PhenoBench — A Large Dataset and Benchmarks for Semantic Image Interpretation in the Agricultural Domain

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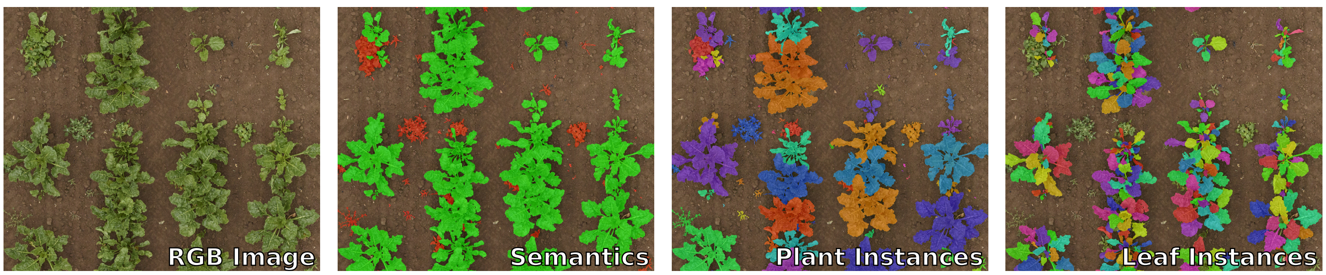

Figure 1. Our dataset, called PhenoBench, provides dense semantic plant-level instance annotations (shown by different colors) of sugar beet crops and weeds (green and red in the semantics) and leaf-level instance annotations of crops (different colors correspond to different instances) for high-resolution images recorded with a UAV. The dataset consists of images collected at different times during a growing season, which captures various growth stages of plants.

Abstract

The production of food, feed, fiber, and fuel is a key task of agriculture. Especially crop production has to cope with a multitude of challenges in the upcoming decades caused by a growing world population, climate change, the need for sustainable production, lack of skilled workers, and generally the limited availability of arable land. Vision systems could help cope with these challenges by offering tools to make better and more sustainable field management decisions and support the breeding of new varieties of crops by allowing temporally dense and reproducible measurements. Recently, tackling perception tasks in the agricultural domain got increasing interest in the computer vision and robotics community since agricultural robotics are one promising solution for coping with the lack of workers and enable a more sustainable agricultural production at the same time. While large datasets and benchmarks in other domains are readily available and have enabled significant progress toward more reliable vision systems, agricultural datasets and benchmarks are comparably rare. In this paper, we present a large dataset and benchmarks for the semantic interpretation of images of real agricultural fields. Our dataset recorded with an unmanned aerial vehicle provides high-quality, dense annotations of crops and weeds, but also fine-grained annotations of crop leaves at the same time, which enable the development of novel algorithms for visual perception in the agricultural domain. Together with the labeled data, we provide novel benchmarks for evaluating different visual perception tasks on a hidden test set comprised of different fields: known fields covered by the training data and a completely unseen field. The tasks cover semantic segmentation of crops and weeds, panoptic segmentation of plants, leaf instance segmentation, detection of plants and leaves, and the novel task of hierarchical panoptic segmentation for jointly identifying plants and leaves.

1. Introduction

The agricultural production of food, feed, fiber, and fuel has to cope with several challenges in the upcoming decades. The world population is increasing, yet the availability of arable land is limited or even decreasing, climate change increased uncertainties in crop yield, and we observe substantial losses in biodiversity [23]. At the same time, agricultural practices need to be more sustainable and reduce the use of agrochemical inputs, *i.e.*, herbicides and fertilizers, which could potentially negatively impact yield [38] and the environment.

Robots and drones using vision-based perception systems could help with these challenges by offering tools to make better and more sustainable field management decisions and provide supporting tools for breeding new varieties of crops by estimating plant traits in a reproducible manner [79]. Such perception systems enable the development of agricultural robots that can support the monitoring of fields and replace labor-intensive tasks such as manual weeding [101]. Additionally, they enable more targeted crop management, where agrochemicals are applied precisely and only where needed, thereby reducing the negative effects on the environment [59, 97].

With the advent of deep learning for visual perception [54, 47], the field of computer vision has made tremendous progress in image interpretation, achieving remarkable results in several domains. Datasets and associated benchmarks [18, 60, 73] were essential for achieving this progress as they provide a testbed for developing novel algorithms but also provided the necessary data to tackle novel tasks. Progress can be tracked quantitatively with metrics that measure the performance of developed approaches against benchmarks using hidden test sets. Novel tasks with increasing complexity drive the progress of the field by posing novel challenges for the community.

In this paper, we aim to provide a large dataset together with benchmarks for semantic interpretation under real-field conditions enabling similar progress in the agricultural domain. We target multiple tasks: semantic segmentation, panoptic segmentation, plant detection, and a novel task of hierarchical panoptic segmentation, where approaches need to provide a coarse-to-fine interpretation of plants.

For this purpose, we recorded high-resolution images with unmanned aerial vehicles (UAV) of sugar beet fields under natural lighting conditions over multiple days, capturing a large range of growth stages. We annotated these images with dense, pixel-wise annotations to identify sugar beet crops and weeds at an instance level, as needed for semantic segmentation and plant-level instance segmentation tasks. Additionally, we labeled leaf instances of crops to enable the investigation of leaf segmentation (see Fig. 1).

The combination of plant-level and leaf-level annotations enable the investigation of novel tasks that are needed for a holistic semantic interpretation in the agricultural domain. One such task is the hierarchical panoptic segmentation task, which objective is to segment individual leaves and assign them to their associated plant instance to predict the total number of leaves per plant. Plant scientists and breeders commonly assess this information to describe the growth stage of individual plants, which is also linked to yield potential and plant performance [50]. However, this in-field assessment is conventionally done manually outside greenhouses, which is laborious and time-consuming [69]. Thus, developing systems to assess these properties per plant automatically is essential for large-scale, sustainable crop production.

Our provided data shows distinct challenges in terms of plant variation and overlap between different plant and leaf instances that are distinct in the agricultural domain. Such challenges are seldomly addressed by general segmentation approaches prevalent in man-made environments, as shown by our experimental results, where we challenged several state-of-the-art approaches but also provide results for more domain-specific approaches for the agricultural domain.

In summary, our main contributions are:

- We present a large dataset for plant segmentation providing accurate instance annotations at the level of plants and leaves.
- We provide a set of benchmark tasks on a hidden test set for evaluating semantic, instance, and panoptic segmentation, and detection approaches targeted at plants, which enables reproducible and unbiased evaluation.
- We provide baseline results for general and domain-specific models for semantic, instance, detection, and panoptic segmentation.

2. Related Work

In recent years, dense semantic interpretation of images, *i.e.*, semantic segmentation, instance segmentation, and panoptic segmentation [44], made rapid progress due to advances in deep learning [54], but also thanks to the availability of large-scale datasets for object detection [60, 26, 25], semantic segmentation [18, 73, 87], instance segmentation [60], and lately panoptic segmentation [60, 18, 73, 33].

Despite the availability of large datasets in man-made environments, the agricultural domain faces different challenges, such as large intra-class variability due to plant growth. Thus, there has been interest in large datasets to enable studying perception in the agricultural domain [64].

In particular, the crop/weed field image dataset (CWFID) by Haug *et al.* [36] is one of the first semantic segmentation datasets that provides pixel-level annotations of semantics for plants, *i.e.*, sugar beets and weeds using a multispectral camera. Lameski *et al.* [49] also provides a dataset for crops, *i.e.*, carrots and weed segmentation. CVPPP [68, 90, 2] is one of the first datasets providing annotations for leaves in images of individual tobacco and arabidopsis plants recorded in a lab environment, which is also the basis for a series of workshops and competitions hosted at CVPR and ICCV. The dataset by Chebrolu *et al.* [9] provides images of sugar beets and weeds recorded by a ground robot under real field conditions with a ground sampling distance (GSD) of $0.3\,\frac{\mathrm{mm}}{\mathrm{px}}$ and provides annotations for semantic segmentation. Similar to our dataset, the WeedMap dataset [89] provides imagery of UAVs covering a large field with sugar beets and weeds. In contrast to our dataset,

Dataset	#Images	Image Size	Crop			Weed		Field?
			Sem.	Inst.	Leaves	Sem.	Inst.	
CWFID [36]	60	1291 × 966	✓			✓		✓
CVPPP (2017) [68, 90, 2]	1,311	2048 × 2448[1]			✓			
Carrot-Weed [49]	39	3264 × 2448	✓			✓		✓
Sugar beets [9]	280	1296 × 966	✓			✓		✓
WeedMap [89]	1,670	480 × 360	✓			✓		✓
Carrots-Onion [5]	40	2464 × 2056	✓			✓		✓
Oil Radish [72]	129	1600 × 1600	✓			✓		✓
Sunflower [27]	500	1296 × 966	✓			✓		✓
GrowliFlowers [42]	2,198	448 × 368	✓	✓	✓			✓
PhenoBench (Ours)	2,872	1024 × 1024	✓	✓	✓	✓	✓	✓

Table 1. Comparison of datasets in the agricultural domain providing dense pixel-wise annotations. For the crop and weed, we indicate if semantic segmentation (Sem.), plant instances (Inst.), and leaf instances (Leaves) are densely annotated. We also record if the dataset was recorded under field conditions, as opposed to under lab conditions (Field?). [1]We report maximum image size, as it ranges from $441\,\mathrm{px} \times 441\,\mathrm{px}$ to $2048\,\mathrm{px} \times 2448\,\mathrm{px}$.

where we provide the original camera data, WeedMap first generated orthophotos via bundle adjustment. While we considered this option, we noticed that the lack of a detailed elevation model usually leads to artifacts on the boundaries of the plants. Additionally, the images of WeedMap have a coarse GSD between $8.2\,\frac{\mathrm{cm}}{\mathrm{px}}$ and $13\,\frac{\mathrm{cm}}{\mathrm{px}}$ while our images have a GSD of $1\,\frac{\mathrm{mm}}{\mathrm{px}}$ to assess detailed information for individual plants. The Sunflowers dataset [27] provides images collected with a multispectral sensor providing RGB and near-infrared images from a ground robot. The Agriculture-Vision dataset [17] contains aerial images with a coarse GSD between $10\,\frac{\mathrm{cm}}{\mathrm{px}}$ and $20\,\frac{\mathrm{cm}}{\mathrm{px}}$ with corresponding annotations that covers rather large areas but not individual plants, *e.g.*, regions with nutrient deficiencies and weed clusters. More recently, the GrowliFlowers dataset [42] provides images recorded with an UAV showing multiple growth stages of cauliflowers. While we recorded images on three dates roughly a week apart, this data contains images captured on four different dates over a period of one month.

Besides the aforementioned closely related datasets that also provide dense pixel-wise annotations, there have been recently also several datasets in the agricultural domain released for wheat detection [20], localization and mapping [76, 40], image classification of weed species [74], detection for phenotyping [65], crop row detection [108], or fruit detection [88]. Additionally, there are a small number of available datasets for semantic interpretation of 3D agricultural data [91, 41, 24].

In contrast to these datasets, which are great starting points for research, our dataset shows an unique level of annotations, including semantic and instance masks for crops and weeds of an overall larger number individual plants (see Tab. 1). Note that our dataset provides large images with multiple completely visible plants, which is not the case for other pixel-wise annotated datasets [42, 90]. With the provided benchmarks on a hidden test set, we enable comparable and more reproducible results.

3. Our Dataset

In this section, we present our setup for data collection, explain the labeling process, and provide statistics to show the variability of the data.

3.1. Data Collection

Our dataset provides RGB images in real field conditions recorded by an UAV equipped with a high-resolution camera that captures imagery of the field. For recording the data, we employed a DJI M600 and used the PhaseOne iXM-100 camera with a $80\,\mathrm{mm}$ RSM prime lens mounted on a gimbal to obtain motion-stabilized RGB images at a resolution of $11\,664\,\mathrm{px} \times 8750\,\mathrm{px}$. The UAV was flying at a height of approx. $21\,\mathrm{m}$, resulting in a GSD of $1\,\frac{\mathrm{mm}}{\mathrm{px}}$. For covering the entire field, we use the DJI Ground Station Pro app to plan a flight that covers the field row-wise. We set the forward overlap between consecutive images by motion vector at $75\,\%$ and the side overlap between images placed in neighboring rows at $50\,\%$. Each image is geo-referenced by using the on-board GPS.

We performed three missions roughly a week apart to capture different growth stages of the plants. More specifically, we performed the flights on May 15, May 26, and June 6 in 2020. Additionally, we used the same sensor setup to record images at four different points in time in 2021 on a different field: May 20, May 28, June 1, and June 10. As the data was captured in the open field, we have a variety of different lighting conditions with sunny and also overcast weather, as shown in Fig. 4, which significantly changes the visual appearance of the plants.

From the approximately $1300\,\mathrm{m}^2$ sugar beets field, we

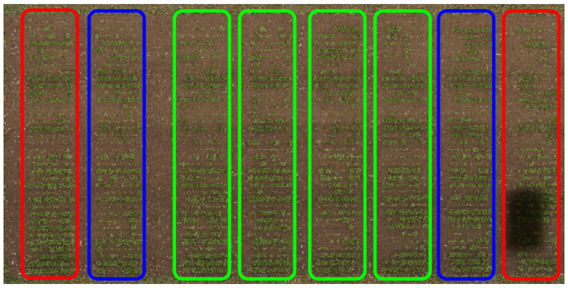

Figure 2. Orthophoto of the field recorded in 2020 and our spatial separation into rows for training (green), validation (blue), and testing (red). Due to the geo-referencing of the images, we extracted the same rows on each of the dates.

selected eight crop rows that were covered by the recording mission. To have a clear spatial separation between the train and test set, we selected four crop rows for extracting training images, two crop rows for validation, and two crop rows for testing purposes as shown in Fig. 2. The additional data recorded in 2021 is only included in the test set to evaluate also the performance in a setting of an unseen field with the same crop but potentially different weeds.

3.2. Labeling Process

The full-sized images, which we denote as global images, I_g, are challenging to annotate due to their large size of $11\,664\,\text{px} \times 8750\,\text{px}$. To parallelize the labeling process and ensure no plant is missed, we extracted from I_g overlapping patches, I_p, of size $2000\,\text{px} \times 2000\,\text{px}$. We extracted multiple iterations of overlapping patches such that we always have in one of the resulting four tilings complete plants visible, *c.f.* Fig. 3. As we ensure that each plant is fully visible in at least one of the patches, we instructed our annotators to label only completely visible plants in I_p.

For labeling the plants and leaves at the same time, we developed a novel tool to enable a hierarchical annotation of the images. Please see the supplement for a more detailed description of the labeling tool and the provided features.

We first labeled the plant instances of sugar beet crops and weeds, which was completed by 9 annotators investing a total of 800 h. Each iteration was validated and corrected before we transferred the annotations to the global images I_g. Then, the next iteration is started with the transferred labels copied to the respective patches I_p, and these steps were repeated till the final fourth iteration.

Annotation of a single patch I_p ranged from approx. 1 h for earlier growth stages to 3.5 h for later growth stages where plants had significant overlap. In sum, we annotated 705 patches over all dates and crop rows.

After the plant instances were labeled, we had 5 annotators labeling leaf instances. Annotators were tasked with identifying crop leaves and annotation of a patch I_p took approx. 1 h to 2 h depending on the number of visible crops.

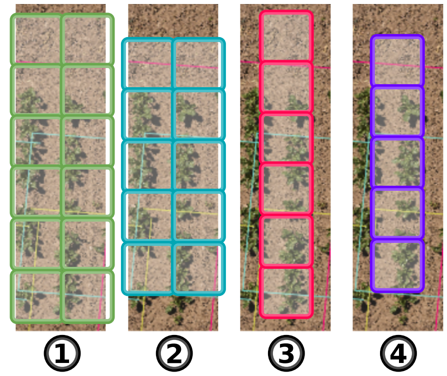

Figure 3. Extracted tiles of each iteration such that the whole row is covered densely with tiles to ensure that all plants are completely visible in at least in a tile. Annotations of tiles are transferred between iterations and aggregated in the global image I_g.

Split	#imgs	#crops	#weeds	#leaves
Train	1407	11,875	8,141	71,264
Validation	772	6,482	3,926	35,503
Test	693	6,201	4,291	33,935
Unlabeled	1000	–	–	–

Table 2. Dataset statistics of the provided splits. Note that we have a hidden test set, *i.e.*, we have a server-sided evaluation. We additional provide unlabeled data of a different part of the fields to enable studying of self-supervised pre-training.

With the masking of plant instances provided by our annotation tool, we ensure that we have consistent leaf labels that are inside the crop instance. Thus, it is possible to associate each leaf instance with its corresponding crop based on the plant instance annotations.

To ensure high-quality, accurate annotations of plants and leaves, we furthermore had an additional round of corrections performed by four additional annotators that revised the annotations. More details on our quality assurance process is provided in the supplementary material.

In total, we had 14 annotators who invested 1,400 h of annotation work and roughly 600 h invested into additional validation and refinement, leading to an overall labeling effort of approximately 2,000 h.

3.3. Dataset Statistics

We finally extracted from I_g smaller images of size $1024\,\text{px} \times 1024\,\text{px}$ to ensure that we have images containing complete crops at later growth stages, but also provide context such as the crop row structure.

Tab. 2 shows an overview of the number of extracted images for the different splits from the earlier described train/validation/test rows, the number of crop instances, the number of crop leaves, and the number of weed instances annotated. Note that only the test data includes data from

Figure 4. Variability in overlap and illumination of plants at the same part of the field on different recording dates. Theses examples show the variation in growth stages ranging from 4 leaf stage (early growth stage) to plants with over 20 leaves (later growth stage) and the variety of illuminations with sunny (left) and overcast (right) weather conditions.

2020 and 2021. As we ensured that we have completely annotated plants, we are able to generate a visibility map and differentiate between mostly visible plants with at least 50 % visible pixels and partially visible plants.

In addition to the labeled data, we also provide unlabeled data from all fields, which can be exploited for pre-training, semi-supervised, or unsupervised domain adaptation.

As motivated earlier, we recorded images under real-world conditions of real agricultural fields leading to a diverse range of plant appearances due to varying growth stages. The crops are affected by different soil conditions leading to a variety of growth stages even on images of the same date. This intra-class variability of the crops poses an interesting challenge for learning approaches that have to correctly segment or detect small but also large crops at the same time. The extra data from a different field captured in 2021 leads to even greater diversity of recording conditions, which is a common challenge in the agricultural domain.

Additionally, we observe a large variability in terms of overlap between plants. They are clearly separated at the beginning of the recording campaign but show a considerable overlap at the last recording date. Fig. 4 shows the same area of the field over the course of three weeks showing the variation in terms of growth stage but also the overlap between crops.

In Fig. 5, we provide an overview of the plant sizes in terms of the area covered by the plant instances that shows the diversity in terms of growth stages. Finally, we present in Fig. 6 the distribution of leaves per plant of completely visible plants in the training and validation split.

4. Benchmarks

In this section, we present the benchmark tasks that we provide together with the dataset. These tasks cover different aspects of a perception system for the crop production domain in agriculture. While we cover classical, well-established tasks, we also want to provide a novel task of hierarchical panoptic segmentation that provides a complete picture of the plant structure.

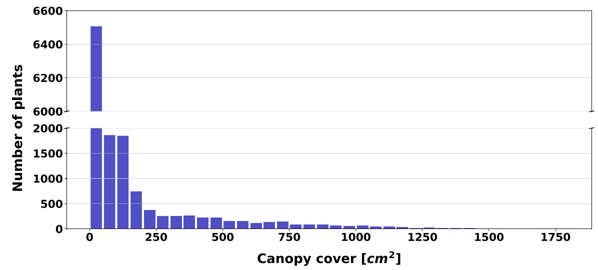

Figure 5. Distribution of crop sizes in terms of canopy cover in cm^2 for mostly visible plants in the training and validation set.

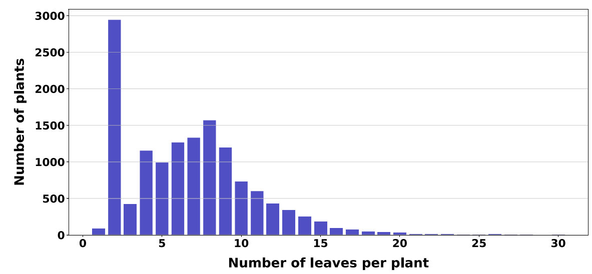

Figure 6. Distribution of leaf count of mostly visible plants in the training and validation set.

We provide metrics on the test set of our dataset including data from known and unknown fields for all investigated baseline approaches. Note that we provide more details on the training setup, including hyperparameters and qualitative results, in the supplement. We furthermore will provide code for the baselines in our code release. In the supplement, we furthermore provide qualitative results together with more fine-grained quantitative results differentiating between the different fields of the test set.

4.1. Semantic Segmentation

Task description. Semantic segmentation in images aims to train models capable of predicting each pixel's class. Thus, we provide annotated ground truth data that assigns each pixel to the class soil, crop, or weed. Consequently, an approach for this task needs to provide dense predictions assigning each pixel to one of the before-mentioned classes.

State of the Art. Semantic segmentation is a classical task that was first mainly tackled using conditional random fields [48, 45] to exploit the neighboring structure of images. With the advent of deep learning and the success in image classification [46], dense prediction tasks are nowadays mainly tackled by encoder/decoder architectures [61, 1] with skip connections pioneered by U-Net [86]. Recently, refined architectures add larger context [10, 11, 13] and multi-resolution processing [93] or rely on Transformers [99] for the encoder [109, 16, 96]. We refer to surveys for an overview of recent developments [95, 51].

In the agricultural domain, most approaches [62, 63, 67]

Approach	mIoU	IoU		
		Crop	Weed	Soil
ERFNet [85]	85.98	94.30	64.37	99.28
DeepLabV3+ [11]	85.97	94.07	64.59	99.25

Table 3. Baseline results for semantic segmentation on the test set.

follow the development and adopt the pipelines to account for the row structure [62] or leverage additional background knowledge to cope with less labeled data [67].

Baselines. As baselines, we select established general approaches, such as DeepLabV3+ [11] and ERFNet [85] at different ends of model capacity.

Metrics. To evaluate the performance of semantic segmentation models, we report the common intersection-over-union (IoU) for each class individually, where higher values indicate a better performance [18]. Additionally, we compute the mean intersection over union (mIoU) across all classes as the main metric.

Results and Discussion. In Tab. 3, we show quantitative results of the selected baselines. The investigated off-the-shelf semantic segmentation methods already show an overall good performance in terms of mIoU. However, we observe a relatively low IoU for weeds which are often wrongly assigned to pixels of crops. In terms of model capacity, the different investigated methods perform very similarly, indicating that the models' capacity cannot resolve the aforementioned issues Surprisingly, the smaller, simpler, and faster architecture ERFNet (2.1 M params) performs on par with the more complex DeepLabV3+ (39.8 M params) model that commonly shows better performance in the context of autonomous driving.

4.2. Panoptic Segmentation

Task description. Panoptic segmentation [44] tackles the task of jointly estimating a pixel-wise semantic label and distinguishing instances. This task differentiates between so-called "stuff" and "thing" classes. The former corresponds to instance-less classes, *i.e.*, soil, and the latter refers to classes with clearly separable objects, *i.e.*, crops and weeds. Consequently, an approach for this task needs to produce semantic masks assigning each pixel to crop, weed, or soil and an instance segmentation for crops and weeds.

State of the Art. Most approaches for panoptic segmentation [43, 77, 14, 103, 78, 12, 113, 58] extend classical semantic segmentation approaches with an instance branch or head to separate "thing" classes. Generally, there are two main paradigms for generating instances prevalent: top-down and bottom-up approaches. Top-down approaches [43, 77, 57, 58] use detection-based bounding box predictions to locate instances and mask predictions in bounding boxes to segment the located instances pioneered by Mask R-CNN [37]. Bottom-up approaches [14, 103] use a separate decoder to estimate embedding vectors and offsets to find clusters corresponding to instances of "thing" classes guided by the semantic segmentation branch. The main focus of research in this field concentrates on improving the architecture to achieve better separation between instances [113, 70, 12, 58, 78]. However, recent approaches [15, 111, 110, 92] based on Vision Transformer [21] show substantial improvements in this task.

In the agricultural domain, most methods adopt panoptic segmentation pipelines for crop and weed detection [8, 34] to contribute towards sustainable crop production and targeted weed management in real field conditions.

Approach	$PQ^{\dagger}$	PQ_{crop}	PQ_{weed}	IoU_{soil}
Panoptic DeepLab [14]	57.97	52.02	22.61	99.27
Mask R-CNN [37]	65.79	67.61	31.30	98.47
Mask2Former [15]	69.99	71.21	40.39	98.38

Table 4. Baseline results for panoptic segmentation on the test set.

Baselines. We use Panoptic DeepLab [14] and Mask R-CNN [37]. Further, we show Mask2Former [15] performance of a Transformer-based approach.

Metrics. We separately compute the panoptic quality [44] for the predicted instance masks of crops (PQ_{crop}) and weeds (PQ_{weeds}). During evaluation, we treat predicted instances associated with a partially visible instance, *i.e.*, a plant where less than 50% of its pixels are inside the image, as "do not care" regions not affecting the score. Additionally, we report the IoU for the semantic segmentation of soil (IoU_{soil}) to consider predictions related to "stuff". In our final metric, we compute the average over all three values and denote it as $PQ^{\dagger}$ as proposed by Porzi *et al*. [77].

Results and Discussion. In Tab. 4 we show that Mask2Former [15] achieves the best overall performance. However, qualitative results reveal that the instance segmentation of crops is especially sub-optimal in cases of large overlap, while well-separated crops can be better separated in instances. This suggests that domain-specific models could potentially exploit the plant structure.

4.3. Detection

Task description. While pixel-wise segmentation of instances allows for extracting fine-grained information, often detecting instances is sufficient. Therefore, we also propose using our data for studying plant or leaf detection in separate tasks. For plant detection, we distinguish between the classes of crop and weed. Similar to COCO [60], we extract bounding box annotations from the instance-level plant and leaf annotations to allow training of object detection approaches. An approach for either plant or leaf detection

Approach	mAP	mAP_{50}	mAP_{75}	AP	
				Crop	Weed
Faster R-CNN [83]	40.43	65.07	40.19	63.23	17.62
Mask R-CNN [37]	38.68	63.72	38.07	60.32	17.05
YOLOv7 [102]	60.48	82.47	62.30	83.06	37.91

Table 5. Baseline results for plant detection on the test set.

Approach	mAP	mAP_{50}	mAP_{75}
Faster R-CNN [83]	33.91	64.61	31.30
Mask R-CNN [37]	34.41	66.02	32.15
YOLOv7 [102]	57.90	86.85	62.92

Table 6. Baseline results for leaf detection on the test set.

needs to provide bounding boxes and confidence scores for each detected instance.

State of the Art. Early approaches for object detection relies on sliding window-based classification methods [100] and research before 2014 mainly concentrates on better feature representations [19, 30], part-based representations [28, 29, 56], or better proposal generation [98].

Since 2013, CNN-based approaches have been prevalent as pioneered by R-CNN [32] and follow-up work [83, 31, 37]. Generally, one can distinguish between single-stage and two-stage approaches. Nowadays, single-stage approaches are mainly employed and YOLO [80]-based approaches are popular choices [81, 82, 102]. Recently, also keypoint-based approaches [52, 22, 114] were proposed that divert from the anchor-based methods. Similarly to other tasks, the field recently shifted towards Transformer-based approaches [7, 94].

In the agricultural domain, most methods use detectors to identify crops or weeds [34, 35] or suggest domain-specific adaptations, *e.g.*, for fruit detection [66].

Baselines. We select established approaches for object detection, such as Faster RCNN [83], Mask R-CNN [37] and YOLOv7 [102], which are commonly used approaches. Since this task refers to either plant or leaf detection, we train models for each task separately. Although Mask R-CNN also provides an instance segmentation, we do not consider these predictions in this task but rely on its predicted bounding boxes.

Metrics. In line with established benchmarks [26, 25, 60], we report the average precision (AP) for each class and mean average precision (mAP) across all classes, which uses multiple IoUs for matching between 0.5 and 0.95 with a step size of 0.05. Furthermore, we report the mean average precision at 0.5 IoU (mAP_{50}) and 0.75 IoU (mAP_{75}). As previously, we treat each predicted bounding box associated with a partially visible instance as "do not care" regions. Thus, these predictions do not affect the scores.

Approach	PQ_{leaf}
Mask R-CNN [37]	59.74
Mask2Former [15]	57.50

Table 7. Baseline results for leaf instance segmentation on test set.

Results and Discussion. In Tab. 5, we show results for plant detection, where we see that more modern approaches have a clear edge over the other approaches. Apparently, weed detection is more difficult than crop detection, which could result from smaller plant sizes. In Tab. 6, we summarize the results for leaf detection, which shows lower performance across all methods compared with plant detection, indicating the need for domain-specific approaches.

4.4. Leaf Instance Segmentation

Task description. Leaf instance segmentation is relevant for estimating the growth stage of a plant [50] and also the basis for leaf disease detection [71]. Such approaches are involved in phenotyping activities to investigate new varieties of crops [69]. An automatic, vision-based assessment of such traits has the potential to have reproducible and objective measurements at a high temporal frequency. Consequently, an approach for this task needs to predict an instance mask for each visible crop leaf.

State of the Art. Instance segmentation is closely related to object detection. Therefore earlier approaches rely on object detection approaches [83, 80] to perform top-down instance segmentation by predicting segmentation masks for bounding boxes [37, 3, 3, 55, 4, 112]. A different line of research [6] investigated the usage of bottom-up processing, where first pixel-wise embedding vectors are estimated such that pixels belonging to the same instance are near in embedding space, while embedding vectors of different instances are separated. The estimated embedding vectors can then be clustered, resulting in instances. Recently, several methods [104, 105] were proposed that directly estimate masks for each object instance. Most recently, also Transformer-based approaches [53, 15] for instance segmentation gained interest. Popularized by the CVPPP dataset [68], several approaches tackle the task of leaf instance segmentation [39] or leaf counting [107].

Baselines. As baselines for our experiments, we employ Mask R-CNN [37] and Mask2Former [15]. While the former method represents a traditional top-down approach, the latter belongs to more recent methods relying on a Transformer decoder and masked attention.

Metrics. We compute the panoptic quality [44] for the predicted instance masks of crop leaves, denoted as PQ_{leaf}. As previously, any instance prediction associated with a partially visible instance does not affect the score.

Approach	$PQ^{\dagger}$	PQ	PQ_{crop}	PQ_{leaf}	IoU	
					Weed	Soil
HAPT [84]	65.27	50.73	54.61	46.84	61.11	98.50
Weyler [106]	-	40.49	38.37	42.60	-	-

Table 8. Baseline results for hierarchical panoptic segmentation on the test set.

Results and Discussion. Tab. 7 shows the results of the investigated baselines. In this setting, the approaches generally struggle to separate leaves in large overlap situations, where the plant canopy is very dense and contains many overlapping leaves. Again, we suspect that more domain-specific approaches could induce prior knowledge to achieve a better separation.

4.5. Hierarchical Panoptic Segmentation

Task description. Models for hierarchical panoptic segmentation target objects, which can be represented as an aggregation of individual parts, *e.g*., plants can be represented as the union of their leaves [106]. Consequently, these methods provide a simultaneous instance segmentation of the whole object and each part. Thus, they are capable of providing more detailed information about each object, *e.g*., the association of individual leaves to a specific plant allows obtaining the total number of leaves per plant, which correlates to its growth stage [50]. We provide the annotated instance masks of all crops and their associated leaves. Since there are no leaf annotations for weeds, we do not consider them under the guise of a hierarchical structure. Thus, we also relate to weeds as "stuff" for this task.

State of the Art. Several recent works exploit the underlying hierarchical structure of objects to obtain a panoptic segmentation [75, 84, 106]. Generally, there are methods distinguishing between two types of objects. First, objects which have a strong prior assumption about their total number of parts, *e.g*., in the case of human pose estimation [75]. Contrary, objects with a high variation in their number of parts, *e.g*., the number of leaves per plant depends strongly on its growth stage. In the agricultural domain, recent methods [84, 106] operating in real field conditions exploit the hierarchical structure of plants to predict the instance segmentation of individual crops and their leaves.

Baselines. We select the methods by Weyler *et al*. [106] and Roggiolani *et al*. [84], called HAPT, as baselines performing a simultaneous instance segmentation of crops and their associated leaves. The first method is bottom-up approach that first predicts leaves, which are then associated to a plant instance. In contrast, HAPT uses a hierarchical feature aggregation starting at the plants and providing plant-level features to then predict jointly leaves.

Metrics. To evaluate the performance of this task, we compute the panoptic quality [44] for the predicted instance masks of all crops (PQ_{crop}) and leaves (PQ_{leaf}) separately. We report the average panoptic quality over both values, denoted as PQ. As previously, any instance prediction assigned to a partially visible instance does not affect the metrics. To account for methods that filter pixels related to weeds or soil with an additional semantic segmentation, we also report the IoU for both classes. Finally, we compute $PQ^{\dagger}$ as the average over PQ_{crop}, PQ_{leaf}, and both IoU values.

Results and Discussion. In Tab. 8, we show the results of the hierarchical approaches. Here, we can see that both methods do not obtain consistent predictions for plants at a large growth stage, where individual plants and their leaves overlap. In particular, instance separation of leaves seems most challenging in line with the plant instance segmentation. Thus, methods targeting these scenarios could improve the performance.

5. Potential Impact on Other Research Areas

Besides the already covered supervised tasks in agricultural perception, our dataset providing labeled and unlabeled images has the potential to impact also other fields of research and applications in the agricultural domain, such as research in self-supervised representation learning, domain generalization, and unsupervised domain adaptation that is currently getting increasing interest in the computer vision and robotics community. Exploiting developments in semi-supervised, but also unsupervised learning of vision models seems like a indispensable step to reduce the burden of annotating data and unlocking the scalable deployment of vision models in the agricultural domain.

Furthermore, the combination with other agricultural datasets providing pixel-wise annotations, *e.g*., GrowliFlowers [42], opens the door for studying cross-domain transfer between different plant species towards the goal of developing more generalizable visual perception systems in the agricultural domain.

6. Conclusion

In this paper, we present a novel dataset for studying visual perception in the agricultural domain of crop production using real-world field images captured by an UAV. Together with dense pixel-wise annotations of crops and weeds that distinguish instances of plants, we also provide leaf-level pixel-wise annotations of crop leaves.

In line with the dataset, we presented our benchmark tasks that will be evaluated on a hidden test set to allow an unbiased and controlled evaluation of developed approaches. The server-side evaluation also ensures that metrics are consistent and reliable allowing to compare approaches based on published results.

For each task, we also provide baseline results that show the performance of off-the-shelf approaches for the different tasks. These results show that certain tasks need further research to tackle the specific challenges of the agricultural domain. We believe that more domain-specific approaches exploiting domain knowledge could boost performance.

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