Synthetic Arabidopsis Dataset

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Abstract

We introduce a synthetic dataset of 10,000 top down images of *Arabidopsis* plants. Leaf instance segmentation labels for each image are also presented. This dataset was designed to accompany the real dataset provided with the Leaf Segmentation Challenge of the Computer Vision Problems in Plant Phenotyping. Furthermore, we release a leaf instance segmentation pretrained model based on the Mask-RCNN architecture. More information about the dataset can be found at: https://research.csiro.au/robotics/databases/synthetic-arabidopsis-dataset/.

1 Introduction

Precision agriculture involves using advanced technology, such as imaging and sensing systems, to observe, automate and improve agricultural systems [1]. Plant phenotyping is the identification and evaluation of plant properties and traits under different environmental conditions. It can provide important information in seed production and plant breeding settings and hence, is an important aspect of precision agriculture.

The Computer Vision Problems in Plant Phenotyping (CVPPP) workshop[1] has been held to address the challenges and extend the state of the art in the use of computer vision in plant phenotyping [2]. Further, the Leaf Segmentation Challenge[2] (LSC) of the CVPPP aims to benchmark and advance the state of the art in leaf segmentation, an prominent part of plant phenotyping [3].

We present a synthetically generated dataset of *Arabidopsis* plants. This is designed to accompany data presented with the CVPPP LSC. Our dataset contains top down view renders of synthetically generated plants similar to the real images presented in [2]. We also release a pretrained model for leaf instance segmentation based on the Mask-RCNN architecture [4].

2 The Dataset

Within this section, our synthetic dataset is introduced and described. Ward *et al.* [3] outlines the details of the design and production of this dataset. The images and the leaf instance segmentation labels are presented in Section 2.1. A number of example data samples are visualised in Section 2.3.

2.1 Data Description

The synthetic *Arabidopsis* dataset contains 10,000 top down images (width$\times$height: 550$\times$550 pixels). All images are stored in PNG format.

Leaf Instance Segmentation Labels: Each RGB image has a corresponding leaf instance segmentation annotation. These are the same size as the RGB images and stored in PNG format. Each leaf in an image is uniquely identified by a single colour. A pixel with value 0, depicted as black, corresponds to the background in the image. By converting the segmentation label to a 2D grayscale image and obtaining a set of unique values (excluding 0 as background), the pixel values for each individual leaf can be obtained. To produce a mask for a single leaf, all pixels but those of a value equal to that of the desired leave must be set to 0.

File types and naming conventions: This data follows the same naming convention as the CVPPP LSC [2]. The filenames have the form:

[1] https://www.plant-phenotyping.org/cvppp2018

[2] https://competitions.codalab.org/competitions/18405

- **plantXXXXX_rgb.png**: the RGB colour image of the synthetic data;
- **plantXXXXX_label.png**: the corresponding leaf instance segmentation label;

where **XXXXX** is an integer number representing the sample number within the dataset.

2.2 Obtaining The Data

This dataset can be downloaded from https://doi.org/10.25919/5c36957c0af41 [5]. When making use of this data we ask that [3, 5] are cited.

2.3 Example Data Visualisations

Figure 1 displays eight example images and their corresponding leaf instance segmentation label.

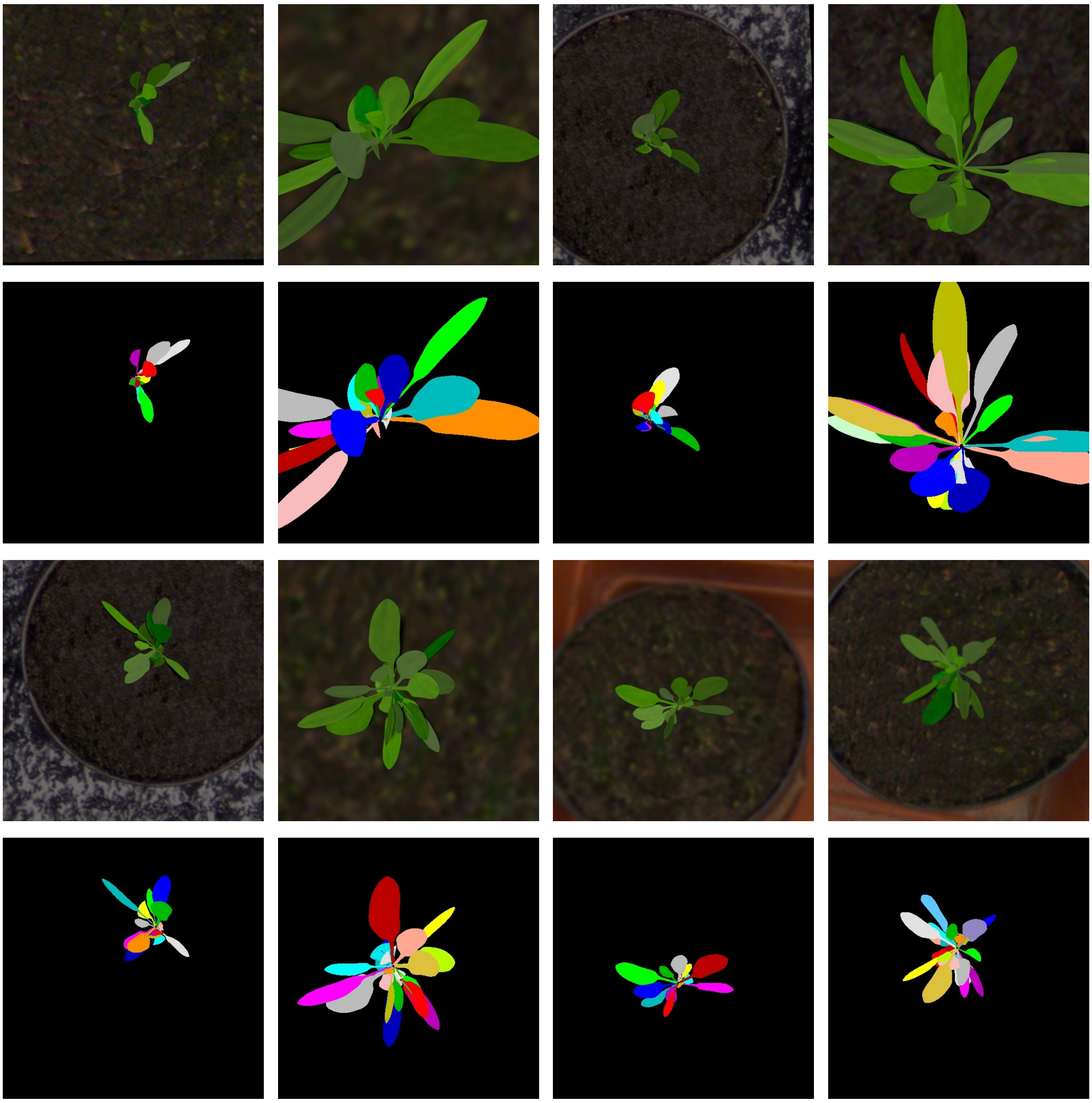

Figure 1: A visualisation of selected images from the synthetic *Arabidopsis* dataset with their corresponding leaf segmentation labels.

3 Pre-trained Model and Code

A leaf segmentation model trained on this synthetic data is also available. The deep learning model can be downloaded from [5]. Furthermore, a python script to run this model is available at: https://bitbucket.csiro.au/scm/ag3d/leaf_segmenter_public.git. The model requires Matterport's [6] implementation of Mask-RCNN [4]. Instructions for setting up and running the code can be found in the code repository readme file.

4 Future Work

Current leaf segmentation pipeline works only on 2D top-down RGB images. In Future work, we develop new segmentation methods that could work on other modalities such as Thermal [7, 8, 9, 10], RGB-D [11, 12, 13] and hyperspectral [1].

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