-9c2d1f01d5dd>. 1
- [16] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, Nov. 1998. <https://doi.org/10.1109/5.726791>. 2
- [17] M. D. Zeiler and R. Fergus. Visualizing and Understanding Convolutional Networks. *CoRR*, abs/1311.2901, 2013. <http://arxiv.org/abs/1311.2901>. 1