Template for Technical Reports
DL-IC 2018 Project

Alessandro Erba Mirco Manzoni
Giuseppe Mascellaro
Politecnico di Milano, Piazza Leonardo da Vinci 32, 20133 Milan, Italy
{alessandro2.erba, mirco.manzoni, giuseppe.mascellaro}@mail.polimi.it

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, combined together, 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 the image classification task of ten tomato plant classes (one healthy and nine diseases) using the PlantVillage dataset [10] and secondly on the targeted sensitivity analysis of the dataset which has been, in fact, used in state-of-the-art works [2, 12] about the task at hand. As first step we reproduce the experiments of the related works 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 model visualization, give insights on the dataset actual robustness. 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 the plant disease 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 [?]. The previous methods show outstanding performance, but 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 use the image processing approach among other approaches, for instance, double-stranded ribonucleic acid (RNA) analysis, nucleic acid probes, and microscopy. Several handcrafted feature-based methods have been widely applied specifically for image classification. Some of the best-known handcrafted feature methods 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; extracting shape feature method to determine leaf and lesioning area [?]; extracting texture feature such as inertia homogeneity, and correlation. Combination of all these features provides a robust feature set for image improvement and better classification. In [?], the authors have presented a survey of well-known conventional methods of feature extraction. These methods are usually combined with classifiers (e.g., Support Vector Machines [4], Neural Networks [?], Adaptive Boosting [?], K-Nearest Neighbors [?], ensemble methods [?]).

However, Deep Learning has allowed researchers to consider and design systems as a unified process [8]. In particular, Convolutional Neural Networks (CNNs), first introduced in [16], showed, in fact, how to bridge feature extraction to classification in image recognition task by means of the LeNet architecture. For the first time, the authors of [?] applied the principle of CNN to plant diseases recognition in different crops using LeNet and image processing to recognize two leaf diseases out of healthy ones.

Other works that use deep convolutional neural networks for disease recognition have been proposed, showing good performance on different crops.

3. Proposed approach

4. Experiments

Datasets.

Experiments setup.

Results and discussion.

5. Conclusion

Acknowledgements

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A. Supplementary Material

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