

Leaf counting from uncontrolled acquired images from greenhouse workers

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Abstract

Active monitoring and assessment of a plant growth is one of the main challenges in plant phenotyping. An important application is leaf counting because it enable to estimate the plant yield via the plant mass, infer the plant development in different cultivars, environments and subject to different treatments, and to address other phenotyping studies that help for instance plant breeders to improve the quality of the plants [4, 9]. Automatic leaf counting is a challenging task, as plants have a complex structure and leaves tend to overlap, causing occlusions. As of recent, several efforts have been made to address the leaf counting problems, with the use of machine learning and, in particular, deep learning [10]. Although state-of-the-art solutions present high-accuracy counting predictions [2, 3, 6], they mostly rely in controlled experimental setups and often high-resolution imagery.

In [11], the authors use computer-generated models of Arabidopsis rosette to augment the training data set and consequently improve the leaf counting using deep learning. It was demonstrated that leaf counting performs significantly well when real and computer-generated plants are interchanged during training. Synthetic image data augmentation was also proposed by [12], where the authors claim that they can reduce the prediction error about 16.67%. In [6], the authors propose two deep learning strategies for participating in the CVPPP 2017 Leaf Counting Challenge dataset. The first uses regression analysis and the second through the detection of the leaves centers. The authors argue that have overcome the results from previous years competition (with 95% average precision). Finally, in [3], they propose a multi-modal deep learning architecture for counting plant leaves from different species and image modalities. They show that the leaf counting prediction error was within ± 1 leaf in the $\sim 90\%$ of the cases.

The current state-of-the-art approaches rely on controlled and selected imagery with the finality of plant phenotyping. In this work we aim to give a step forward and explore how a current state-of-the-art deep learning approach

for leaf counting (e.g., Pheno-DC [3]) perform in uncontrolled imagery provided by greenhouse practitioners and workers. The final goal of this application is to develop an intelligent system where greenhouse practitioners – experts and non-experts – upload plant images in the cloud acquired with mobile phones and obtain real-time information. Thus, here we show our proof-of-concepts results.

The images were acquired in the March 13th of 2017 inside a greenhouse with Orache (*Atriplex*) from 3 to 10 weeks old. The greenhouse is located in the North Holland province in The Netherlands. The images have been acquired by different persons at different ranges (0.3m - 1.5m) between 9am and 3pm. In Figure 1, we display a few samples of the acquired images. Overall, 13 images were collected and annotated for the leaf counting.

Images were manually cropped and rescaled to 320×320 and we used the Pheno-DC network [3] pretrained on the CVPPP 2017 dataset [1, 7, 8]. The network consists of a ResNet-50 [5], which acts as a feature extractor, followed by three fully connected layers of size 1024-512-1. Given the low amount of training data, we performed a leave-one-out cross-validation. In order to reduce overfitting, we applied several dataset augmentations. Together with geometrical transformations as in [2, 3], we also applied random brightness changes to increase data variability, mimicking the different light conditions in the greenhouse.

Experimental results are shown in Table 1. We used the CVPPP LCC evaluation metrics and, as in [3, 4], we also added the percentage agreement when the error is up to ± 1 leaf off (± 1 in the table). Overall, the MSE is < 1 and the exact leaf counting is predicted in the 46% of the cases (92% with up to ± 1 leaf count error), demonstrating that Pheno-DC can learn well to perform leaf counting on images taken under uncontrolled acquisition.

In this work, we show preliminary results on training a deep network to perform leaf counting on plant images acquired by greenhouse workers with hand-held devices. Future works will focus on the acquisition of a larger data set not only of plants grown in the greenhouse, but also from in-field plants with the use of e.g. unmanned aerial vehicles, such as quad-copter drones.

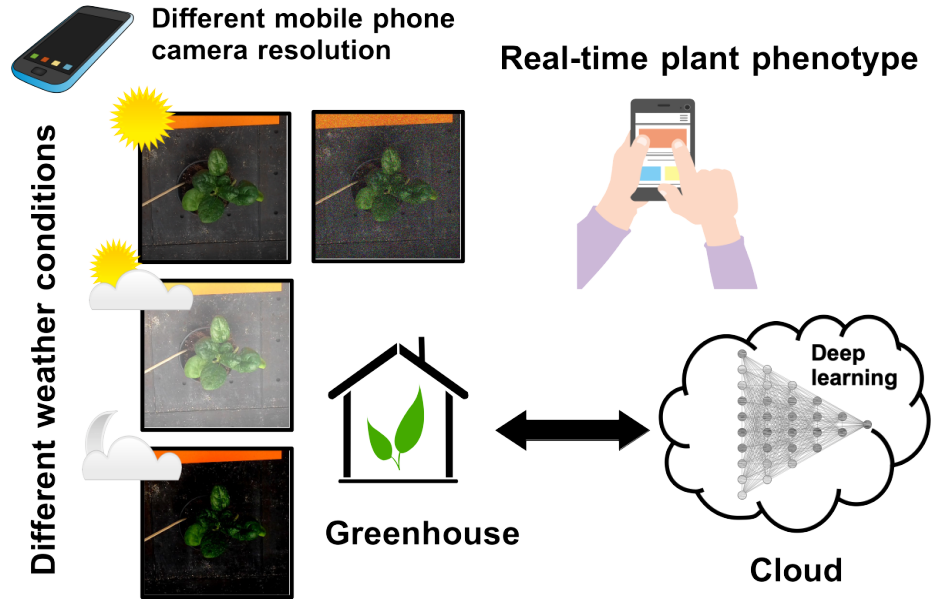


Figure 1. Conceptual scheme of the general approach proposed: 1) Uncontrolled acquisition of plants pictures by the greenhouse workers; 2) Images are sent to a cloud endowed with the deep learning strategy proposed; 3) Greenhouse workers receive phenotype information.

DiC	DiC	MSE	%	± 1	R^2
0.31 (0.85)	0.62 (0.65)	0.77	46%	92%	0.88

Table 1. Leave-one-out results of Pheno-DC [4] trained on our data.

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