# Machine Learning for Plant Phenotyping Needs Image Processing

**Article** *in* Trends in Plant Science · December 2016

DOI: 10.1016/j.tplants.2016.10.002



**3 authors:**

Sotirios Tsaftaris
The University of Edinburgh


Massimo Minervini
IMT School for Advanced Studies Lucca


Hanno Scharr
Forschungszentrum Jülich

Letter

# Machine Learning for Plant Phenotyping Needs Image Processing

Sotirios A. Tsaftaris,[1,*] Massimo Minervini,[2] and Hanno Scharr[3]

We found the article by Singh *et al.* [1] extremely interesting because it introduces and showcases the utility of machine learning for high-throughput data-driven plant phenotyping. With this letter we aim to emphasize the role that image analysis and processing have in the phenotyping pipeline beyond what is suggested in [1], both in analyzing phenotyping data (e.g., to measure growth) and when providing effective feature extraction to be used by machine learning. Key recent reviews have shown that it is image analysis itself (what the authors of [1] consider as part of pre-processing) that has brought a renaissance in phenotyping [2]. At the same time, the lack of robust methods to analyze these images is now the new bottleneck [3–5] – and this bottleneck is not easy to overcome. As the following aims to illustrate, it is coupled not only to the imaging system and the environment but also to the analytical task at hand, and requires new skills to help deal with the challenges introduced.

A successful high-throughput image-based phenotyping system starts with the imaging approach itself. The choices are to image many plants simultaneously or one plant at a time, requiring movable systems to bring the plant to the camera or vice versa. These systems add cost but have the benefit of isolating the object of interest. In turn, this simplifies its processing, for example facilitating object segmentation, in other words the image analysis process isolating the plant from background (e.g., soil), as Figure 1A shows (many image-processing tasks are related to how we perceive and analyze an object of interest, such as segmentation, detection, tracking, and many others).

When this is not the case, plant segmentation can be extremely complex because here the objects of interest may touch and overlap each other (known as occlusion), as in Figure 1B. In the open field [6] this becomes exceedingly more complex: light variations, plant movements due to wind, and other factors are introduced, and background (e.g., other plants) may resemble the subject of interest, as Figure 1C illustrates. Thus, the process of extracting information from image data is directly linked with the setup and the environment.

In some cases the actual analytical task becomes difficult merely by the information sought-after, as a recent article describes in depth [3]. To offer an example, Figure 1D illustrates the task of segmenting individual plant leaves [7] for estimating per-leaf growth (when this task is repeated in a longitudinal fashion [8]). Here occlusion and lack of discernible boundaries (edges) between leaves make the segmentation task difficult and additional information (e.g., depth) may be required.

While image analysis may help us to identify plant parts and extract relevant traits, typically their agglomeration across a study could provide suitable input for machine learning. There is a need for mechanisms to represent the image data in a way that machine-learning algorithms can use, and this process is known as feature extraction (another component bundled under pre-processing in [1]). At present, features need to be designed and extracted carefully by expert supervision requiring specific domain knowledge (a process known as feature engineering), the translation of this to image-analysis protocols and image filters (e.g., edge detectors) does require significant image-processing expertise and skills. For example, in drought-tolerance studies one can rely on the overall amount of green or yellow pixels as potential features. However, this simple approach may not always allow us to discriminate between stressed and not stressed plants. It is well known in machine learning that finding good features for the application at hand is intrinsic to an effective use of learning approaches (even sophisticated ones). Thus, image processing is key to obtaining accurate and reliable phenotypic results.

Solving the phenotyping bottleneck requires machine learning, but also good image processing and good features, significantly broadening the required skill-set from a practitioner's perspective. The past few years have brought significant progress towards bringing the image-analysis experts closer to plant biology by using a variety of targeted actions to help diffuse skills and know-how. There are currently isolated workshops aimed at training biologists in image analysis (e.g., IAMPS[i]), as well as new workshop series that run in conjunction with major computer vision conferences[ii,iii] to help to introduce new scientists into this exciting application area of image analysis (e.g., Computer Vision Problems in Plant Phenotyping, CVPPP). A recent special issue on computer vision and image analysis in plant phenotyping [9] provided a good summary of the advances that occurred based on these efforts. These workshops also served as the hosting venue to image-based phenotyping challenges[iv], which led to a summarizing collation study [7].

However, we should not dismiss the recent potential to actually devise intelligent algorithms that can start from raw images to arrive directly at a phenotyping decision or trait. After all, this is the promise of deep learning that is making waves in the news when a significant amount of annotated data to learn from is available. These algorithms find optimal features from the raw data (the images) – in a process known as representation learning – which are then

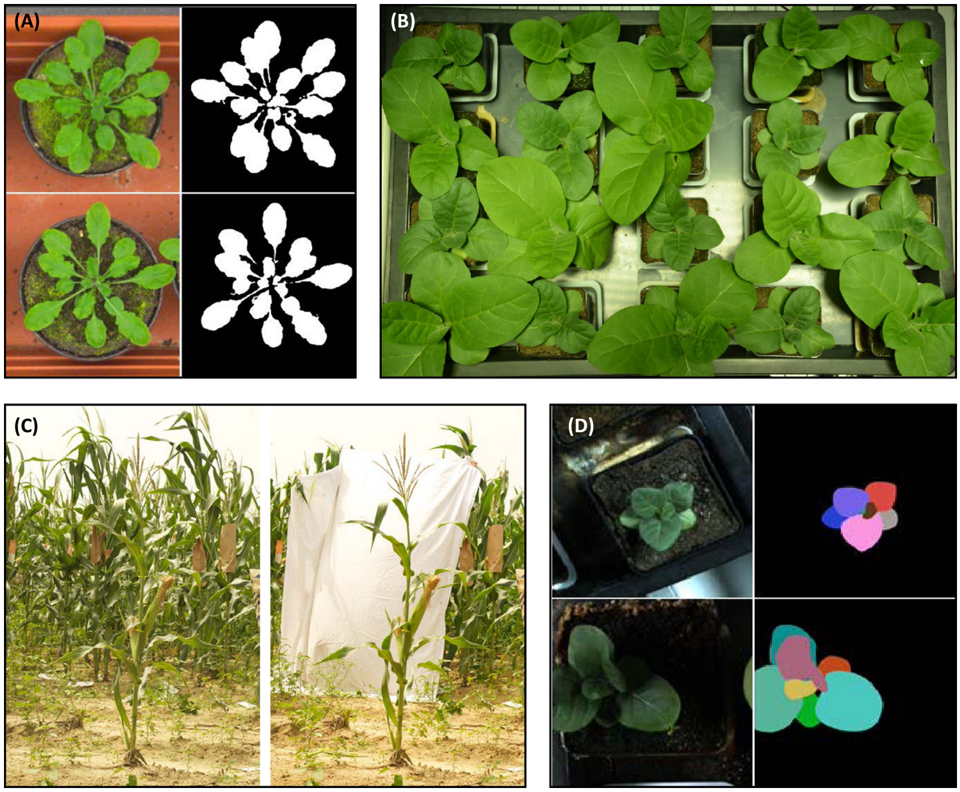


Figure 1. The Process of Segmentation (Delineation of Plant from Background or Leaves from Each Other) Changes in Complexity According to the Imaging Conditions and Task at Hand. (A) Plant segmentation of isolated plants. (B) Tray with overlapping plants. (C) Image from the field (adapted from the dataset presented in [6] reproduced according to the Creative Commons Attribution 4.0 International License, http://creativecommons.org/licenses/by/4.0/). (D) Leaf segmentation of isolated plants. When plants are isolated (A or C, right), reliable segmentation procedures exist. However, when we image many plants together in the lab (B), or in the field (C, left), segmentation becomes much more difficult when plants touch each other and overlap. The process is inherently demanding when objects cannot be isolated before segmentation, for example when we want to delineate each leaf within a single plant (D). Before machine learning can be used for phenotyping, the process of segmentation is more often than not necessary to be able to design good features.

used to train supervised counterparts. We are not there yet, but some early findings have appeared in the context of phenotyping, for example to count leaves for phenotyping purposes [10].

The promise of deep learning (and machine learning in general) cannot be materialized without the availability of annotated data. Thus, recent efforts to lower the entry barrier and accelerate this process were aimed at releasing open-access data together with suitable performance evaluation protocols (see [11,12] and the Plant Phenotyping Datasets resource of the International Plant Phenotyping Network[v]). The diffusion and adoption of such datasets as benchmarks will allow the parallel growth of methods and the fair comparison of approaches across the years to come. In addition, in the field, where experimental design is poorer owing to reduced control over confounding variables and the imaging setup is less than ideal, it is the combination of machine learning and computer vision that can make a significant contribution in meeting phenotyping challenges in this challenging domain. Again the availability of data here will be crucial, and efforts such as that described in [6] are a good start towards this goal.

To conclude, to make leaps towards addressing future issues of agricultural demand, phenotyping will certainly play a key role and will be aided by innovations in machine learning and computer vision as well as by multidisciplinary collaboration among the biological, engineering, and computer sciences.

## Resources

[i] International Workshop on Image Analysis Methods for the Plant Sciences (IAMPS) 2016; https://iamps2016.sciencesconf.org

[ii] CVPPP 2014 in conjunction with the European Conference on Computer Vision (ECCV) 2014; www.plant-phenotyping.org/CVPPP2014

[iii] CVPPP 2015 in conjunction with the British Machine Vision Conference (BMVC) 2015; www.plant-phenotyping.org/CVPPP2015

[iv] Leaf Segmentation and Counting Challenges; www.plant-phenotyping.org/CVPPP2015-challenge

[v] www.plant-phenotyping.org/datasets-home

[1]Institute for Digital Communications, School of Engineering, University of Edinburgh, Edinburgh EH9 3FG, UK

[2]Pattern Recognition and Image Analysis (PRIAn), IMT School for Advanced Studies, Lucca 55100, Italy

[3]Institute of Bio- and Geosciences: Plant Sciences (IBG-2) Forschungszentrum Jülich GmbH, 52425 Jülich, Germany

*Correspondence: S.Tsaftaris@ed.ac.uk (S.A. Tsaftaris).

http://dx.doi.org/10.1016/j.tplants.2016.10.002

## References

1. Singh, A. *et al.* (2016) Machine learning for high-throughput stress phenotyping in plants. *Trends Plant Sci.* 21, 110–124
2. Spalding, E.P. and Miller, N.D. (2013) Image analysis is driving a renaissance in growth measurement. *Curr. Opin. Plant Biol.* 16, 100–104
3. Minervini, M. *et al.* (2015) Image analysis: the new bottleneck in plant phenotyping (applications corner). *IEEE Signal Process. Mag.* 32, 126–131
4. Rousseau, D. *et al.* (2015) Imaging methods for phenotyping of plant traits. In *Phenomics in Crop Plants: Trends, Options and Limitations* (Kumar, J. *et al.*, eds), pp. 61–74, Springer India
5. Pridmore, T.P. *et al.* (2012) What lies beneath: underlying assumptions in bioimage analysis. *Trends Plant Sci.* 17, 688–692
6. Kelly, D. *et al.* (2016) An opinion on imaging challenges in phenotyping field crops. *Mach. Vis. Appl.* 27, 681–694
7. Scharr, H. *et al.* (2016) Leaf segmentation in plant phenotyping: a collation study. *Mach. Vis. Appl.* 27, 585–606
8. Dellen, B. *et al.* (2015) Growth signatures of rosette plants from time-lapse video. *IEEE/ACM Trans. Comput. Biol. Bioinform.* 12, 1470–1478
9. Scharr, H. *et al.* (2016) Special issue on computer vision and image analysis in plant phenotyping. *Mach. Vis. Appl.* 27, 607–609
10. Giuffrida, M.V. *et al.* (2015) Learning to count leaves in rosette plants. In *Proceedings of the Computer Vision Problems in Plant Phenotyping (CVPPP)* (Scharr, H. *et al.*, eds), pp. 1.1–1.13, BMVA Press
11. Minervini, M. *et al.* (2016) Finely-grained annotated datasets for image-based plant phenotyping. *Pattern Recognit. Lett.* 81, 80–89
12. Cruz, J.A. *et al.* (2016) Multi-modality imagery database for plant phenotyping. *Mach. Vis. Appl.* 27, 735–749