Transfer Learning from Synthetic In-vitro Soybean Pods Dataset for In-situ Segmentation of On-branch Soybean Pods

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1. Appendix

A. Addition results of our two-step transfer learning method with different instance segmentation networks

We conduct our two- step transfer learning method with different instance segmentation networks (Yolact [1], Mask RCNN [3], BlendMask [2], tiny Swin Transformer-based [4] instance segmentation network) on our on-branch soybean pods phenotyping task. We also compare our two-step transfer learning method with the model purely trained by our synthetic in-vitro soybean pods dataset and the model only finetuned on a real world mature soybean plants dataset. The visualized results can be seen in Figure 1. we can find that the performance of all the instance segmentation models can be improved observably by our two-step transfer learning method. And we can conclude that the model purely trained by our synthetic in-vitro soybean pods dataset can realize a very rough segmentation; the model only finetuned on a few real world mature soybean plants dataset can realize in-situ segmentation of on-branch soybean pods with low accuracy; the performance can be increased by our two-step transfer learning method which firstly trained by our synthetic dataset and then finetuned by a real world mature soybean plants dataset.

B. Addition results of different real world mature soybean plants

As shown in Figure 2 and Figure 3, we report another on-branch soybean pod in-situ instance results of different mature soybean plant in the test dataset with the best model which finetuned the tiny Swin transformer based instance segmentation network with the 1600 synthetic in-virtu soybean pods images with 0.1 overlapping degree and a few samples of real world mature soybean plant images. These samples evaluation results of the best model as shown in Table 1.

Table 1. Some mature soybean plant samples evaluation results of the best model.

Sample	(1)	(2)	(3)	(4)
Recall@[.5;.95]	0.566	0.517	0.596	0.577
AP_{50}	0.924	0.779	0.876	0.777
AP_{75}	0.637	0.581	0.689	0.680
AP@[.5;.95]	0.763	0.618	0.686	0.698

References

[1] Daniel Bolya, Chong Zhou, Fanyi Xiao, and Yong Jae Lee. Yolact: Real-time instance segmentation. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 9157–9166, 2019. 1

[2] Hao Chen, Kunyang Sun, Zhi Tian, Chunhua Shen, Yongming Huang, and Youliang Yan. Blendmask: Top-down meets bottom-up for instance segmentation. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 8573–8581, 2020. 1

[3] Kaiming He, Georgia Gkioxari, Piotr Dollár, and Ross Girshick. Mask r-cnn. In *Proceedings of the IEEE international conference on computer vision*, pages 2961–2969, 2017. 1

[4] Ze Liu, Yutong Lin, Yue Cao, Han Hu, Yixuan Wei, Zheng Zhang, Stephen Lin, and Baining Guo. Swin transformer: Hierarchical vision transformer using shifted windows. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 10012–10022, 2021. 1

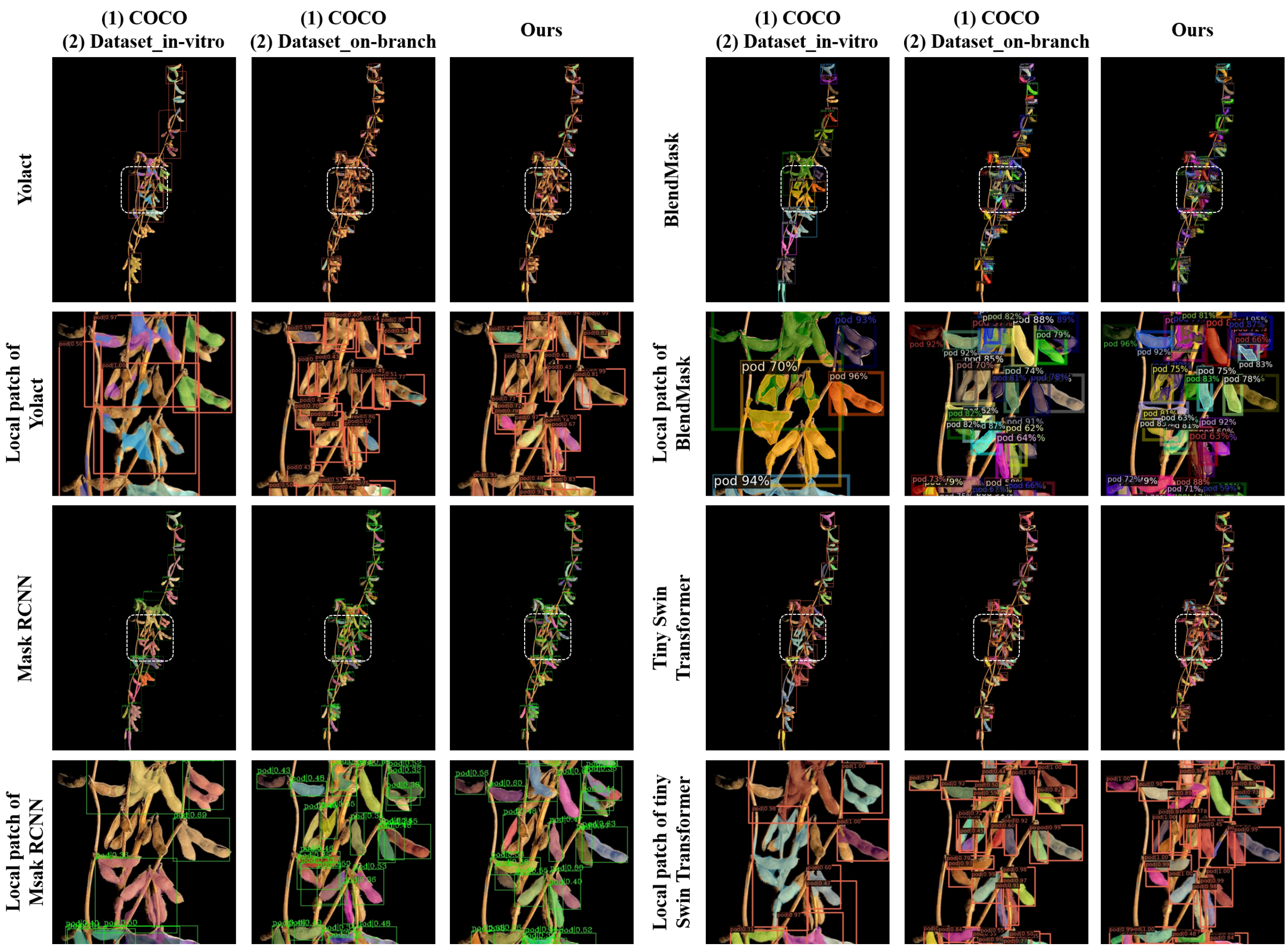

Figure 1. The effectiveness and efficiency of our two-step transfer learning method with different instance segmentation network

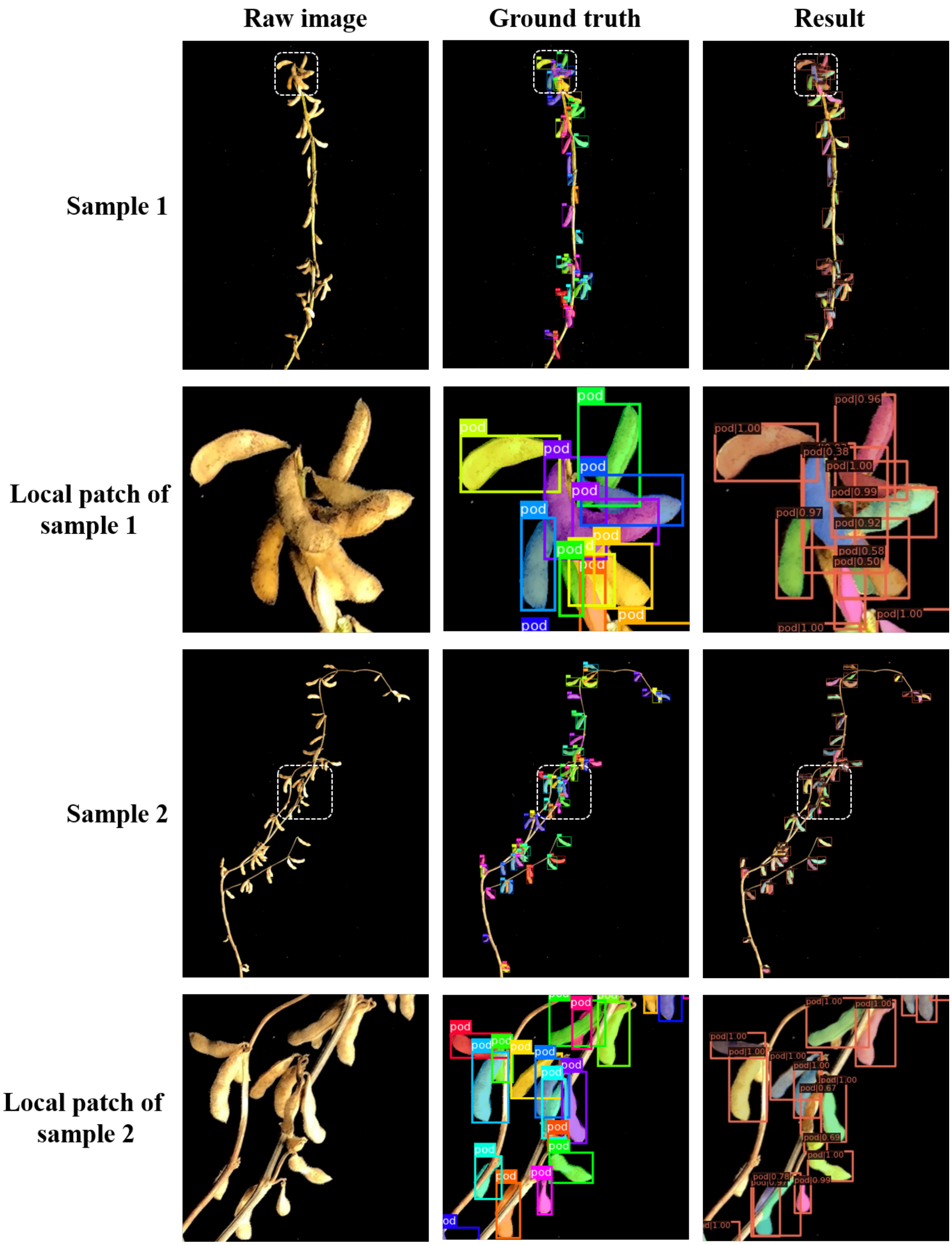

Figure 2. On-branch soybean pod in-suit instance result of different mature soybean plant sample in the test dataset with the best model

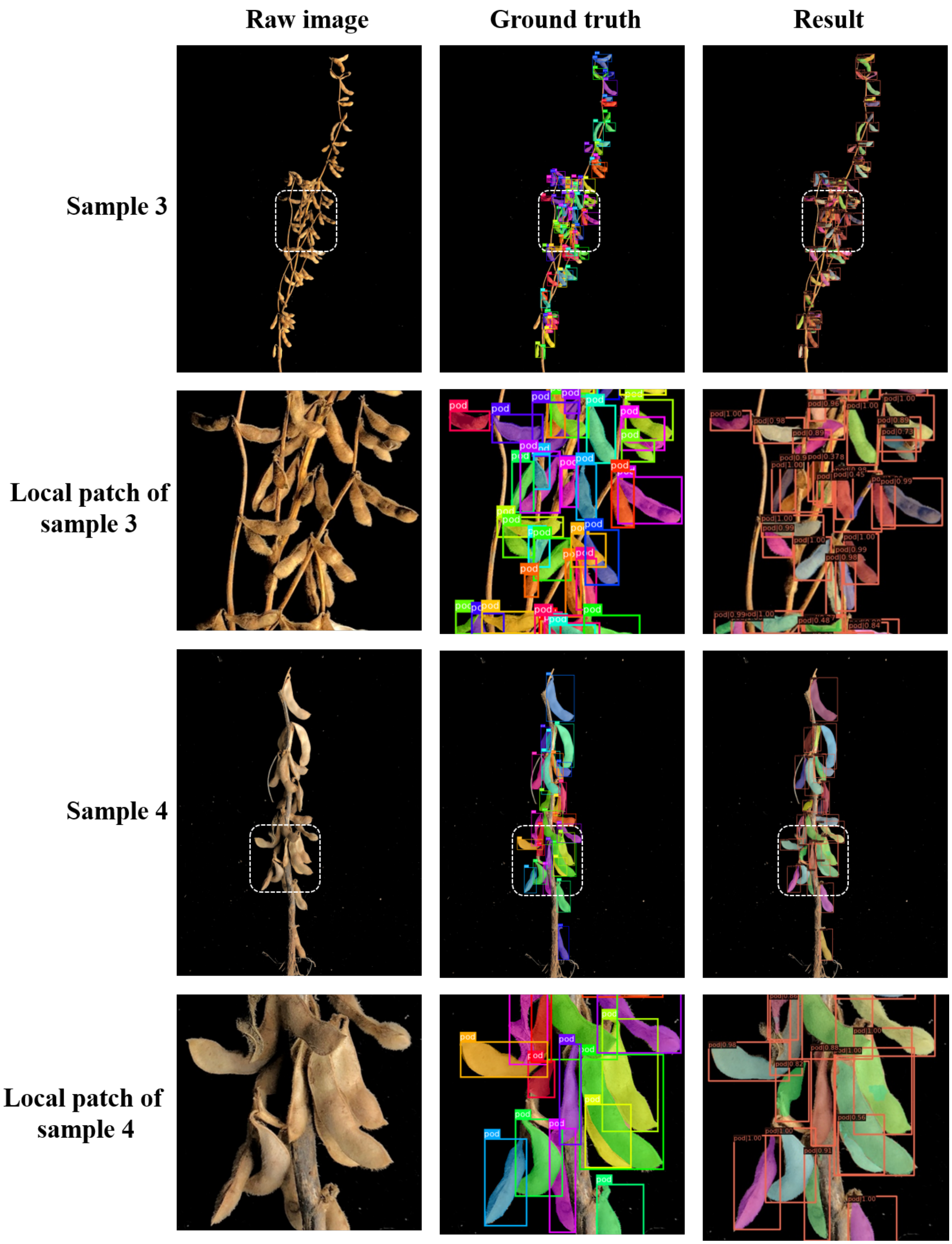

Figure 3. On-branch soybean pod in-suit instance result of different mature soybean plant sample in the test dataset with the best model