An Image Labeling Tool and Agricultural Dataset for Deep Learning

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Abstract—We introduce a labeling tool and dataset aimed to facilitate computer vision research in agriculture. The annotation tool introduces novel methods for labeling with a variety of manual, semi-automatic, and fully-automatic tools. The dataset includes original images collected from commercial greenhouses, images from PlantVillage, and images from Google Images. Images were annotated with segmentations for foreground leaf, fruit, and stem instances, and diseased leaf area. Labels were in an extended COCO format. In total the dataset contained 10k tomatoes, 7k leaves, 2k stems, and 2k diseased leaf annotations.

I. INTRODUCTION

Over the past decade computer vision research has shifted away from the design of manually defined feature descriptors and towards learning directly from data. As a result of innovations in deep learning, models have achieved super-human levels of performance on a variety of vision tasks. Convolutional neural networks use layers of artificial neurons to increasingly learn higher levels of object representations, beginning with simple lines and corners and towards complete objects such as fruits and flowers.

A major challenge to computer vision using supervised deep learning is the large amount and variety of annotated images required to automatically discover salient features for object recognition, detection, and segmentation. Due to this challenge, pioneering deep learning studies focused on classification tasks and used images with single prominent objects collected using web searches of associated filenames and metadata. This approach simplified the annotation process, as only short text descriptions were necessary. As more advanced forms of scene understanding were developed, the need arose for more sophisticated annotation tools.

The Common Objects in COntext (COCO) dataset introduced images with detailed annotations of objects in the context of their natural surroundings with the goal of advancing computer vision beyond image classification. In total there were 2.5 million instances from 80 categories in 328k images labeled. The annotations in COCO included bounding boxes and pixel-level segmentation of each object instance. Images on average contained 7 instances and took 1 minute and 19 seconds to annotate. Annotations were created using the opensurface-segmentation-ui annotation tool, which only drew shapes using vertex-clicking.

Precision agriculture is a quickly growing market segment, with a substantial research effort focusing on computer vision. The agriculture community has a considerably smaller collection of publicly available data to use in computer vision experimentation compared with more generalized computer vision research. The limited access to public data presence barriers to creating comparative studies, peer review of papers, and measuring the progress the community is making over time. Agriculture studies have traditionally collected their own data and used it to develop and test new algorithms. As a result, datasets are often relatively small and not made public. In circumstances where data is released, there is no common format to follow which complicates testing and advancement of methods by third parties.

There have been some efforts to collect large amounts of public agricultural image data, most notably by PlantVillage in 2015. The dataset contained over 50k leaf images organized by experts into plant and disease type categories. The PlantVillage project is focused on helping small growers better manage crops through the use of technology to help increase the global food supply. One of the most pressing concerns for small growers is disease, as it is frequently the cause of a total-loss harvest. The original dataset contained high resolution imagery of the diseased leaves, and was announced as a public dataset. However, as project focus shifted to other research areas access to the data was removed. A low resolution version of the dataset is still currently available in an online code repository for a related research publication.

A. Contribution

We introduce an annotation tool and dataset aimed at facilitating computer vision research in agriculture. The annotation tool provides novel methods for labeling, with a variety of manual, semi-automatic, and fully-automatic tools. In order to facilitate future integration and expansion of the dataset, we also introduce a dataset format compatible with many existing computer vision tools in the community. The dataset builds on images from PlantVillage by adding pixel-level segmentations of diseased areas, and includes images compiled from Google Image searches, and from originally collected images of commercial greenhouse plants.

II. LABELING TECHNIQUES

The annotation tool introduced here builds on previous techniques used to label images and incorporates several novel annotation workflows. As agricultural images often have many more individual objects and with more intricate shapes than those in many general datasets, this tool focused on increasing the efficiency of labeling these types of images.

The labeling tool was designed to be used with a keyboard and mouse, and includes several keyboard shortcuts and mouse gestures to help improve annotation efficiency.
The annotator’s labeling techniques could be used independently or in combination to label each object. Annotated objects can be composed of several disjoint segments to accommodate occlusion. Besides a main label, each object can be associated with an unlimited amount of metadata to provide additional context. For example, a fruit can have meta-data describing its ripeness and associated plant ID.

The following is a description of each annotation technique.

A. Free-form polygons

The vertex-clicking technique used in previous system focused on manufactured objects with simple and sharp corners. When used to annotate natural objects with curved edges, such as those found in typical agricultural scenes, the resulting shapes exhibited low fidelity boundaries. Higher quality boundaries were possible by adding many intermediate points along a curve but at the cost of significantly increasing annotation time and effort.

The free-form polygon tool allows users to click-drag-release around objects to annotate them, while the system automatically assigns points along the boundary. Polygon precision and the minimum distance between the first and last point to automatically complete the shape can be adjusted using a parameter in the user interface. After the polygon is generated, the select tool can be used to individually move each vertex independently to fine tune the final shape.

This is the tool which was most often used during annotation of the included dataset.

B. Flood fill

The flood fill tool selects areas of uniform color and automatically generates an enclosing polygon with adjustable vertices.

Two selectable parameters adjust the color threshold and the size of a gaussian blur used to determine the enclosing area. Areas can be removed by using the shift modifier key and clicking inside an existing polygon.

This tool works best for large intricate areas of uniform color, and can generate complex polygons with a single click.

C. Brush and eraser

The brush tool allowed adding annotation by painting using a technique similar to that of familiar drawing software. The size of the brush could be adjusted using a parameter or keyboard shortcut, and areas were selected using a click-drag-release technique. The resulting area was automatically converted into a detailed polygon which could be further adjusted by moving its vertices.

The eraser tool functioned in a similar way to the brush but removed annotated areas instead of adding them. The eraser was not limited to erasing areas created using the brush tool, and could be used to fine-tune any generated polygon.

D. Key points

Key points are used for describing the spatial relationships between objects or parts of objects. It is most notably used to characterize the human skeleton for analysis and tracking. As a result of this primary application, the original key point system assumed a fixed number of points with unchanging relationships (toe bone connected to the foot bone, etc).

When key points are used to represent the structure of plant stems, key points structure must become dynamic to properly characterize nodes as the plant grows.

The key point annotation tool provides the functionality to describe important specific locations on objects and their relationships to one another. Key points can be used on their own or associated with a segmented annotation. Each point has its own ID, label, list of connected points, and a visibility property, indicating whether the object the point represents is shown or is obscured in some way. Points can be dragged to new locations after being placed, and relationships are created by clicking on corresponding points.

E. Deep Extreme Cut

Deep extreme cut (DEXTR) \cite{13} is semi-automated tool for object segmentation, requiring four only points to be defined by the user to produce precise results. This manual labeling technique produces bounding boxes using the extreme left, right, top, and bottom points of an object instead of the traditional two-point approach. Although twice the input points, the four-point approach was shown to significantly reduce labeling time, as two-point bounding box starting coordinates are often difficult to estimate and require additional adjustment.

The four points are used to guide a convolutional neural network (CNN) which was previously trained on manually annotated examples. The performance measured using intersection over union on unseen categories during training was approximately 80%.

The padding surrounding the bounding box created by the four points can be adjusted through a UI parameter to reduce the effect of errors when defining the extreme points. The resulting annotation is converted into a polygon which can be further manually refined by either moving individual vertices or by using one of the other annotation tools.

F. Mask R-CNN

Mask R-CNN \cite{8} is a deep learning model using convolutional neural networks which learn how to segment every object instance in an image. While this type of model may be the final objective of annotating a dataset, an intermediate version can be used to pre-annotate a portion of image objects and improve overall efficiency.

After an initial fraction of a dataset is annotated, a pre-trained Mask R-CNN model is fine-tuned on the annotated object classes. The training input to a Mask R-CNN model are the annotations made using the techniques previously described.

Once a model is trained the auto-annotate button in the user interface is activated. When pressed, the currently selected
image is sent to the model’s API, which returns a list of objects and their segmentations as polygons. Each object’s polygon is added to the image and can be manipulated using the other techniques to correct errors.

As a larger fraction of the dataset is annotated, the Mask R-CNN model performance improves, further increasing annotation efficiency by requiring fewer corrections.

III. Annotation pipeline

A. Collect images

When collecting images for use with deep learning it is important to consider the intended application of the models. The features learned during the training process are exclusivity derived from the data provided, and if the dataset is biased in an unexpected way, model results can be misleading.

In order to reduce bias between and within object classes, the number of samples between classes should equal and each class should have a minimum of 1000. Variations in the appearance of samples collected should reflect the variation expected during application. In general more samples are required with a less constrained environments.

Another important step to building a dataset is to define a clear problem definition. For example, if locating a specific type of fruit within an image a single class may be sufficient. When grading fruit for ripeness, the dataset should have labels for each stage relevant to the growing and harvesting processes. If predicting when a fruit will reach a ripeness stage, additional metadata indicating a relative measure of time between samples will be required.

The selection of camera configuration and lighting requires careful attention, as they may introduce sources of bias if they are consistent within classes but different between them. This can become especially prominent when inter-class differences are small, as with fruit ripeness or leaf disease applications. Models may learn to discriminate samples based on inconspicuous features such as image noise or white balance.

The “generate” feature of the annotation tool downloads a set of images from Google associated with a selected keyword, and can be used to create a preliminary dataset or to augment an existing one with a wider set of samples.

B. Define datasets, object categories, and metadata

Once images have been collected, a dataset name, object categories, and any additional metadata must be defined. Once this information is recorded by the tool, a corresponding directory on the users’ filesystem will be created to store dataset images. Images can be added to the dataset by placing them into the directory. Labels can automatically be applied to whole images by using descriptive directory names. For example, a directory can be created for each of the stages of tomato ripening, and images can be organized matching each stage. This process can help improve efficiency by reducing the amount of meta-data manually entered during the annotation process.

Using common object categories across datasets allows for the automatic creation meta datasets. When exporting, images containing selected categories can be grouped into larger or more specific datasets.

C. Segment instances and assign metadata

The tool has provisions for adding multiple user accounts, which will be associated with the annotations added to images. The super-user defines the dataset, object categories, and metadata for others to use. Users can be configured to start with an empty image and only see their own annotations, or to begin with a copy of another users result. This feature is intended to help increase efficiency and produce more accurate labels through the combination of multiple results.

In the dataset overview section, image are presented in a grid with annotations overlaid and a note indicating the number of objects annotated. Annotations can be added or modified by selecting an image.

On the annotation view, labels can be added using any of the previously described techniques. A list of annotations is presented in a sidebar which can be used to modify or delete individual labels. Hovering the mouse cursor over each annotation reveals its label and metadata, and double-clicking it brings up a dialog to edit those details.

Work is automatically saved periodically and steps can be undone to correct mistakes. Several per-user statistics are recorded during annotation, including number of images annotated, average annotation sizes, and time per annotation and per image.

Figure 1. Image labeling tool user interface. Labeling techniques are chosen using icons on the left. Annotated objects are listed in the right sidebar. Hovering over an annotation displays its related metadata.

IV. Dataset format

File format conventions have played an important role in standardizing and advancing the state of many digital systems. A common dataset format can help facilitate and accelerate new applications and research in agricultural image scene understanding.

In order to integrate more closely with the general computer vision community the dataset format chosen closely follows the common objects in context (COCO) dataset. COCO is an influential dataset, used for pre-training models and as a benchmark for tracking the state-of-the-art. Maintaining compatibility with COCO provides access to an extensive array of existing support options for images, annotations, and for evaluating results.
The labeling tool generates annotation data in an extended COCO format, adding features helpful for agricultural applications. The dataset format uses JSON to store information about images and annotations using attribute-value pairs. The extended data is stored under the “poco” (Plant Objects in Context) attribute of each COCO data structure. When used with native COCO tools the extra attributes simply ignored and do not impacting original functionality. Figure 2 shows the POCO dataset format.

```
annotation {
  "id": int,
  "image_id": int,
  "category_id": int,
  "segmentation": RLE or polygon,
  "bbox": [x, y, width, height],
  "keypoints": [x1,y1,v1,...],
  ...
  "poco": {
    "maturity_stage": str,
    "plant_id": int,
    "keypoint_names": [str],
    "skeleton": [edge],
    ...
    }
}
categories[{
  "id": int,
  "name": str,
  ...
  "poco": {
    "type": str,
    }
}]
```

Figure 2. Extended attributes for object detection and key point tracking in the COCO dataset format. All extended information is contained within “poco” (Plant Objects in Context) attributes. In order to allow for dynamic skeleton shape each annotation has its own associated skeleton, instead of one defined for the entire category.

V. PLANT OBJECTS IN CONTEXT DATASET

Several thousand agricultural objects were annotated using the labeling tool to create the initial series of POCO (Plant Objects in Context) datasets. Images were organized into subsets to provide finer-grained download options for researchers. The three subsets created, corresponding to different scene understanding and agricultural applications.

1) Plant parts
2) Disease and pests
3) Plant development

The first subset contains images and annotations of a variety of plant parts, including fruit, leaves, and stems. This subset currently focuses on plants grown in greenhouses.

The second subset consists of images from the PlantVillage dataset with annotations indicating the extent of disease on each leaf. This dataset is aimed at better estimating leaf disease severity.

The third dataset contains time-lapse images of plants naturally developing. The particular images in the initial dataset show tomato plants growing in a commercial organic greenhouse over the course of 30 days.

VI. CONCLUSION

In this paper we introduced a labeling tool multiple manual, semi-automatic, and fully automatic annotation techniques, a new dataset format for use in agricultural application, and an initial dataset with annotations for plant parts, disease, and plant development.

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