Instance segmentation for automated weeds and crops detection in farmlands

Segmentación de instancias para detección automática de malezas y cultivos en campos de cultivo

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Keywords

Deep learning; instance segmentation; computer vision; precision agriculture; biodiversity informatics; weed detection; species identification.

Abstract

Based on recent successful applications of Deep Learning techniques in classification, detection and segmentation of plants, we propose an instance segmentation approach that uses a Mask R-CNN model for weeds and crops detection on farmlands. We evaluated our model performance with the MSCOCO average precision metric, contrasting the use of data augmentation techniques. Results obtained show how the model fits very well in this context, opening new opportunities to automated weed control solutions, at larger scales.

Palabras clave

Aprendizaje profundo; segmentación de instancias; visión por computadora; agricultura de precisión; bioinformática; detección de malezas; identificación de especies.

Resumen

Con base en las recientes aplicaciones exitosas de técnicas de Aprendizaje Profundo en la clasificación, detección y segmentación de plantas, proponemos un enfoque de segmentación de instancias utilizando un modelo Mask R-CNN para la detección de malezas y cultivos en tierras de cultivo. Evaluamos el rendimiento de nuestro modelo con la métrica de precisión promedio de MSCOCO, contrastando el uso de técnicas de aumento de datos. Los resultados obtenidos muestran cómo el modelo se adapta muy bien en este contexto, abriendo nuevas oportunidades para soluciones automatizadas de control de malezas a gran escala.

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Introduction

Biologists, agronomists, and other experts in the area of agro-biodiversity science are experiencing a digital era that provides access to massive amounts of visual data. For instance, natural history collections worldwide have recently largely digitized and made freely available large amounts of digital images from their vast collections. In addition to the big data currently available, new technological developments such as autonomous engines applied to agricultural field management lead the way for the development of new research aimed at identifying computational approaches to solve agro-biological problems. Thus, a critical current challenge for computer scientists is to take advantage of this large amount of primary data and new technologies to increase the efficiency of agricultural field management processes.

Fortunately, impressive recent advances in Artificial Intelligence open up new hopes for extracting knowledge automatically from large amounts of visual data. In particular, the use of Deep Learning has had a notable success in the automated classification of images, achieving levels of accuracy of around 90% [13] for the identification of species from plant leaf images.

Furthermore, challenges such as PlantCLEF (conducted in the context of the LifeCLEF2 Lab, [6] organized since 2011, have demonstrated the power of Deep Learning for plant species identification under more demanding conditions, for example, with large species datasets (both in terms of number of species and number of images) and using noisy images of many plants components (e.g., leaves, flowers, and fruits).

Nowadays, a large number of farmers and agronomists use herbicides to deal with weeds that affect growing stages on crops due to the competition for resources (water, light, nutriments). Nevertheless, the use of herbicides, in spite of its efficiency, is dangerous not only for the environment, but also for human health.

In this work, we propose a system capable of automatically detecting and segmenting weed and crop species from photographic material taken *in situ* in farmlands that can be used by an autonomous agent, such as a robot, for weed control tasks with eco-friendly methods.

Related work

Machine learning technologies have recently and largely transformed several aspects of agricultural activities [8], [7]. This includes, for example, the development of new approaches for plant diseases identification on isolated plants species such as maize [17], apple [11], wheat [5], or potato [14] ; in addition to yield production [1] and crops quality evaluation [18]. As weed control has a major impact on agricultural production, several studies have been conducted to improve their detection, such as [15]. Nevertheless, the majority of these studies focus on a few crops or weed species (such as in [2]) and do not try to identify various weed species, in various agricultural systems. Our approach tries to solve that problem, in order to increase the benefit of the use of new deep learning technologies in agriculture.

Methodology

Dataset description

This research was conducted on two crop species, namely, *Zea mays* (corn) and *Phaseolus vulgaris* (green bean), and the following four common weed species: *Brassica nigra*, *Matricaria chamomilla*, *Lolium perenne*, and *Chenopodium album*. The dataset comprises more than 4.000 photos that were collected either manually with smartphones and other digital cameras, or automatically with digital cameras mounted on a robot. This dataset was produced in such way that it reflects different combinations of crop and weed species, illustrating the whole plant at different angles, distances, plant growth stages, and at different times of the year.

Deep Learning Approach

We propose deep model based on the Mask R-CNN architecture [3] due to its robustness and demonstrated efficiency in instance segmentation tasks and challenges such as MSCOCO, which stands for Microsoft Common Objects in Context [10].

We selected the Facebook's Mask R-CNN benchmark [12] with the official implementation on Pytorch [16]. This benchmark offers a set of pretrained ready-to-use models on the MSCOCO dataset, with different configurations for CNN backbone architectures and approaches for bounding box and segmentation estimation. In this work we chose a ResNet 50 [4] and the Feature Pyramid Networks [9]. Our experiments ran on a NVIDIA Geforce RTX 2080 Ti that uses CUDA 10 in Linux.

2 http://lifeclef.org

Experiments and Results

For our first experiments, we annotated manually 129 images following the MSCOCO annotation format, for the 6 classes of plants, where we took 80% for training and the remaining 20% for testing using the average precision metric as described on MSCOCO challenge, common in instance segmentation tasks.

We applied data augmentation techniques, random horizontal flip, random rotations and random variations on color contrast, saturation, brightness and hue color values; to ensure a more dynamic dataset that avoids an overfitted model.

Figure 1 shows results for this approach. We trained the model with 4.000 iterations, where each iteration represents one batch of images and its annotations. We tested how data augmentation affects the model's performance by applying or not the techniques described before. We reached high performance with an average precision between 0.4 and 0.5 in both cases, segmentation and bounding boxing tasks. Some predictions are shown in Figure 2, in which we can appreciate how precise the prediction is for each detected plant.

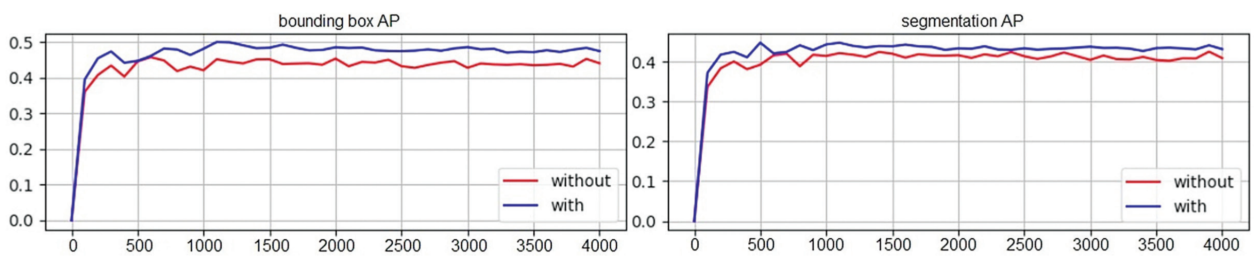

Figure 1. Testing results from the model measured by average precision with 4.000 iterations, red line represents training without data augmentation, blue line, by contrast, with data augmentation.

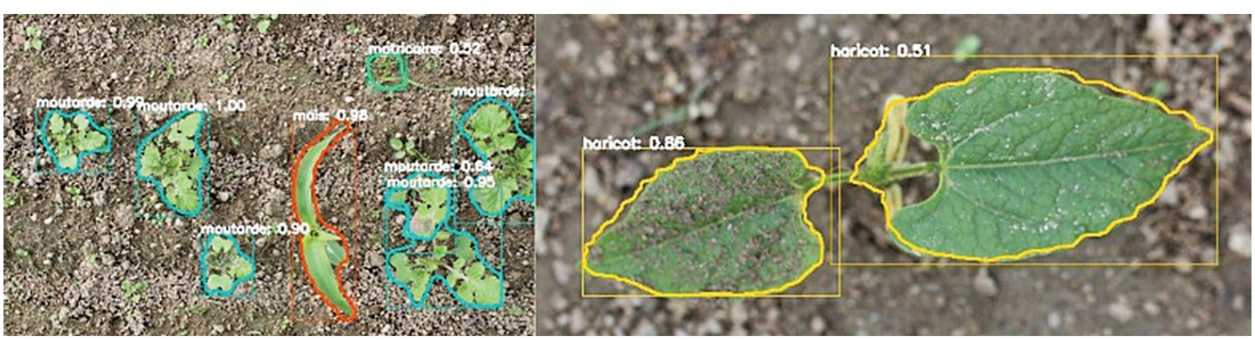

Figure 2. Predictions taken from testing images. Each prediction shows the mask contour (segmentation), bounding box, class predicted, and its individual score that evaluates how good the prediction is.

Conclusions and Future work

We find the results shown on figure 1 and 2 very promising, instance segmentation is a singularly demanding task where the state-of-art performance in MSCOCO reaches 0.5 of average precision. Particularly, the use of Mask R-CNN as baseline fits very well for weeds and crops detection tasks reaching similar results to the state-of-art. As we can see in figure 2, in some cases, the predicted mask seems better than a manual human-made mask. The experiments have shown the importance of using data augmentation and how it enhances the model's performance, therefore, we want to test more data augmentation techniques and more model configurations in order to get a model with the best performance to be used in a real situation by an autonomous robot.

During the annotation process, we faced a common problem, namely, the highly time-consuming task of annotating massive data, especially in this context, where the annotation process involves drawing manually masks for each object of interest in each image. We are working on an automatic active learning system to deal with this problem and annotate more training data in much less time with less human interaction, as we have more than 4.000 images available.

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