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A survey of public datasets for computer vision tasks in precision agriculture

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ABSTRACT

Computer vision technologies have attracted significant interest in precision agriculture in recent years. At the core of robotics and artificial intelligence, computer vision enables various tasks from planting to harvesting in the crop production cycle to be performed automatically and efficiently. However, the scarcity of public image datasets remains a crucial bottleneck for fast prototyping and evaluation of computer vision and machine learning algorithms for the targeted tasks. Since 2015, a number of image datasets have been established and made publicly available to alleviate this bottleneck. Despite this progress, a dedicated survey on these datasets is still lacking. To fill this gap, this paper makes the first comprehensive but not exhaustive review of the public image datasets collected under field conditions for facilitating precision agriculture, which include 15 datasets on weed control, 10 datasets on fruit detection, and 9 datasets on miscellaneous applications. We survey the main characteristics and applications of these datasets, and discuss the key considerations for creating high-quality public image datasets. This survey paper will be valuable for the research community on the selection of suitable image datasets for algorithm development and identification of where creation of new image datasets is needed to support precision agriculture.

1. Introduction

Precision agriculture, as the hallmark of agriculture 4.0 era (De Clercq et al., 2018), has promised to revolutionize agricultural practices through the use of monitoring and intervention technologies for increasing production efficiency while reducing environmental impacts. Computer vision technologies that use digital images to interpret and understand the world, are capable of providing accurate, site-specific information about crops and their environments. Depending on applications, a computer vision system uses different sensing modalities, such as color or RGB (red-green-blue) imaging that simulates human vision for visual inspection, near-infrared (NIR) multispectral or hyperspectral imaging for detecting more elusive biological processes, or ranging sensors for geometrical measurements. Today, computer vision has been extensively utilized for supporting precision agriculture (also known as agro-vision) tasks, such as crop monitoring and phenotyping, weed control, harvesting, vehicle guidance and yield mapping (Bulanon et al., 2020; Mavridou et al., 2019; Patrício and Rieder, 2018; Wang et al., 2019).

Computer vision-based agricultural robotics and artificial intelligence are being increasingly recognized as a key enabler for precision agriculture. Agricultural robots (e.g., unmanned autonomous vehicles) have the potential to conduct the majority of the tasks that are conventionally undertaken by human-operated agricultural machines or humans (Bechar and Vigneault, 2016; Bogue, 2016), such as field scouting, weed management and harvesting (Shamshiri et al., 2018). A field scouting robot, in the form of an unscrewed ground rover or aerial system, allows monitoring and diagnosis of crop growth and health at varied spatial and temporal scales. Robotic weeding uses computer vision for crop and weed detection, and removes weeds by selectively applying herbicides to the detected weeds (Lamm et al., 2002; Raja et al., 2020) or through a mechanical cultivator (Tillett et al., 2008), providing novel chemical-reduced or non-chemical weeding strategies. Similarly, robotic harvesting relies on the detection of agricultural products on the plant and then instructs manipulators and end effectors for performing harvesting operations (Bac et al., 2014; Sarig, 1993).

Common to all computer vision-based precision agriculture tasks is presumably the goal of detecting the objects of interest (e.g., crop, weed or fruit) and discriminating them from the rest of the scene. To achieve this requires, in addition to a well-designed hardware system, a robust data analysis pipeline that generally involves training of machine learning models with specific image datasets. A high-quality, large-scale dataset is of vital importance to the performance of the developed data analysis pipeline and the success of the end task. Preparation of such a dataset, however, is not trivial because of the efforts and costs required for image acquisition, categorization and annotation, as well as physicochemical measurements of crops in some cases. Data sharing, which is seen to have a vast potential for fostering scientific progress, provides an effective way for addressing the difficulty with data preparation for precision agriculture tasks. Making datasets publicly

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Table 1
Public image datasets dedicated to weed control.

Datasets	Modality	Platform	# Images	Annotation	ULR
CWFI dataset (Haug and Ostermann, 2015)	Multispectral	Ground vehicle	60	Pixel level	https://github.com/cwfid/dataset
Carrot-Weed (Lameski et al., 2017)	RGB	Hand-holding	39	Pixel level	https://github.com/lameski/rgbweeddetection
Plant seedlings (Giselsson et al., 2017)	RGB	Ground fixed platform	407	Image level	https://vision.eng.au.dk/plant-seedlings-dataset/
Grass-Broadleaf (dos Santos Ferreira et al., 2017)	RGB	UAV	> 10,000	Patch level	https://www.kaggle.com/fpeccia/weed-detection-in-soybean-crops
Sugar Beets 2016 (Chebrolu et al., 2017)	Multimodal	Ground vehicle	> 10,000	Image level	https://www.ipb.uni-bonn.de/datasets_IJRR2017/annotations/
Synthetic SugarBeet Weeds (Cicco et al., 2017)	RGB	No imaging platform	8518	Pixel level	http://www.dis.uniroma1.it/~labrococo/fds/syntheticdatasets.html
weedNet (Sa et al., 2017)	Multispectral	UAV	465	Image level	https://github.com/inkyusa/weedNet
Joint stem detection (Lottes et al., 2018)	Multispectral + RGB	Ground vehicle + UAV	1321	Pixel level	https://www.ipb.uni-bonn.de/people/lottes/
Leaf counting (Teimouri et al., 2018)	RGB	Hand-holding	9372	Image level	https://vision.eng.au.dk/leaf-counting-dataset/
Weed Map (Sa et al., 2018)	Multispectral	UAV	> 10,000	Pixel level	https://projects.asl.ethz.ch/datasets/doku.php?id = weedmap:remotesensing2018weedmap
DeepWeeds (Olsen et al., 2019)	RGB	Ground vehicle	> 10,000	Image level	https://github.com/AlexOlsen/DeepWeeds
Crop weed discrimination (Bosilj et al., 2020)	Multispectral	Ground vehicle	40	Pixel level	https://lcas.lincoln.ac.uk/wp/research/data-sets-software/crop-vs-weed-discrimination-dataset/
Early crop weed (Espejo-Garcia et al., 2020)	RGB	Hand-holding	508	Image level	https://github.com/AUAgroup/early-crop-weed
Ladybird Cobbitty Brassica (Bender et al., 2020)	Multimodal	Ground vehicle	Unspecified	No annotations	https://cloudstor.aarnet.edu.au/plus/S/N0giZD5QTMB32Xj?path = %2FJFR_2018
Open Plant Phenotype Database (OPPD) (Madsen et al., 2020)	RGB	Ground fixed platform	7590	Image level, bounding box	https://gitlab.au.dk/AUENG-Vision/OPPD/-/tree/master/

available saves the significant resources associated with data preparation, and also enables benchmarking of image analysis and machine learning algorithms developed among different research groups (Lobet, 2017).

The computer vision community has enjoyed a proliferation of public, annotated image datasets, such as PASCAL VOC (Everingham et al., 2010), COCO (Lin et al., 2014), ILSVRC (Russakovsky et al., 2015), and recently Open Images V4 (Kuznetsova et al., 2020), leading to remarkable successes in object detection/segmentation tasks and novel modeling architectures. These datasets that consist of images from the Internet sources or for natural scenes or objects, however cannot directly translate to precision agriculture applications. While there are also a variety of image datasets dedicated to plants, such as Leafsnap (Redmon and Farhadi, 2018), PlantVillage (Mohanty et al., 2016) and among others (Lobet, 2017; Lobet et al., 2013), they are primarily targeted for botanical taxonomy or plant phenomics, and generally collected under controlled laboratory conditions. Enabling computer vision for precision agriculture requires more specialized datasets for such tasks as robotic management and crop monitoring, especially datasets collected under more realistic field conditions. Moreover, there is a need for vast amounts of data (e.g., tens or hundreds of thousands of images) to power advanced deep learning systems (Sun et al., 2017), so as to account for a wide range of field conditions (e.g., crop growth status, surface soil characteristics and variable light). As computer vision and machine learning continue to impact agriculture, since 2015 there have been an increasing number of public image datasets designated for precision agriculture tasks. Some of them are released through dataset publications and others are shared accompanied with the associated research articles.

To the best of our knowledge, no survey of public image datasets for precision agriculture has previously been carried out or published. Given the significant progress in this area, we believe such a survey would be greatly valuable for the research community by providing a compilation of resources and inspiring new efforts on algorithm development and benchmarking for computer vision tasks in agriculture. This paper is therefore to provide the first survey and analysis of the public image datasets for precision agriculture. To identify the datasets, a literature search was conducted in a systematic manner. The common databases, including Google Scholar, ScienceDirect, Springer, Web of Science, IEEE Xplore and the USDA Ag Data Commons repository, were searched with the following keywords, that is, “dataset”, “agriculture”, “crop” and “computer vision”. The search retrieved 5870 records in Google Scholar, 1201 in Science Direct, 1170 in Springer, 49 in Web of Science, 52 in IEEE Xplore and 3 in USDA Ag Data Commons. These records were further filtered based on the two inclusion criteria: 1) the dataset is publicly available without the need to make a request to the authors, and 2) it was collected in the field or quasi-field conditions instead of in the controlled laboratory environment. Since most of the datasets in literature were not released to the public, as a result, only 34 search records agreed with the inclusion criteria and selected in this survey, among which the most prevalent applications are weed control (15 datasets) and fruit harvesting (10 datasets).

The remainder of the paper is organized as follows. The main characteristics and details of the surveyed public image datasets are described in Section 2. Given the importance of image annotation and hosting platforms for dataset creation and sharing, these topics are discussed in Section 3. The recommendations and practical consideration for future creation of datasets are also provided in this section, followed by a brief conclusion given in Section 4.

2. Public image datasets

In this section, the public image datasets, based on targeted precision agriculture tasks, are categorized into three classes, i.e., weed control, fruit detection and others, as summarized in Table 1–3 respectively. The description of each dataset is made systematically and

Table 2
Public image datasets dedicated to fruit detection.

Datasets	Modality	Platform	# Images	Annotation	URL
DeepFruits (Sa et al., 2016)	RGB	Ground based	587	Bounding box	https://drive.google.com/drive/folders/1CmsZb1caggLRN7ANfika8WuPiywo4mBb
Orchard Fruit (Bargoti and Underwood, 2017a)	RGB	Ground vehicle	3704	Bounding box, circle	http://data.acfr.usyd.edu.au/ag/treecrops/2016-multifruit/
Date Fruit (Altaheri et al., 2019b)	RGB	Unspecified	> 10,000	Image levels	https://doi.org/10.21227/x46j-sk98
KFuji RGB-DS (Gené-Mola et al., 2019b)	RGB-D	Ground vehicle	967	Bounding box	http://www.grap.udl.cat/en/publications/KFuji_RGBDS_database.html
MangoNet (Kestur et al., 2019)	RGB	Hand-holding	49	Pixel level	https://github.com/avadesh02/MangoNet-Semantic-Dataset
MangoYOLO (Koirala et al., 2019)	RGB	Ground vehicle	1730	Bounding box	https://nextcloud.qriscloud.org.au/index.php/s/wvYJBt2rBX2dFJj
WSU apple dataset (Bhusal et al., 2019)	RGB	Ground vehicle	2298	Bounding box	http://hdl.handle.net/2376/17721
Fuji-SfM (Gené-Mola et al., 2020c)	RGB	Ground based	288	Bounding box	http://www.grap.udl.cat/en/publications/Fuji-SfM_dataset.html
LFuji-air dataset (Gené-Mola et al., 2020b)	LiDAR	Ground vehicle	Unspecified	Bounding box	http://www.grap.udl.cat/en/publications/LFuji_air_dataset.html
MinneApple (Häni et al., 2020b)	RGB	Hand-holding	> 10,000	Pixel level	https://conservancy.umn.edu/handle/11299/206575

Table 3
Public image datasets dedicated to other precision agriculture applications.

Dataset	Modality	Platform	# Images	Annotation	Application	URL
3D Broccoli (Kusumam et al., 2016)	RGBD	Ground vehicle	Unspecified	No annotation	Flower detection	https://lcas.lincoln.ac.uk/nextcloud/shared/agritech-datasets/broccoli/broccoli_datasets.html
Apple Trees (Akbar et al., 2016)	RGBD	Hand-holding	Unspecified	No annotation	Tree pruning	https://engineering.purdue.edu/RVL/CVPRW_Dataset/
Capsicum Annuum (Barth et al., 2018)	RGB	No imaging platform	> 10,000	Pixel level	Semantic plant segmentatic	https://data.4tu.nl/repository/uuid:884958f5-b868-46e1-b3d8-a0b5d91b02c0
Fruit flower dataset (Dias et al., 2018)	RGB	Ground vehicle + hand-holding	190	Pixel level	Flower detection	https://data.nal.usda.gov/dataset/data-multi-species-fruit-flower-detection-using-refined-semantic-segmentation-network
Sugarcane billets (Alencastre-Miranda et al., 2018)	RGB	Ground based	156	Image level	Damage detection	https://github.com/The77Lab/SugarcaneBilletsDataset
Maize disease (Wiesner-Hanks et al., 2018)	RGB	Multiple platforms	> 10,000	Line level	Disease detection	https://osf.io/p67rz/
DeepSeedling (Jiang et al., 2019)	RGB	Ground based	5743	Bounding box	Seedling counting	https://figshare.com/s/616956f8633c17ceae9b; https://github.com/UGA-BSAIL/deepseedling
GrassClover (Skovsen et al., 2019)	RGB	Ground based	> 10,000	Pixel level	Canopy species and biomass prediction	https://vision.eng.au.dk/grass-clover-dataset
Oil radish growth (Mortensen et al., 2019)	RGB	Ground vehicle	129	Pixel level	Yield estimation	https://vision.eng.au.dk/oil-radish/

Fig. 1. Field robot for image acquistion (left), a sample of collected images (mid) and the annotioon (right). Reproduced from (Haug and Ostermann, 2015) with permission.

includes a collection of characteristics, including imaging device and configurations, image number, format and resolution, annotation type, applications and possible limitations. The image format, most often in png or jpg/jpeg, and resolution, which vary with imaging device and post-processing operations, are only described when they are consistent in a specific dataset. The datasets are presented in chronological and alphabetical order.

2.1. Weed control

2.1.1. CWFI dataset

The CWFI (crop/weed field image) dataset (Haug and Ostermann, 2015) is among the first public field datasets for weed control. A multispectral camera, mounted to an autonomous field robot Bonirob (Ruchelshausen et al., 2009), as shown in Fig. 1, was used for image collection at a carrot farm. The camera was shaded and artificially lit to avoid changing light conditions, and the Red (R) and NIR channels of the camera were selected for imaging (but the images in the dataset are saved in the 3-channel format of R-NIR-R). The dataset consists of a total of 60 raw images of 1296 × 966 pixels in resolution, in png format, along with the corresponding binary images representing vegetation masks and the pixel-level annotations that define weed, crop and soil background. The annotations are provided as three-channel images, as shown in Fig. 1(right) and also stored in separate YAML files. Although this dataset is relatively small, it has been utilized for evaluating machine learning models for robotic weeding platforms (McCool et al., 2017; Fawakherji et al., 2019).

2.1.2. Carrot-Weed dataset

This dataset (Lameski et al., 2017), like the CWFI dataset, contains the images collected in a carrot field but using a low-cost phone camera under natural light conditions. It is also a small-scale dataset consisting of 39 RGB images, which are of jpg format and 1296 × 966 pixels in resolution, in addition to two sets of images defining vegetation masks and pixel-level annotations for the crop, weed and soil background, respectively. This dataset has been used for the crop and weed discrimination using textural features combined with random forest (Kamath et al., 2020).

2.1.3. Plant seedlings dataset

The plant seedlings dataset (Giselsson et al., 2017) contains a total of 407 RGB images of png format and varied size, which were acquired from plant seedlings belonging to 12 crop and weed species, at multiple times over a 20-day growth period. The authors built a portable, enclosed frame that held the camera at a fixed distance from the soil surface and ensured even and comparable light conditions for image acquisition. Each acquired image corresponds to a single plant species, and hence this dataset can be used as a benchmark for the crop and weed classification tasks (Dyrmann et al., 2018). Without detailed weed annotations, this dataset is not suitable for weed segmentation or detection tasks.

2.1.4. Grass-Broadleaf dataset

This dataset (dos Santos Ferreira et al., 2017) was created based on a set of the RGB images captured by an unpiloted aerial vehicle (UAV) flying at an altitude of about 4 m above ground level in a soybean field. Each of these images were automatically segmented into different patches using a linear iterative clustering super-pixel algorithm (Achanta et al., 2012) and then manually annotated into four classes (i.e., soybean, grass, broadleaf and soil). As a result, the dataset comprises a total of 15,336 image patches of varied resolution in tiff format, being 3249 of soil, 7376 of soybean, 3520 grass and 1191 of broadleaf weeds. In addition to image classification, the authors used the dataset for evaluating unsupervised clustering algorithms for facilitating image annotations (dos Santos Ferreira et al., 2019).

2.1.5. Sugar Beets 2016 dataset

The Sugar Beets 2016 dataset (Chebrolu et al., 2017), represents an early effort of using a field robot equipped with multiple sensors to acquire a large-scale dataset for weed control as well as localization and navigation. The Bonirob robot (Ruchelshausen et al., 2009) was used to acquire four-channel RGB and NIR images, which are of 1296 × 966 pixels in png format, under controlled lighting, on a sugar beet farm over a period of three months. In addition to the data for navigation, this dataset comprises 283 multi-class (i.e., sugar beet and nine different types of weeds) annotated images at a pixel level, and an even larger set of about 12,340 images with three-class (i.e., crop, weed and background) pixel-level annotations. This dataset has been widely used for developing robotic crop and weed detection algorithms (Lottes et al., 2018; Milioto et al., 2018; Bosilj et al., 2020)).

2.1.6. Synthetic SugarBeet weeds dataset

The synthetic data (Cicco et al., 2017) represents a novel effort of artificially generating large-scale datasets for robotic weed control. Unlike most public datasets that are physically collected using vision sensors, this dataset was algorithmically created through procedural content generation (PCG) that is a widely used technique in computer graphics (Shaker et al., 2016), by modeling targeted plants and agricultural scenes with a few real-world textures (Cicco et al., 2017). The dataset contains a total of 8518 synthetic RGB images of 480 × 360 pixels in png format, which are divided into four image sets composed of the mixture of sugar beet instances and different species of weeds. Each synthetic image is pixel-wise annotated for the crop, weed and soil backgound. Fig. 2 shows an example of a synthetic image and the corresponding annotations. The synthetic dataset can be directly used to train machine learning models or as a supplement to a relevant real-world image dataset with a limited amount of data, which would enable dramatic reduction of human efforts required for data collection and labeling.

2.1.7. weedNet dataset

The weedNet dataset (Sa et al., 2017) was collected from a controlled sugar beet field experiment, which contained three field sites for crop alone, a mixture of crop and weed, and weed alone. A UAV

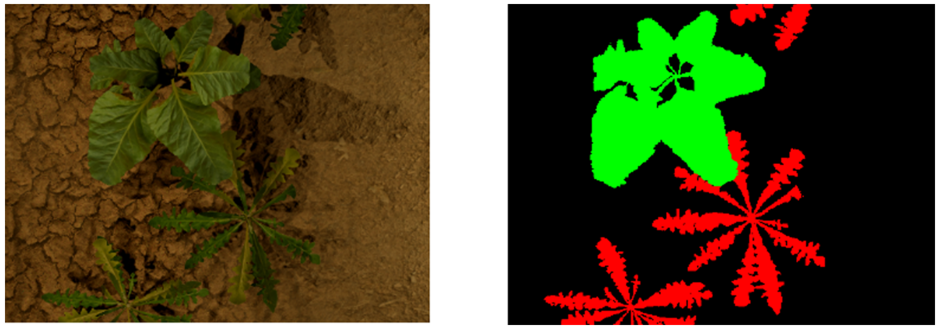

Fig. 2. An example of a synethically generated RGB image (left) and the corresponding ground-truth pixe-wise annotations (right). These two images are randomly selected from the Synthetic dataset (Cicco et al., 2017).

equipped with a four-channel multispectral camera at 2 m height was controlled for image acquisition. The resulting dataset comprises 375 training images, including 132 for crop and 243 for weed, and 90 test images for the mixture of crop and weed, and all the images are in png format. Either training or test images evenly consist of three sets, i.e., Red, NIR and NDVI (normalized difference vegetation index, derived from Red and NIR images) of monochromatic images. The images are annotated, at pixel level for the crop, weed and background.

2.1.8. Joint stem detection dataset

This dataset (Lottes et al., 2018) was aimed at the task of detecting and differentiating dicot weed and grass weed, which may require different weeding methods, and also the stems of crop and the dicot weed, which would facilitate the implementation of plant-specific mechanical weed removal. The released data contains two sub-datasets; the first one is derived from the Sugar Beets 2016 Dataset, including 921 RGB + NIR images of 1296 × 966 pixels in png format, and the second consists of 400 RGB images of 512 × 384 pixels in png format, which was acquired by a UAV. For these images, pixel-level annotations for the crop, dicot weed, grass weed and background, and the stem positions are provided for semantic segmentation and stem detection tasks (Lottes et al., 2020).

2.1.9. Leaf counting dataset

The objective of this dataset (Teimouri et al., 2018) was to estimate weed growth stages by counting the leaf number of weeds to optimize herbicide spraying for weed removal. It contains 9372 RGB images of png format and varied resolution, for 18 weed species at different growth stages. The dataset is categorized into 9 classes based on the leaf number of each plant, ranging from 1 to more than 9 leaves, and the image number of each class ranges from 160 to 3292. All these images were acquired using smartphone cameras, in various field sites covering a range of soil types, image resolutions and light conditions. This dataset is well suitable for evaluating multi-class image classification tasks with respect to leaf numbers, but not for weed species classification and semantic segmentation.

2.1.10. Weed Map dataset

The Weed Map dataset (Sa et al., 2018), which was created by the authors who published the weedNet dataset (Sa et al., 2017), is presumably the largest multispectral aerial dataset for sugar beet weed segmentation and mapping publicly available. Two UAVs with a four-channel and five-channel multispectral cameras respectively were used for collecting images at 10 m height from sugar beet fields. It comprises eight sets of high-resolution orthomosaic maps with pixel-level annotations for the crop, weed and background, and a total of 10,196 title images that were small image patches or tiles cropped from these orthomosaic maps, in a sliding window manner. This dataset provides a new benchmark of machine learning algorithms for generating large-scale orthomosaic map based weed mapping.

2.1.11. DeepWeeds dataset

The DeepWeeds dataset (Olsen et al., 2019) was to provide a large collection of weed images for deep learning based classification of weed species. This dataset comprises a total of 17,509 RGB images, which are of jpg format and 256 × 256 pixels in size, collected by a customized ground weed control robot, for eight weed species and various non-weed plants in natural field conditions without lighting control. Each weed species has more than 1000 images, which is desired for training complex deep learning models. Since this dataset only provides class labels for each image, it is tailored for the weed classification tasks (Lammie et al., 2019; Olsen et al., 2019), but without provision of pixel-level annotations, cannot be readily used for weed segmentation and localization.

2.1.12. Crop weed discrimination dataset

This dataset was used in (Bosilj et al., 2020) for evaluation of transfer learning from a model trained on a different crop for crop and weed segmentation, so as to reduce model training times and the efforts for dataset preparation. The dataset contains two small-scale image sets for carrot and onion crops respectively. The image data were acquired using a two-camera configuration with RGB and NIR cameras mounted apart on a manually pulled cart. Both crop sets consist of 20 high-resolution (2428 × 1985 pixels for carrots and 2419 × 1986 pixels for onions) RGB-NIR images in png format. Two types of pixel-level annotations are provided for the dataset, including full annotations for the crop, weed and soil background, and partial annotations in which some image regions are not annotated and marked as a mixed class, which would enable evaluating the performance of using imperfectly annotated data for saving image annotation times.

2.1.13. Early crop weed dataset

This dataset (Espejo-Garcia et al., 2020) was created to apply pretrained deep learning models for crop and weed identification. The dataset targets two weed species, black nightshade and velvetleaf, at an early growth stage with 3–4 leaves, and also contains two crops, tomato and cotton. The image data were collected using a RGB camera in different field locations under natural light conditions. The resulting dataset contains 123, 130, 54 and 201 images, which are of jpg format and 4256 × 2832 pixels in size, for black nightshade, velvetleaf, tomato and cotton, respectively, which are organized into the different folders denoting corresponding plant categories. Since each image contains a single plant species, the dataset is not suitable for crop-weed semantic segmentation and localization tasks.

2.1.14. Ladybird Cobbitty Brassica dataset

The Ladybird Brassica dataset (Bender et al., 2020) was collected by an autonomous robot Ladybird (Underwood et al., 2017), designed at the Australian Center for Field Robotics. Like the Sugar Beets 2016 Dataset, this dataset also contains multimodal sensing data for crops as well as environment, and to our knowledge, it is the first public dataset of field crops having the combined data by stereo vision, thermal and hyperspectral (in the wavelngth range of 400–1000 nm) imagery. Weekly scans were performed for cauliflower and broccoli vegetables over a 10-week period from transplant to harvest. Due to high-resolution hyperspectral data, the whole dataset of over 2.8 T is significantly larger than the aforementioned datasets. While this dataset provides a rich source of information for research opportunities in crop detection and growth modeling, they are not annotated at either image or pixel level, which, also given computer memory constraints, may discourage future explorations of the dataset by other users.

2.1.15. Open plant Phenotype Database (OPPD)

The OPPD (Madsen et al., 2020) is a dataset collected from a diversity of plant seedlings of 47 weed species. These plants were cultivated in a semi-field, controlled setting under three different (i.e., ideal, drought and natural) growth conditions to ensure a high degree of intra-species variations of plant visual appearances. Data collection was performed over four trial growth seasons, and the plants from each trial were temporally tracked after from seedling emergence to the stages of up to 6–8 leaves. The resulting dataset consists of 7,590 RGB images in jpg format, which represent 64,292 individual plants. Each of the images is annotated with a label of corresponding weed species and, and bounding boxes for the plants, which were achieved via a machine learning based annotation tool RoboWeedMaPS (https://vision.eng.au.dk/roboweedmaps/) in conjunction with manual corrections. This datasets allows for evaluating both the tasks of plant classification and instance detection.

2.2. Fruit detection

2.2.1. DeepFruits dataset

This dataset was utilized for fine-tuning for pre-trained deep learning models for fruit detection (Sa et al., 2016). While the authors examined two image modalities in their work, the published dataset only consists of RGB images, which were collected in greenhouses and open fields. The dataset comprises 7 subsets of images for different fruits, including sweet pepper, rock melon, apple, mango, orange and strawberry, each of which has 42–170 images of varied resolution in png format and is partitioned into training and test sets. Bounding box annotations are provided for performing fruit detection.

2.2.2. Orchard fruit dataset

The dataset was collected in the orchard fields for three fruit varieties (i.e., apple, mango and almond) (Bargoti and Underwood, 2017a). The images for the apple and mango trees were acquired using an autonomous ground vehicle, while the almond data was acquired with a hand-held camera. The dataset consists of 1120 (size 308 × 202 pixels), 1964 (size 500 × 500 pixels) and 620 (size 308 × 202 pixels) color images (in png format) for apple, mango and almond fruits, respectively. These images have been cropped into small patches from the raw high-resolution data for the ease of training deep neural networks that prohibit using large images due to hardware memory constraints. As shown in Fig. 3, circular annotations are provided for apples, while rectangular bounding box annotations are for mangoes and almonds, and in addition, pixel-level fruit annotations are also available for apples. This dataset is suitable for benchmarking of transferring learning algorithms and also developing new deep learning architectures for fruit detection and segmentation (Bargoti and Underwood, 2017a,b).

2.2.3. Date fruit dataset

This dataset is the first one that is publicly available for date fruit pre-harvesting and harvesting applications (Altaheri et al., 2019b). The dataset was acquired in natural orchard environments and divided into two separate subsets for different applications. The first subset consists of 8079 color images of size 224 × 224 pixels in jpg format, with rich variations resulting from varied imaging angles and scales, variable illumination, different fruit varieties and maturity stages, and also different fruit bagging states. The images are labelled into different classes according to fruit variety, maturity and harvesting decision, which have been utilized for evaluating deep learning algorithms for fruit classification (Altaheri et al., 2019a). The second subset contains the images, videos, and weight measurements of date brunches that were acquired during the harvesting period. This dataset can be used for aiding in such tasks as yield estimation.

2.2.4. KFuji RGB-DS dataset

The KFuji RGB-DS dataset (Gené-Mola et al., 2019b; Gené-Mola et al., 2019a) is a collection of three-modality images integrating RGB, depth (D) and range-corrected IR intensity (S) data, for ‘Fuji’ apples on trees. The image data were acquired using Microsoft Kinect v2 cameras with depth image resolution of 512 × 424 pixels in jpg format, mounted on a mobile platform and in the night time under artificial lighting. Geometric registration was performed onto the raw data to build pixel-wise correspondences among the RGB, D and IR channels. The resulting dataset contains 967 multimodal images and bounding box based fruit annotations for a total of 12,839 apples. This dataset provides a new benchmark of fruit detection and localization algorithms for RGB-D sensor based field robots.

2.2.5. MangoNet dataset

The MangoNet dataset was collected for mango detection by a customized deep semantic segmentation model MangoNet (Kestur et al., 2019). It consists of 49 high-resolution 4000 × 3000 color images in jpg format, which were collected in a mango orchard under natural illumination conditions, with 45 images for training and 4 for testing. Pixel-level annotations are made for fruit and non-fruit classes for each image. To train deep learning models with the dataset, users need to crop the raw large images into small patches, e.g., 200 × 200 pixels in size for the MangoNet (Kestur et al., 2019), to circumvent the computation memory issues. Image cropping can be readily performed by sampling the entire image using a sliding window of the same size of the desired model input images.

2.2.6. MangoYOLO dataset

This dataset, which is also dedicated to mango fruit, was created for benchmarking of a deep learning architecture MangoYolo (Koirala et al., 2019), which is adapted from the object detectors YOLOv2 (Redmon and Farhadi, 2017) and YOLOv3 (Redmon and Farhadi, 2018), towards real-time fruit detection and orchard load estimation. In contrast to the MangoNet dataset, this dataset was collected at night with artificial lighting, with more consistent and better image contrasts. The images were captured by a RGB camera mounted on a ground vehicle. The resulting dataset has 1730 images (1300, 130 and 300 images for training, validation and testing, respectively) of 612 × 512 pixels in jpg format, and the bounding box fruit annotations, which were performed using a graphic image annotation tool *labelImg* (Tzutalin., 2015), are stored in XML files in the same fashion of the PASCAL VOC data (Everingham et al., 2010).

2.2.7. WSU apple dataset

This dataset (Bhusal et al., 2019) was created by the Agricultural Automation and Robotics Laboratory at Washington State University (WSU) for robotic harvesting and yield estimation. It consists of 2298 RGB images (of varied resolution in png format) of apple trees, with the provision of bounding box fruit annotations. These images were acquired from multiple growth seasons and fruit varieties. The Laboratory also released another set of 1600 images acquired by RGB-D cameras (Fu et al., 2017), and some other dataset dedicated to agricultural robotics research (Zhang et al., 2020b; Zhang et al., 2020c).

2.2.8. Fuji-SfM dataset

The Fuji-SfM dataset was used in (Gené-Mola et al., 2020c) for detecting and locating apples in 3D space by integrating deep learning segmentation and structure-from-motion (SfM) photogrammetry. The

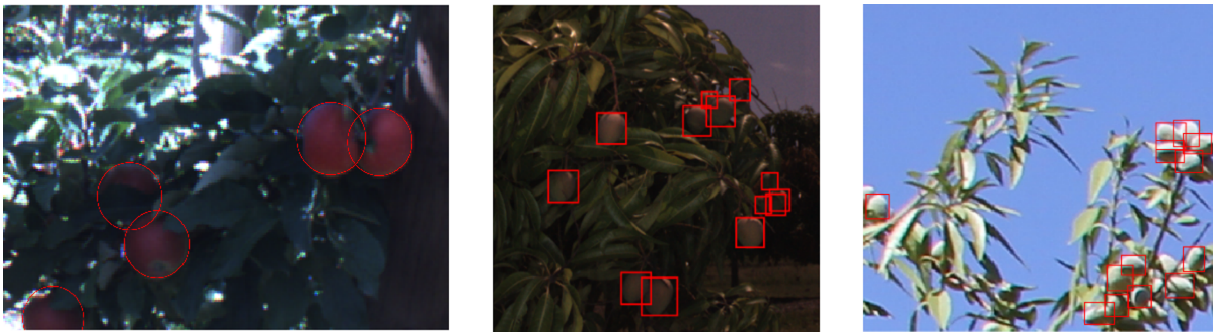

Fig. 3. Examples of images (apple, mango and almond from left to right) with ground-truth fruit annotations. These images are randomly drawn from the dataset (Bargoti and Underwood, 2017a) and annotated based on the given annotations.

image data were collected using a handheld color camera in the natural orchard conditions, for 11 'Fuji' apple trees. The dataset consists of three parts, including a total of 288 RGB images of 1024 × 1024 pixels in jpg format and the corresponding pixel-wise fruit annotations, which can be used for evaluation of 2D vision based fruit detection and segmentation algorithms, the multi-view images used for generating the 3D model of the fruit trees by SfM, and the 3D point cloud of the scanned scene with 3D bounding box fruit annotations, which allows for benchmarking of 3D fruit detection and localization.

2.2.9. LFuji-air dataset

The LFuji-air dataset (Gené-Mola et al., 2020b) was created by the same research team for the KFuji RGB-DS (Gené-Mola et al., 2019b) and Fuji-SfM (Gené-Mola et al., 2020c). Like the other two datasets, the LFuji-air dataset also provides 3D information of the scene towards enhanced fruit detection, but it was collected using a light detection and ranging (LiDAR) system, which was mounted on an air-assisted sprayer for generating different air flow conditions (Gené-Mola et al., 2020a). Compared to RGB cameras, LiDAR sensors are advantageous in accurate 3D measurements without being affected by varying outdoor illumination conditions. The dataset contains, in addition to the raw LiDAR data files in *.pcap* format, the generated point cloud data in *.mat* format and the corresponding 3D bounding box annotations in *.txt* format for a total of 1353 apples of 11 fruit trees. This dataset represents the first one of 3D LiDAR data publicly available for fruit detection.

2.2.10. MinneApple dataset

The MinneApple data (Häni et al., 2020b) was created by a research team at University of Minnesota for apple detection. Compared to many other image datasets that are focused on a single fruit variety or from a single growth season, this dataset includes diverse images from multiple fruit varieties over two growth seasons. Data collection was done using a cell phone camera in video mode under natural illumination conditions, and the images were then extracted from the recorded video sequences. This dataset is divided into two sets of images that are dedicated to fruit detection and counting tasks (Häni et al., 2020a, b). The detection set consists of 670 and 311 images of size 1280 × 720 pixels in png format for training and test respectively. Pixel-level fruit annotations, which were made using VGG Image Annotator (VIA) (Dutta and Zisserman, 2019), are provided for the training images, representing a total of 41,325 object instances. The counting set consists of 64,595 images of jpg format, 2875 and 3395 images of png format and varied resolutions for training, validation and test respectively, and ground-truth fruit counts, ranging from 0 to 6, are provided for the training and validation images.

2.3. Other applications

2.3.1. 3D broccoli

The 3D Broccoli dataset was created for broccoli flower heads detection based on 3D vision, aimed at selective robotic harvesting (Kusumam et al., 2016, 2017). The image data was collected using a RGB-D camera (Microsoft Kinect v2) mounted on a tractor in different broccoli field sites under artificial lighting conditions. This dataset consists of 16 recorded videos, the accompanying 3D point cloud (*.pcd*) data files, and a set of color images of size 1920 × 1080 pixels in png format for one field site. This dataset provides a good resource for evaluating object segmentation and localization tasks using 3D point clouds as well as color images.

2.3.2. Apple trees

The Apple Trees dataset (Akbar et al., 2016) is also a collection of 3D vision data but focused on geometric reconstruction of fruit trees to facilitate robotic tree pruning. The data were acquired for 9 apple trees of varied structure, i.e., 6 in outdoor orchard environments and 3 present indoor, at different viewpoints. There are five types of information about individual trees in the dataset, including depth and color images, which were also acquired using a Kinect v2 camera, labeled ground-truth images by a regular color camera, ground-truth diameter measurements of primary tree branches, and relative distances between a consecutive pair of primary branches. This dataset provides a new benchmark of 3D reconstruction and modeling algorithms of trees for pruning purposes.

2.3.3. Capsicum Annuum dataset

This dataset represents a novel effort of using synthesis methods for dataset creation for agricultural computer vision tasks (Barth et al., 2018). Unlike many other datasets, the Capsicum Annuum (i.e., sweet pepper) dataset was created synthetically rather than through manual image acquisition. The image synthesis was achieved by modeling of plant geometric parameters, color and textural features based on empirical measurements of realistic plants, followed by computational rendering. This dataset consists of 10,500 synthetic color images in png format, with pixel level segmentation of 8 classes of plant parts including stem, node, side shoot, leaf, peduncle, fruit and flower. The synthetic dataset provides a good starting point for benchmarking semantic segmentation tasks, but for real-world generalization, empirical or realistic images are needed for fine tuning of object detection and segmentation algorithms.

2.3.4. Fruit flowers

The Fruit Flowers dataset (Dias et al., 2018) was created for evaluation of semantic segmentation networks for flower detection of tree fruits. The image data was collected for the flowers of three species, apple, peach and pear, using color cameras in natural orchard conditions. In the dataset, there are four sets of images, two for apple flowers and the other two for peach and pear flowers respectively, and the entire dataset contains 130 images of size 5184 × 3456 pixels and 60 images of size 2704 × 1520 pixels. Pixel-wise annotations for flowers are provided in the form of separate sets of binary images, which were performed by initial freehand annotations followed by region growing refinement (Dias et al., 2019).

2.3.5. Sugarcane billets

The Sugarcane billets dataset (Alencastre-Miranda et al., 2018) is collection of the images of sugar billets, which are short segments of sugarcane stalks used for mechanized planting, with different types of harvest-induced damage, aiming to identify billet damage as an initial effort of developing a robotic planter. Image acquisition was performed in both indoor and outdoor lighting conditions for a total of 786 billets of six classes (five types of damage plus no damage). The resulting dataset consists of 156 images of size 2448 × 2048 pixels in bmp format, most of which each comprises five billets of the same class. Class labels but no semantic segmentations are provided for this dataset.

2.3.6. Maize disease

The Maize Disease dataset (Wiesner-Hanks et al., 2018) was dedicated to automated, field-based detection of North leaf blight (NLB), a common and devastating fungal foliar disease of maize. This data set contains RGB images of maize leaves taken in three different ways, including using a hand-held camera, a camera mounted on a boom and a camera mounted on a small UAV (at an altitude of 6 m). The images were taken in the field trials of maize that had been inoculated with the causal pathogen (*Setosphaeria turcica*) of NLB. The resulting dataset contains more than 18,222 images annotated with more than 105,735 NLB lesions, representing the largest collection of images for any one plant disease (Wiesner-Hanks et al., 2018). The annotations were performed by human experts who drew lines down the main axis of individual lesions, as indicated in Fig. 4, but did not delineate the lesion margins. In a later study, the authors investigated pixel-level annotations for the UAV images through crowdsourcing tasks, in which non-experts were asked to perform the lesion annotations based on the line annotations by the experts (Wiesner-Hanks et al., 2019).

2.3.7. DeepSeedling

The DeepSeedling dataset was created for detection and counting of cotton seedlings in the field using deep learning models (Jiang et al., 2019). The raw data were recorded in the form of videos using three different color cameras with the same resolution of 1920 × 1080 pixels, and the data collection was performed over two growth seasons at three field locations, but only for the seedlings at early growth stages of 7–11 days after planting. RGB images were extracted from the video clips to build up the dataset for plant seeding detection. In the dataset, there are three sets of images acquired at different locations, which contain 2391, 1821 and 1531 images of jpg format, respectively, and the corresponding bounding box annotations for cotton seedlings and a small portion of weeds.

2.3.8. GrassClover

The GrassClover dataset (Skovsen et al., 2019) is a diverse image segmentation and biomass dataset designed to support robust image analysis of heavily occluded mixed crops for precision management. The images contain dense populations of grass and clover mixtures with heavy occlusions and occurrences of a diversity of weeds. The dataset was collected with three ground based different acquisition platforms with digital cameras. Fig. 5 shows these imaging platforms and example images collected. The dataset is split into training and test sets. The training set consists of 8000 synthesized images with pixel-wise annotations, 31,600 unlabeled images, and additionally 152 images with plant canopy biomass composition information, which are all of jpg format. The synthesized images were generated based on the random integration of the plant crop-outs of different species and soil backgrounds from raw images (Skovsen et al., 2019), which allows creating large sets of annotated images with reduced efforts. The test set consists of 15 manually annotated images and 283 images with biomass information. This dataset is the first one that supports the tasks of both image segmentation and biomass composition prediction.

2.3.9. Oil radish growth

The Oil Radish Growth dataset (Pire et al., 2019), which was created by the same institution for the GrassClover dataset, contains the image and biomass data from an oil radish field plot experiment. The image data were acquired using a RGB camera mounted in front of a tractor, which are of size 1601 × 1601 pixels in jpg format. In the released dataset, there are 95 training images with pixel-wise annotations for seven classes, including oil radish, barley/grass, weed, soil, equipment, stubble and the unknown, and 34 test images without annotations. Field data including fresh weight, dry weight, and the nitrogen content and contents of plant samples are provided for the training images.

3. Discussion

The scarcity of public image datasets remains a key bottleneck in developing next-generation computer vision and intelligent systems for precision agriculture. Despite the progress made in the past few years, significant efforts are needed to create new public image datasets, especially for many specific application domains where there are still no any dedicated public image datasets (Zhang et al., 2020a). This section therefore discusses the key considerations of addressing the bottleneck, regarding image acquisition, augmentation, annotation and data sharing, so as to provide some recommendations to assist researchers in the future tasks of public image dataset creation.

3.1. Image acquisition

Among the reviewed 34 public datasets, 24 datasets involve using RGB cameras for image acquisition, confirming the prevalence of this modality. RGB is advantageous in its low cost, high image resolution and fast speed, which are all desirable for precision agriculture applications. Moreover, the acquired images can be readily fed into a wide range of existing machine learning frameworks for computer vision tasks as classification and object detection. RGB images, however, are sensitive to the light condition variations in the field, which pose challenges to the image segmentation and object detection. To alleviate

Fig. 4. Examples of images randomly chosen from the Maize Disease dataset (Wiesner-Hanks et al., 2018), where the red lines denote the position of disease lesions based on the provided line annotations. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 5. Three imaging platforms (top row) and example images (bottom row) from the corresponding platforms above. Images are reproduced from (Skovsen et al., 2019) with permission.

the issue, one may construct an enclosed imaging chamber with lighting control (Giselsson et al., 2017), or acquire images at steady light conditions, e.g., during overcast days or in the night with artificial lighting (Koirala et al., 2019), at the cost of reduced working hours. An alternative solution highlights the need for collecting a large-scale set of images in the varied natural light conditions and exploiting the capacity of deep learning models to tackle the light interference. The use of integrative RGB and NIR, i.e., multispectral color-infrared (CIR) modality is becoming increasingly popular, which can potentially provide enhanced performance given the fact that NIR is less susceptible to the variations of visual appearance of plants.

Imaging platforms are also a critical consideration for dataset creation. Currently most of the public datasets are collected using a ground-based platform, either an unscrewed field robot or a fixed platform, or simply by hand holding a camera. Although UAVs are gaining momentum in precision agriculture, the acquired data are not made publicly available in most cases. For real-world success, the dataset should be tailored to targeted applications by matching the imaging platform with that to be used in realistic scenarios. For instance, for a dataset that is aimed at developing a robotic weeder, a ground-based , proximal imaging platform is more suitable than aerial imaging; and a camera-equipped ground robot or moving cart with a top-down imaging view camera and a proper plant-camera distance is more preferable over hand-holding imaging, in which both the view angle and plant-camera distance are not easy to maintain. UAVs are well suited for large-scale crop scouting, while hand-hold imaging is useful when a specialized and cost-effective ground robot is not available.

Many of the published datasets in this survey are rather small-scale in terms of image numbers ($<$ 1000 per class), plant species included, and the diversity of environmental factors (e.g., different weather conditons and field sites), crop growth stages and seasons and or camera view angles, thus restricting their practical deployment. While some precision agriculture tasks, such as fruit picking, are generally completed within a short time window (e.g., one week), many other tasks such as weed control and crop scouting generally take a time span of several weeks or months throughout a growth season, which would require collecting images over multiple growth stages to fully capture the morphological and physiological features of the plants. Even for time-sensitive tasks such as harvesting, the plant parts may vary greatly in morphology and texture with growth seasons or geographic locations. Presently only very few datasets were aimed at addressing the diversity of crop growth by acquiring images at varied crop growth stages (Bender et al., 2020; Chebrolu et al., 2017), during multiple growth seasons (Häni et al., 2020b; Jiang et al., 2019), or in geographically different field sites (Olsen et al., 2019). Thus, more efforts are needed to fill the gap when new datasets are to be created.

3.2. Data augmentation

Having large-scale datasets is highly desirable for boosting the performance of machine learning models (Halevy et al., 2009; Sun et al., 2017). As a rough rule of thumb, training deep learning models from scratch requires thousands of images per category for achieving human-level performance (Goodfellow et al., 2016). Transfer learning can reduce the image number requirement to as few as hundreds or even tens of images (Espejo-Garcia et al., 2020; Suh et al., 2018), but it should be noted that such approaches heavily rely on fine turning of the models pre-trained using the images that are generally irrelevant to domain precision agriculture tasks, which hence may not generalize well in practical applications. Despite the recognized need for larger datasets, the collection of sufficiently large datasets can be a daunting task due to the manual efforts and costs involved, and in some cases even infeasible for certain classes (e.g., rare diseases or weed species) that have very few occurrences in the field.

Data augmentation, which algorithmically expands the scale of datasets, provides a promising means to address the insufficiency of physically collected image data. Among the datasets surveyed above, three of them used image synthesis methods (Barth et al., 2018; Cicco et al., 2017; Skovsen et al., 2019), based on PCG, physical modeling of plant texture and color features, and image shading, for data generation or augmentation. In addition to these methods, there are a suite of many other data augmentation techniques (Shorten and Khoshgoftaar, 2019), among which data warping through geometric or color transformations are conventionally used in computer vision tasks. Recently, generative adversarial networks (GANs), which represent a novel framework of generative modeling through adversarial training (Creswell et al., 2018; Goodfellow et al., 2014), have received increasing attention as a new strategy for data augmentation. Much of the research on GANs for data augmentation has initially been done on the biomedical images (Yi et al., 2019) for disease recognition, and very recently this technique has been used for image generation for agro-vision tasks (Barth et al., 2020; Madsen et al., 2019). Currently these data augmentation techniques, including data warping and GANs, are mainly used during the model training processes, and have not been used for creating public image datasets for precision agriculture tasks.

3.3. Image annotation

Image annotation is a process of defining and describing regions of interest (ROIs) with labels in an image, or simply labeling the entire image rather than specific ROIs. It is an essential step to prepare a dataset with ground-truth information for subsequent tasks such as image classification and object detection, and also facilitate the reuse of the dataset by other researchers. Providing poor annotations or no annotations will significantly limit the usability of any public dataset in the research community, despite the efforts made for image acquisition.

An image can be annotated manually or automatically (Bhagat and Choudhary, 2018). Automatic automation attempts to train a learning model with given image data and use the trained model to assign image or semantic labels automatically. This approach, although very attractive due to its efficiency, may not always work satisfactorily for challenging images, such as those for agricultural pattern recognition. Manual annotation that uses human labor to annotate individual images is currently predominantly used for computer vision tasks in agriculture. For assisting in manual image annotations, numerous software tools have been developed and publicly available, such as *labelImg* that was used for annotating the MangoYOLO dataset (Koirala et al., 2019), and VIA (Dutta and Zisserman, 2019) that was used for annotating the MinneApple dataset (Häni et al., 2020b). Table 4 presents a list of common open-source image annotation tools and their basic functionalities.

With the dedicated tools as summarized in Table 4, image annotation can be readily done for a small set of images with high accuracy. However, when it comes to a large-scale, high-resolution dataset that consists of tens of thousands of images or even more, manual image annotation, especially at a pixel level, can be tremendously laborious and time consuming especially when performed by a single worker. For instance, it is reported that pixel-wise annotating an image in the crop weed discrimination data (Bosilj et al., 2020) took 15–20 min and in MinneApple dataset (Häni et al., 2020b) took up to 30 min. This likely explains the fact that some fully annotated datasets, such as the CWFI Dataset (Haug and Ostermann, 2015) and the Carrot-Weed Dataset (Lameski et al., 2017), only consist of a small number of images, while for the large datasets, like the GrassClover (Skovsen et al., 2019), only a subset of images have pixel-precision annotations.

One solution to annotating a large set of images is to take a large cohort of individuals to perform the task, that is, annotate images via crowdsourcing, which requires much less time and has been successfully deployed in annotating large-scale image sets in computer vision (Kovashka et al., 2016). Crowdsourcing is available via commercial platforms, among which Amazon's Mechanical Turk (MTurk) (Buhrmester et al., 2011; Rashtchian et al., 2010) has enjoyed great popularity due to its large number of available workers. MTurk allows a requester to post the task, called human intelligence task, and the turkers (workers) around the world execute the assigned task in a short span of time and get paid on a task-by-task basis. Since image annotations on MTurk are performed by non-experts, quality control is important to obtain high-quality annotated data. Recently, MTurk based crowdsourcing has been used for annotating image datasets for detection of corn tassels (Zhou et al., 2018) and leaf disease (Wiesner-Hanks et al., 2019). Given the ease of large-scale image annotation, more efforts will be anticipated on crowdsourcing image datasets in precision agriculture.

3.4. Data sharing

To create a public dataset, the image data, including ground-truth annotation files, need to be shared to be accessible to the community. Apart from sharing these data, the experimental setup and image acquisition protocols need to be sufficiently documented to facilitate data reuse in future algorithm design, test and comparison, and also creation of new datasets, especially for new researcher entering a specific domain. To give a reference, we identify some minimum information, as summarized in Table 5, to document when sharing image datasets.

A public dataset can be shared on either external platforms (see Table 6 for examples) or internal websites. It is noted that more than one half of the public datasets in this survey were shared on a research group, university or personal website. However, there is a risk that these webpages may change over time (e.g., due to university website updates or group name changes), leading to invalid links to the shared data or even data loss. The external platforms as shown in Table 6, on the other hand, are less likely to change in the near future, as they have a large volume of registered users worldwide. Moreover, these platforms provide useful capabilities such as backup, version control, collaboration management and digital object identifier assignment, all of which help ensure better sustainability of the data. Hence whenever possible it is more preferable to share image datasets on such external platforms that allow the data to be preserved over time and help others to find it easily.

4. Conclusions

Publicly available image datasets are valuable in precision agriculture as they reduce the effort for data collection and preparation and enable development and evaluation of better-performing algorithms for various vision tasks. This survey paper fills a critical gap in precision agriculture literature by providing the first comprehensive review of the public image datasets of the application of computer vision since 2015. We have identified a total of 34 public image datasets and categorized them into three classes based on targeted applications, including 15 datasets on weed control, 10 datasets on fruit detection and the remaining 9 datasets for other applications. This survey covers the main characteristics of each dataset, involving image acquisition,

Table 4
Examples of common image annotators.

Annotator	Annotation type	URL
COCO Annotator	Bounding box, polygon, point, freehand	https://github.com/jsbroks/coco-annotator
CVAT	Bounding box, polygon, polyline, points	https://github.com/opencv/cvat
ImageTagger	Bounding box, polygon, line, point	https://github.com/bit-bots/imagetagger
imglab	Bounding box, polygon, circle, ellipse, point	https://github.com/NaturalIntelligence/imglab
labelImg	Bounding box	https://github.com/tzutalin/labelImg
LabelMe	Bounding box, polygon, circle, line, point	https://github.com/wkentaro/labelme
OpenLabeling	Bounding box	https://github.com/Cartucho/OpenLabeling
Yolo_mark	Bounding box	https://github.com/AlexeyAB/Yolo_mark
VIA	Bounding box, polygon, circle, ellipse, polyline, point	http://www.robots.ox.ac.uk/~vgg/software/via/
VoTT	Bounding box, polygon	https://github.com/microsoft/VoTT

Table 5
Minimum information to be documented for public image datasets.

Category	Specific Information
Imaging device	Camera type (e.g., smartphone or camcorder) and modality (e.g., RGB or multispectral), model and manufacturer information
Imaging configuration	Platform (e.g., handholding or ground vehicle based), lens information (e.g., focal length, F-number), camera distance from the scene, and controlled lighting used or not
Field site	Open fields or greenhouse settings, weather conditions during image acquisition, and crop information (e.g., crop type and growth stage)
Image data	Image format (e.g., png and jpeg), resolution, image number, and raw or preprocessed data
Annotation	Annotation types (e.g., image level or bounding box), classes of annotated objects, number of instances per category

Table 6
Common repositories for storing research datasets.

Name	URL	Size limitation	Cost
CyVerse	https://cyverse.org/	100 GB/user	Free
DRYAD	https://datadryad.org/stash/	None stated	$ 120/submission
FIGSHARE	https://figshare.com/	5 GB/file	Free
Github	https://github.com/	1 GB	Free
Harvard Dataverse	https://dataverse.harvard.edu/	2.5 GB/file	Free
Open Science Framwork	https://osf.io/	5 GB/file	Free
Mendeley Data	https://data.mendeley.com/	10 GB/dataset	Free
Zenodo	https://www.zenodo.org/	50 GB/dataset	Free

dataset structure, annotations, applications and potential limitations, and thereafter discusses the key considerations regarding image acquisition, augmentation, annotation and data sharing, for creating high-quality public image datasets. This paper will allow researchers to readily select the datasets appropriate for their needs and also facilitate creating new image datasets for enabling precision agriculture tasks.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

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