DNN-Based Tiller Number Estimation for Coping with Shortage of Labeled Data

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In this paper, we propose tiller number estimation methods based deep neural networks (DNNs). A tiller is a branch on a grass plant, and a tiller number is one of the most important traits to yield. Since the tiller number is usually counted by hand, its automation is necessary for high-throughput phenotyping.

When you count a tiller number, you have to check the root of the plant, and count the number of branches. Therefore, side-view plant images are used for counting tiller numbers, unlike the leaf counting problem of rosette plants, which uses top-view images [5, 1]. Some methods use regression to estimate tiller numbers [3, 2]. They used heuristic features for regression. As those methods just use few heuristic features from appearances of plants, those methods do not take full advantage of appearance information of plants.

Based on the recent great success of DNNs in the computer vision area, using DNN-based features instead of heuristic features is expected to improve the estimation accuracy. However, as DNNs generally require a large number of data for training, it is hard to use them to the estimation in which a large training dataset is unavailable. In order to overcome the insufficient training data problem, methods requiring few or no labeled data have been proposed: transfer learning [6], which transfers networks learned with another data, semi-supervised learning [7], which uses partly labeled data for learning, and self-supervised learning [4], which uses self-generating labels. Among them, some self-supervised learning methods which learn features by solving other tasks show compared performance to supervised methods [4, 9, 8]. The other tasks are called pretext tasks, and they can be applied to the problems in which large unlabeled data are available.

In this paper, we use two strategies to overcome the insufficient training data problem: one is to use a pre-trained DNN model and the other is to use pretext tasks for learning feature representation. We extract features by using those models, and estimate tiller numbers by using regression.

In experiments, We used the dataset which appears in [3], which are potted Setaria Viridis images taken in a controlled laboratory environment. The proposed methods using the pre-trained model and the several models which solved some pretext tasks showed better mean absolute error (MAE) than the conventional method [3].

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