Contribution Title*

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Abstract. The abstract should briefly summarize the contents of the paper in 150–250 words.

Keywords: Plant Phenotyping · Instance Segmentation · Object Detection.

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1 Introduction

High throughput plant phenotyping is one of the most complicated and time expensive challenge of this day. Nowadays cameras are getting involved in many fields. Manually look along each plant and each component takes a long of time, cameras can be helpful in order to improve speed of control and it's accuracy. With only RGB 2D images spatial information can be extrapolated and some spectral ones. With 3D ones instead, crucial information can be discovered such as: dimensions, height, weight. In order to measure this phenotyping traits we need more than one computer vision task, locate a plant with object detection, segment single leaf with instance or semantic segmentation, where deep learning techniques can provide general and precise data [1].

Morphological changes are a crucial aspect of plant growth, leaf area and leaf height are commonly used to understand how plant is changing during time. Using only RGB images can be hard to extrapolate this information due to environmental light, shades and so on. CNNs are widely used in this field obtaining great results. Teimouri, Dyrmann, Nielsen, Mathiassen, Somerville and Jørgensen [3], tried to count leaves in 18 different species, in order to do this they used deep CNNs and trained them with a lot of images. They have used Inception-v3 [2] architecture for its good performance. In a second time the authors tried to predict growth stage of plants and they have found that with more plants in the same image the accuracy is worst. With the Inception-v3 they obtained an accuracy by 83%, with a count estimation typically overestimated. Bhugra, Garg, Chaudhury, and Lall, in order to analyze shape variation, have created a new methodology to segment each leaf instance. To avoid scene variability they have used Mean-shift [4] Bandwidths Searching Latent Dirichlet Allocation. To enhance the results given by Mean-Shift the authors have employed the distance between texture descriptors, then they nominate leaf candidate so leaf representative can be extracted. Masks can be finally created and different approaches for estimate if a leaf is a non-overlapped ones are used. Gaussian Mixture Models was found to be noisy while different method like Minervini's algorithm K-means and Otsu's threshold overestimate the foreground giving disconnected regions. Instead Two approaches based on Mean-Shift, using the orientation field map and a polar transformation of the leaf tips, done with Harris-Stephens angle detector. While the second, starts from the polar transformed images, from which skeletal image is taken. This kind of approaches oversegment non-overlapped leaves but has a good ground truth for the corresponding ones. Based on Plant phenotyping images database, the authors obtained a DICE score map of 89.9% [5]. In Fine-grained recognition in high-throughput phenotyping [6] the authors aimed to classify the single plant inside the cultivars. In order to do that, all plants of the dataset were divided into different growth stages, then they have localized the plants with a prior knowledge and after that the authors have segmented the same with Otsu's threshold or green based brightness. Data were post-processed with different methods. Radial Object Descriptors are completed with ResNet18 [7] and Histogram of Oriented Gradients with Softmax regression. They have tested different combination of this methods and have analyzed the results with for mean accuracy, which aims to analyze the goodness of classification. ROD-HOD-Softmax outperforms the ResNet18 method in one of the four dataset used, and only in the early stages, but the gap is lower when the plants start growing. Instead for the remaining three datasets, the combination of resnet with the radial object descriptor outperforms the histogram of oriented gradients.

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