# SemanticSugarBeets: A Multi-Task Framework and Dataset for Inspecting Harvest and Storage Characteristics of Sugar Beets (Supplementary Material)

Gerardus Croonen Andreas Trondl Julia Simon Daniel Steininger AIT Austrian Institute of Technology Center for Vision, Automation & Control

{gerardus.croonen,andreas.trondl.fl,julia.simon,daniel.steininger}@ait.ac.at

This supplementary complements the main paper with a more detailed description of the image acquisition protocol, extended dataset statistics and additional discussion of results.

#### A. Image acquisition protocol

For the purpose of repeatability and consistency, we performed the following steps during image acquisition:

- 1. Compose a group of beets (3 to 5) to fit inside the camera frame, held in landscape mode
- 2. Put a folding ruler (or other object of known size) in the frame, ensuring its full visibility
- 3. From a standing position, take two (almost identical) photographs from a top-view perspective
- 4. Flip the beets and put them back in roughly the same position
- 5. Force a camera refocus by taking a photograph of a nearby object, such as your hand. This photo will also allow for the quick identification of separate beet groups and beet sides when viewing and meta-annotating the photos.
- 6. Repeat steps 2-3.

#### **B.** Extended dataset analysis

Tab. 1 provides a complete list of recording sessions and corresponding statistics and meta-parameters. The distribution of bounding box centers across all beet instances is depicted in Fig. 1. Representative examples for both classes of annotated reference markers are visualized in Fig. 2.

## C. Extended methodology

As the original annotations usually contain multiple polygons of different fine-grained classes for a single sugar-beet, a method for automatic pre-processing is required to extract the final annotations compatible with instance segmentation. This process is visualized in Fig. 3. It consists of



Figure 1. Distribution of normalized bounding-box centers of all annotated sugar-beet instances.



Figure 2. Representative examples of annotated reference objects.

identifying the largest component of each beet and then extending it with all overlapping smaller components to derive annotations compatible with the coarse-grained instancesegmentation task described in Sec. 4.1 of the main paper.

### **D. Extended evaluation results**

Tab. 2 provides the full evaluation details of our semanticsegmentation ablation study, a summary of which is provided in Fig. 5 of the main paper. Regarding the influence

SID	Images	Beets	B/I	Lighting	Moisture	Marker	Stage	Loc
0	33	165	5.0	Sunny	Dry	None	Sample	Α
1	92	300	3.3	Sunny	Dry	Ruler	Sample	Α
2	40	120	3.0	Diffuse	Dry	Ruler	Sample	A
3	40	120	3.0	Sunny	Dry	Ruler	Sample	Α
4	4	12	3.0	Sunny	Dry	Ruler	Sample	Α
5	31	93	3.0	Sunny	Wet	Ruler	Harvest	B/C
6	288	864	3.0	Diffuse	Wet	Ruler	Harvest	C
7	282	846	3.0	Sunny	Dry	Ruler	Harvest	D
8	116	319	2.8	Diffuse	Wet	Sign	Storage	E
9	28	83	3.0	Artificial	Wet	Sign	Storage	E
	954	2922	3.1					

Table 1. Parameters of recording sessions, including Session ID, numbers of annotated Images and Beets, average ratios of Beets per Image, Lighting conditions, beet Moisture, the presence of folding-ruler elements or plastic signs as Marker devices, processing Stages and cultivation Locations.

**All Beet Annotations** 



**38.7% sugar-beet annotations only tiny parts** 4,866 annotated components vs. 2,982 real sugar beets

**Beet Instances** 



Largest beet components Verified on all annotated samples

extended with other labels

**Extended Beets** 

Extended with other labels Beet parts, damage, cut, soil and rot

Figure 3. Annotation-synthesis pipeline to convert original annotations to instance-segmentation annotations of entire sugar beets.

of meta-parameters on performance, the exact values forming the basis for Fig. 7 of the paper is summarized in Tab. 3.

Architecture	Encoder	512	768	1024	Mean	t <sub>512</sub>	t <sub>768</sub>	t <sub>1024</sub>
	EfficientNet	61.2	62.1	65.4		9.5	9.9	12.1
	MIT	64.0	64.5	65.6		6.2	7.8	13.9
MANet	MobileOne	59.5	61.2	61.3	62.8	14.4	16.6	19.6
	MobileNetV31	60.6	64.4	60.9		6.5	8.3	10.6
	RegNetY	RegNetY 60.1 65.4 66.1			7.9	9.2	10.6	
	EfficientNet	62.5	63.0	63.5		2.6	3.4	5.3
	MIT	63.1	63.9	63.9	62.2	4.5	5.3	9.6
PSPNet	MobileOne	63.4	64.7	64.6		6.1	6.5	8.2
	MobileNetV31	61.6	62.5	62.5		2.3	2.6	3.3
	RegNetY	58.1	58.0	57.8		1.7	1.9	2.3
	EfficientNet	66.7	68.3	68.6		8.1	10.2	14.0
	MIT	65.6	66.7	66.3		7.0	8.7	15.5
U-Net	MobileOne	65.8	66.7	67.6	67.0	15.3	16.1	19.5
	MobileNetV31	66.0	67.9	67.9		7.1	8.3	11.4
	RegNetY	65.9	66.9	67.5		7.0	8.9	12.6
	Mean	62.9	64.4	64.6				

Table 2. Results of semantic segmentation on the test set including all combinations of architectures, encoders and image sizes. Performance numbers are mIoUs, reported in percentages. The rightmost three columns show the inference time for each image size in ms.

		mIoU
	Sunny	68.6
Lighting	Diffuse	68.1
	Artificial	64.8
Moisturo	Dry	70.4
WIDIStul	Wet	66.0
	Sample	78.4
Stage	Harvest	65.2
	Storage	66.4

Table 3. Test set performance of semantic segmentation, separated by meta-parameter.