Instance segmentation for assessment of plant growth dynamics in artificial soilless conditions

Dmitrii Shadrin
dmitry.shadrin@skolkovotech.ru
Victor Kulikov
V.Kulikov@skoltech.ru
Maxim Fedorov
https://faculty.skoltech.ru/people/maximfedorov

Skolkovo Institute
of Science and Technology
Moscow, Russia

Abstract

The paper presents a technology for plant growth dynamics estimation in an artificial soilless system. The approach consists of a hardware setup for automated image acquisition, plant feeding system, conditional monitoring and a software for automatic leaves segmentation and tracking. The software part of the system relies on a convolution neural network for instance segmentation. To train the neural network a manually annotated dataset was made.

We conducted experiments on salad. Observations were taken for 31 days with the fixed time frame of 30 minutes, resulting in a large image dataset for each plant. It was shown how obtained results on instance segmentation for a particular leaf can serve for detailed reconstruction of the dynamics of plant growth.

Datasets and source code are publicly available:
https://github.com/DmitriiShadrin/PlantGrowthDynamics.

1 Introduction

Precision agriculture attracts more and more latest computation, data-intensive and engineering solutions. As computational capabilities are increasing and application of modern robust mathematical algorithms becomes readily available, it becomes beneficial to use them in precision agriculture. Plant phenotyping by using of an image-based approach opens a wide avenue for automation analysis of increasing variety of plant cultivates. However, it is one of the most challenging tasks in the area and gives us huge benefits in automation of processes and plant function description. Using image-based approach gives us a possibility to avoid a huge amount of empirical and heterogeneous data, parameters and models that describe plant growth dynamics which is essential for making predictive and control models for growth conditions. Also, the number of different plants species are increasing very rapidly and it is almost impossible to perform comprehensive analyses of each for development of a strict mathematical model that describes it growth under different conditions. The capabilities of computer vision systems go beyond the limited abilities of humans to evaluate long-term processes, as an example by continuous plant monitoring and phenotyping it is possible to recognise hidden dynamics in plant growth and this additional information can serve as a very useful tool for future optimisation of plant growth. Having an annotated dataset which has typical annotations such as leaf masks, bounding boxes as well as reference to the regular time frame is crucial for solving such type of tasks. In this paper data set was obtained by using of a hydroponic system for plant growth and it can serve as a good inspiration for how image-based phenotype can be used for in-situ optimisation of plant growth in such closed artificial systems, which is possible to be as a basis for food production in the nearest future.

2 Related work

2.1 Artificial soilless systems

Usage of artificial soilless systems for conducting studies on plant growth is in high demand due to the possibility of full control of environmental conditions. The other advantage is that such systems also can be used for root phenomics studies [23], which can be coupled with image-based technologies [13]. Artificial soilless systems also widely used in the industry and design of them becomes more and more complicated and productivity of these systems was increased during last years [24],[5], [27], [29]. This became possible due to the wide implementation of optimisation technologies in this industry. Such systems proposed in [16], [15], [17], [42]. In-situ image analysis is very popular and well developed for monitoring and diagnosing large-scale crop fields aimed at optimisation of resources consumption [43],[1], [7]. For greenhouses and indoor farming image-based technologies started to implement recently [19], [8]. However, automotive small-scale monitoring and dynamics diagnosing of each plant or each leaf can bring optimisation technologies for greenhouses to a new level [41]. Study of the plant growth dynamics responses to the environment [12] is a key component for improvement of combined image-based and dynamic controlled closed artificial systems. Knowing the plant structure and function in an automotive manner by image processing allow to perform predictive analysis and create recommendation models for growing plant in the best possible conditions in certain resources constraints [11].

2.2 Leaves instance segmentation

There are lots of reviews that describe the development and application of image-based technologies for doing analyses of plant structure and function presented in the literature. A collation study of image-based plant phenotyping by an implementation of leaf segmentation was proposed by Sharr *et al*. [34], more generally possible areas application of convolutional neural networks (CNNs), that are commonly used for plant phenotyping, are described in Gu *et al*. [14]. On the basis of each developed computer vision algorithm evaluation lies good quality annotated database. The most popular the first comprehensive benchmark data that can be used for typical computer vision tasks was obtained by Minervini *et al*. [21] and Cruz *et al*. [3]. Previously obtained datasets that can serve for solving of a smaller range of computer vision problems described in Silva *et al*. [36] and Nilsback *et al*. [26]. High demand on benchmark data can be reflected in the big number of their usage. For example, open-source dataset [21] was used for evaluating precise recurrent instance segmentation algorithm developed by Romera *et al*. [31] or by Ren *et al*. [30] in which it was proposed end-to-end RNN architecture with an attention mechanism. In [4] an instance embedding approach was proposed; pixels of an object are encoded into vectors and clustered using popular mean-shift algorithm.

As the process of annotated dataset preparation is time-consuming and not always precise, for example, it takes a long time to do leaf masking, computer-generated models or so-called synthetic plants proposed in Giuffrida *et al*. [10] and Ubbens *et al*. [37] can help to overcome this problem. For sure it is very attractive to process 3D images of plant growth as we can derive more information about plant structure compare to 2D images, but systems for receiving precise 3D imaging data are typically on several orders of magnitude more expensive than 2D imaging systems. 3D phenotyping platform for laboratory experiments was successfully developed and 3D dataset with environmental information was obtained in one of the most recent works [38]. Different approaches for 3D plant reconstruction described in [9], [20], [28], [40], and [2]. Obtaining high-quality image and data associated with plant growth is highly relevant for training machine learning algorithms, thus affordable hardware and software setup for plant phenotyping is in high demand. One of the proposed system with such features presented in Minervini *et al*. [22] that is equipped with the possibility for leaf area counting based on robust machine learning algorithm. The other one [6] can perform time resolved analyses of plant growth which is also essential for understanding growth phenotypes.

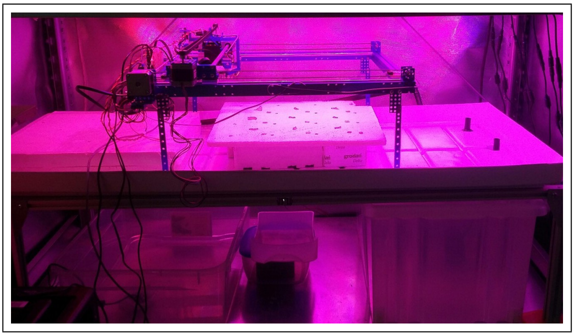
3 Methods

3.1 Experimental setup

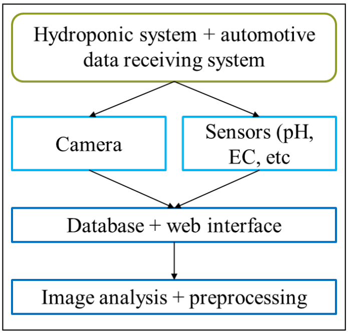
As an experimental setup for growing plants, we designed an assembled hydroponic system based on constant feeding layer technology (NFT). This type of systems showed its' reliability and used worldwide for plants cultivation. In our system, it is possible to grow up to 20 medium size plants in $1m^3$ (salad or dwarf tomatoes as an example) in 0.65 l (10x10x6,5*cm*) rock wool blocks that we used as a substrate. Constant - 1.5 cm. feeding layer was maintained by recirculating of feeding solution that was performed by 10 *Watt* pump and 60-liter tank. We used 150 *Watt* multispectral light emitting diodes (LED) as LEDs' are compact it is much easier to control them during the experiment compare to other types of plant illumination. Performed calculations showed that intensity and spectrum of light and recycling rate (1-2 full recycling of fertiliser per hour) fits the optimal requirements for the common systems of this type. Feeding solution was prepared by using the recommended recipe of popular commercial fertiliser concentrate *Flora NOVA* produced by company GHE. For our particular system period from germination to the end of vegetation for salad is approximately one month. The summary of the system design showed in Table 1. We decided to use the artificial soilless system as it is much easier to maintain all necessary growth parameters in the certain optimal range, thus we can overcome perception-action problems that typically occur when plants are grown traditionally - in the soil. This becomes possible because plant roots are in direct contact with fast recycling feeding solution, the composition of which we can easily control in combination with the second important factor - light. Altogether these lead to fast system response and allow to provide conditions that we need for correct setup of the particular experiment for receiving good quality data. The hydroponic system with image acquisition system is shown in Figure 1a.

Feature	Value/description
Max. amount of plants	20
Illumination	150 *Watt* multispectral LED
Feeding solution recycle	60 liter tank, 10 *Watt* pump and 1.5 *cm* of feeding layer
Substrate	0.65 liter rock wool blocks
Fertiliser	Flora NOVA produced by GHE

Table 1: System hardware design summary



(a)



(b)

Figure 1: (a) Hydroponics system and hardware setup; (b) relations among subsystems

3.2 Image and data collection system

XY plotter *MakeBlock* was assembled and adapted for automotive obtaining raw images of plants. Camera *Logitech c920* was mounted in the working place of the plotter. This design allowed us to take top-down colour photos of each plant by moving the camera in a 2D plane. This approach gave us such benefits as that is was possible to take high-resolution image of each plant separately without shadowing of plants for a long time and also there is no need to perform angle corrections of camera view. The experimental setup was equipped with sensors such as: pH, humidity, electrical conductivity, air and solution temperature, recycling rate of solution. These sensors continuously measured environmental and system parameters and measurements were recorded concurrently along with images to a database each 30-ty minutes. Additional white LEDs were mounted around the digital camera for providing as equal as possible illumination conditions for taking photos. Sensors were calibrated and several tests were performed before launching continuous long-term experiment for dataset collection. The LED system was controlled and had a duty cycle 18h/6h (day/night) at the beginning of the experiment and by the end of the experiment, duty cycle was slightly decreased to 16h/8h (day/night). It is very important to monitor conditions during the experiment, thus custom user-friendly web-interface for monitoring growth conditions was developed. Hardware control and data-receiving sensors was synchronised, also such features as plotter auto-calibration and automotive relaunching of the system were developed as planned experiments are long-term and interruption of it could make all the received data useless. Simplified relations among experimental subsystems demonstrated in Figure 1b. We successfully performed the continuous one-month experiment in which we collected image and environment parameters dataset. The experiment was on growing 9 salad plants. All the condition parameters were maintained in the optimal range during this experiment.

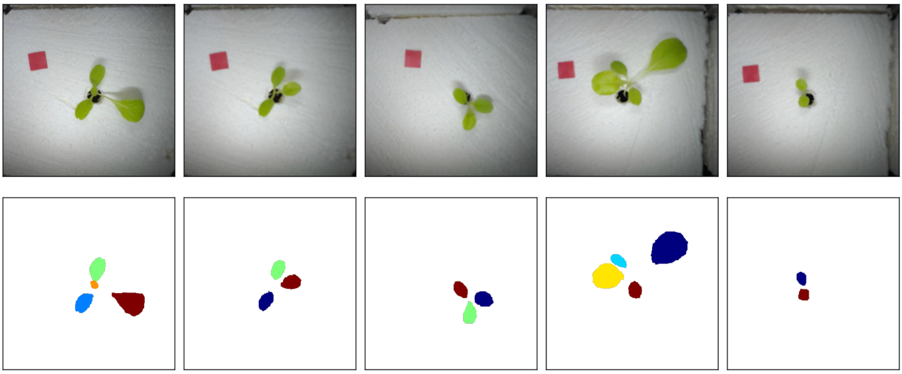


Figure 2: Examples of salad images at different growth stages with corresponding leaf masks; the pictures are taken from *manually annotated* data set.

Totally, during the experiment with salad it was obtained 8541 raw images. Not all of the images were included into the dataset for solving machine vision problems as by the end of the experiment almost all of the plants outgrew and were out of a field of view and had too complicated structure of overlapped leaves.

3.3 Annotated dataset

The system, described in Section 3.1 allowed us to collect the dataset of raw top-down images of plants which were further labelled plants images that is perfect suits for testing semantic and instance segmentation algorithms for phenotype and also opens a wide vista for other types of computer vision tasks. Public available `https://github.com/DmitriiShadrin/PlantGrowthDynamics` dataset includes 4815 raw salad images for the period of 11 days growth after germination and 75 carefully manually annotated image data. All this data has the time reference that gives a possibility for plant growth dynamics assessment. For these images leaves masks and leaves bounding boxes were extracted manually by using online labelling tool *LabelMe* [33]. Figure 2 shows examples of images from the dataset with corresponding leaf masks (bounding boxes were included in the dataset, but are not represented in Figure 2 as the image will be confusing). Totally, 356 leaf masks and bounding boxes were obtained. The dataset contains both: relatively simple annotated images - 62 with three instances, 47 with four instances, and really complicated - eight images with rich structure and 10 instances. By now we annotated 75 images as it was enough for training instance segmentation model, but the amount of annotated images will be increased by our working group in time.

3.4 Image processing

The estimation of individual leaf growth dynamics, requires separation between leaf instances on the image. In order to solve this task we have used Deep Coloring method [18]. Deep Coloring reduces instance segmentation to the task of pixel classification (coloring). The latter task can be accomplished using almost any of the recently developed deep convolutional architectures for semantic segmentation. In this work we have used U-net [32] as semantic segmentation backbone.

Simply speaking, this method enforces all pixels of the same object to take the same color, while also enforcing pixels belonging to different but adjacent object instances to take different colors. The example of output of this method is depicted in Figure 3 (top). A simple component analysis allows to extract individual leaves on the image.

To train instance segmentation network we have used the annotated dataset described in section 3.3. The training set was split into two parts: training and test set, 65 and ten image respectively. The training set was augmented with random crops, rotations, flips and scaling. Other training parameter were taken from [18].The instance segmentation accuracy, achieved on our test set was 0.74 symmetric best Dice coefficient (SBD) (c.f. [34]). This score is slightly worst that the score of [18] on CVPPP A1 dataset, were the instance segmentation method achieves 0.80 SBD.

The instance segmentation algorithm produces labels for instances independently for each image and they may differ between sequential frames. In order to estimate the leaf growth dynamics we have implemented a post-processing step, that tracks labels and makes sure that each instance will have with same index for the whole sequence. For each sequential pair of labeled images we solve the linear assessment problem [25] based on the inverted pairwise intersection over union between instance. Linear assessment provides us correspondences between labels, the labels on the second frame are modified to match the labels from the first frame. To make this procedure more stable, over-segmented images were removed from the each sequence.

We have parametrised the leaves growth dynamics according to the model proposed in [39], [35]:

$$S(t) = S_{max} * \frac{S_0 e^{\mu t}}{S_{max} + S_0(e^{\mu t} - 1)}, \tag{1}$$

where S_{max} and S_0 are constant and set to $100 cm^2$ and $0.1 cm^2$ respectively according to [39], μ is the estimated parameter, that can be used to compare growth dynamics between plants. That model shows the correspondence between size of the leaves and time.

Plant sample	Growth rate of 3-rd leaf cm^2/day	Growth rate of 4-th leaf cm^2/day
1	0.57	0.77
2	0.61	0.75
3	0.60	0.80
4	0.61	1.00
5	0.62	-
6	0.61	0.86
7	0.59	0.94
8	-	-
9	0.57	0.93
	0.597 ± 0.018	

Table 2: Growth rate estimation

4 Results

We reconstructed dynamics of growth for each plant in the experiment, described in Section 3.1 for the period of 11 days after germination. For each image, the instance segmentation

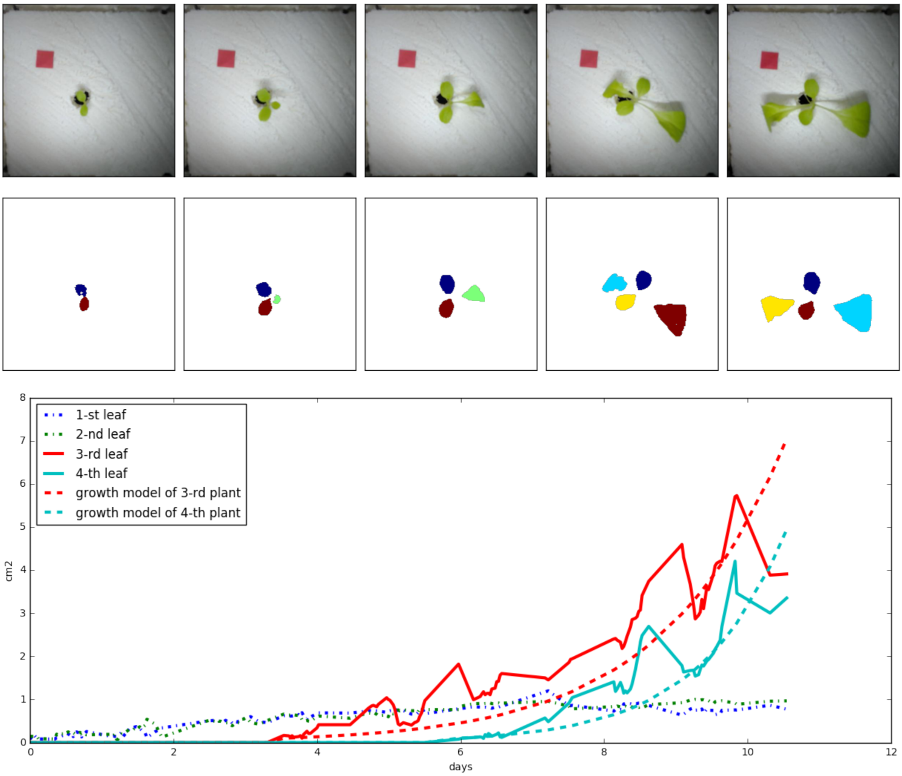


Figure 3: Results of dynamics reconstruction. Dotted lines depicted the fitted growth model for third and fourth leaves. Pictures above represents raw salad images with segmented leaf instances masks by *instance recognition*; the images approximately correspond to the graph time frame

network was applied provided with detailed masks of individual leaves Figure 3 (top). Each leaf instance was tracked thought all time sequence providing information about its size in pixels. In order to convert the size to real-world units a calibration objects (red square of size $1 \times 1cm$) was used.

Observed growth dynamics is presented in Figure 3 (bottom), where we can observe the exponential growth of third and fourth leaves. first and second leaves that appeared in the beginning grew up to $1cm^2$ and than size remained stable for all investigated plants. This is happened due to physiological reasons in plant function. For almost all plants we received similar and feasible growth rate μ which are presented in Table 2. It wasn't possible to calculate such dynamics for eighth salad sample due to its' side location relative to the camera. For the fifth salad sample, the fourth leaf didn't appear by the 11-th day.

5 Conclusions

We have developed and presented a new method for analysis and prediction of plant growth dynamics by a combination of modern computer vision and modelling techniques. We designed and assembled an experimental setup which is based on a combination of hydroponic and imaging systems; as a result of the study a large collection of salad growth images had been collected for 31 days with the time frame of 30 minutes. In addition, an annotated dataset for 11 days growth was obtained under controlled conditions. Our methodology was tested on the obtained datasets; the results of the tests shown the possibility of making the detailed reconstruction of dynamics of plant growth. We hope that this pilot study can provide a background for development of systems for automatic optimisation of plant growth in artificial conditions.

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References

[1] Mahyar Aboutalebi, Alfonso F Torres-Rua, and Niel Allen. Multispectral remote sensing for yield estimation using high-resolution imagery from an unmanned aerial vehicle. In *Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping III*, volume 10664, page 106640K. International Society for Optics and Photonics, 2018.

[2] Ayan Chaudhury, Christopher Ward, Ali Talasaz, Alexander G Ivanov, Norman PA Huner, Bernard Grodzinski, Rajni V Patel, and John L Barron. Computer vision based autonomous robotic system for 3d plant growth measurement. In *2015 12th Conference on Computer and Robot Vision (CRV)*, pages 290–296. IEEE, 2015.

[3] Jeffrey A Cruz, Xi Yin, Xiaoming Liu, Saif M Imran, Daniel D Morris, David M Kramer, and Jin Chen. Multi-modality imagery database for plant phenotyping. *Machine Vision and Applications*, 27(5):735–749, 2016.

[4] Bert De Brabandere, Davy Neven, and Luc Van Gool. Semantic instance segmentation with a discriminative loss function. *arXiv preprint arXiv:1708.02551*, 2017.

[5] PC P De Silva and PC A De Silva. Ipanera: An industry 4.0 based architecture for distributed soil-less food production systems. In *Manufacturing & Industrial Engineering Symposium (MIES)*, pages 1–5. IEEE, 2016.

[6] Stijn Dhondt, Nathalie Gonzalez, Jonas Blomme, Liesbeth De Milde, Twiggy Van Daele, Dirk Van Akoleyen, Veronique Storme, Frederik Coppens, Gerrit TS Beemster, and Dirk Inzé. High-resolution time-resolved imaging of in vitro arabidopsis rosette growth. *The Plant Journal*, 80(1):172–184, 2014.

[7] T Duan, SC Chapman, Y Guo, and B Zheng. Dynamic monitoring of ndvi in wheat agronomy and breeding trials using an unmanned aerial vehicle. *Field Crops Research*, 210:71–80, 2017.

[8] Michel Edmond Ghanem, Hélène Marrou, and Thomas R Sinclair. Physiological phenotyping of plants for crop improvement. *Trends in Plant Science*, 20(3):139–144, 2015.

[9] Jonathon A Gibbs, Michael Pound, Andrew P French, Darren M Wells, Erik Murchie, and Tony Pridmore. Approaches to three-dimensional reconstruction of plant shoot topology and geometry. *Functional Plant Biology*, 44(1):62–75, 2017.

[10] Mario Valerio Giuffrida, Hanno Scharr, and Sotirios A Tsaftaris. Arigan: Synthetic arabidopsis plants using generative adversarial network. In *Proceedings of the 2017 IEEE International Conference on Computer Vision Workshop (ICCVW), Venice, Italy*, pages 22–29, 2017.

[11] Mahmood R Golzarian, Ross A Frick, Karthika Rajendran, Bettina Berger, Stuart Roy, Mark Tester, and Desmond S Lun. Accurate inference of shoot biomass from high-throughput images of cereal plants. *Plant Methods*, 7(1):2, 2011.

[12] Christine Granier and Denis Vile. Phenotyping and beyond: modelling the relationships between traits. *Current opinion in plant biology*, 18:96–102, 2014.

[13] Peter J Gregory, A Glyn Bengough, Dmitri Grinev, Sonja Schmidt, W Bill TB Thomas, Tobias Wojciechowski, and Iain M Young. Root phenomics of crops: opportunities and challenges. *Functional Plant Biology*, 36(11):922–929, 2009.

[14] Jiuxiang Gu, Zhenhua Wang, Jason Kuen, Lianyang Ma, Amir Shahroudy, Bing Shuai, Ting Liu, Xingxing Wang, Li Wang, Gang Wang, et al. Recent advances in convolutional neural networks. *arXiv preprint arXiv:1512.07108*, 2015.

[15] Ahmad Nizar Harun, Robiah Ahmad, and Norliza Mohamed. Plant growth optimization using variable intensity and far red led treatment in indoor farming. In *Smart Sensors and Application (ICSSA), 2015 International Conference on*, pages 92–97. IEEE, 2015.

[16] Werner Kloas, Roman Groß, Daniela Baganz, Johannes Graupner, Henrik Monsees, Uwe Schmidt, Georg Staaks, Johanna Suhl, Martin Tschirner, Bernd Wittstock, et al. A new concept for aquaponic systems to improve sustainability, increase productivity, and reduce environmental impacts. *Aquaculture Environment Interactions*, 7(2):179–192, 2015.

[17] Toyoki Kozai, Genhua Niu, and Michiko Takagaki. *Plant factory: an indoor vertical farming system for efficient quality food production*. Academic Press, 2015.

[18] Victor Kulikov, Victor Yurchenko, and Victor Lempitsky. Instance segmentation by deep coloring. *arXiv preprint*, 2018.

[19] Lei Li, Qin Zhang, and Danfeng Huang. A review of imaging techniques for plant phenotyping. *Sensors*, 14(11):20078–20111, 2014.

[20] Jie Liang, Ali Zia, Jun Zhou, and Xavier Sirault. 3d plant modelling via hyperspectral imaging. In *Proceedings of the IEEE International Conference on Computer Vision Workshops*, pages 172–177, 2013.

[21] Massimo Minervini, Andreas Fischbach, Hanno Scharr, and Sotirios A Tsaftaris. Finely-grained annotated datasets for image-based plant phenotyping. *Pattern recognition letters*, 81:80–89, 2016.

[22] Massimo Minervini, Mario V Giuffrida, Pierdomenico Perata, and Sotirios A Tsaftaris. Phenotiki: an open software and hardware platform for affordable and easy image-based phenotyping of rosette-shaped plants. *The Plant Journal*, 90(1):204–216, 2017.

[23] Naoko Miyamoto, Ernst Steudle, Tadashi Hirasawa, and Renee Lafitte. Hydraulic conductivity of rice roots. *Journal of Experimental Botany*, 52(362):1835–1846, 2001.

[24] JI Montero, E Baeza, E Heuvelink, J Rieradevall, P Muñoz, M Ercilla, and C Stanghellini. Productivity of a building-integrated roof top greenhouse in a mediterranean climate. *Agricultural Systems*, 158:14–22, 2017.

[25] J. Munkres. Algorithms for the assignment and transportation problems. *Journal of the Society of Industrial and Applied Mathematics*, 5(1):32–38, March 1957.

[26] Maria-Elena Nilsback and Andrew Zisserman. Delving deeper into the whorl of flower segmentation. *Image and Vision Computing*, 28(6):1049–1062, 2010.

[27] Pedro Palencia, Jordi Giné Bordonaba, Fátima Martínez, and Leon A Terry. Investigating the effect of different soilless substrates on strawberry productivity and fruit composition. *Scientia horticulturae*, 203:12–19, 2016.

[28] Michael P Pound, Andrew P French, Erik H Murchie, and Tony P Pridmore. Automated recovery of 3d models of plant shoots from multiple colour images. *Plant Physiology*, pages pp–114, 2014.

[29] P Agung Putra and Henry Yuliando. Soilless culture system to support water use efficiency and product quality: a review. *Agriculture and Agricultural Science Procedia*, 3:283–288, 2015.

[30] Mengye Ren and Richard S Zemel. End-to-end instance segmentation with recurrent attention. In *Proceedings of the 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA*, pages 21–26, 2017.

[31] Bernardino Romera-Paredes and Philip Hilaire Sean Torr. Recurrent instance segmentation. In *European Conference on Computer Vision*, pages 312–329. Springer, 2016.

[32] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, pages 234–241. Springer, 2015.

[33] Bryan C Russell, Antonio Torralba, Kevin P Murphy, and William T Freeman. Labelme: a database and web-based tool for image annotation. *International journal of computer vision*, 77(1-3):157–173, 2008.

[34] Hanno Scharr, Massimo Minervini, Andrew P French, Christian Klukas, David M Kramer, Xiaoming Liu, Imanol Luengo, Jean-Michel Pape, Gerrit Polder, Danijela Vukadinovic, et al. Leaf segmentation in plant phenotyping: a collation study. *Machine vision and applications*, 27(4):585–606, 2016.

[35] Dmitrii Shadrin, Andrey Somov, Tatiana Podladchikova, and Rupert Gerzer. Pervasive agriculture: Measuring and predicting plant growth using statistics and 2d/3d imaging. In *2018 IEEE International Instrumentation and Measurement Technology Conference (I2MTC)*. IEEE, 2018.

[36] Pedro FB Silva, Andre RS Marcal, and Rubim M Almeida da Silva. Evaluation of features for leaf discrimination. In *International Conference Image Analysis and Recognition*, pages 197–204. Springer, 2013.

[37] Jordan Ubbens, Mikolaj Cieslak, Przemyslaw Prusinkiewicz, and Ian Stavness. The use of plant models in deep learning: an application to leaf counting in rosette plants. *Plant methods*, 14(1):6, 2018.

[38] Hideaki Uchiyama, Shunsuke Sakurai, Masashi Mishima, Daisaku Arita, Takashi Okayasu, Atsushi Shimada, and Rin-ichiro Taniguchi. An easy-to-setup 3d phenotyping platform for komatsuna dataset. In *Computer Vision Workshop (ICCVW), 2017 IEEE International Conference on*, pages 2038–2045. IEEE, 2017.

[39] Fred van Eeuwijk, Daniela Bustos-Korts, Emilie J Millet, Martin Boer, Willem Kruijer, Addie Thompson, Marcos Malosetti, Hiroyoshi Iwata, Roberto Quiroz, Christian Kuppe, et al. Modelling strategies for assessing and increasing the effectiveness of new phenotyping techniques in plant breeding. *Plant Science*, 2018.

[40] Manuel Vázquez-Arellano, Hans W Griepentrog, David Reiser, and Dimitris S Paraforos. 3-d imaging systems for agricultural applicationsâĂŤa review. *Sensors*, 16(5):618, 2016.

[41] Sarathi M Weraduwage, Jin Chen, Fransisca C Anozie, Alejandro Morales, Sean E Weise, and Thomas D Sharkey. The relationship between leaf area growth and biomass accumulation in arabidopsis thaliana. *Frontiers in Plant Science*, 6:167, 2015.

[42] D Yumeina, GK Aji, and T Morimoto. Dynamic optimization of water temperature for maximizing leaf water content of tomato in hydroponics using an intelligent control technique. In *V International Symposium on Applications of Modelling as an Innovative Technology in the Horticultural Supply Chain-Model-IT 1154*, pages 55–64, 2015.

[43] X Zhou, HB Zheng, XQ Xu, JY He, XK Ge, X Yao, T Cheng, Y Zhu, WX Cao, and YC Tian. Predicting grain yield in rice using multi-temporal vegetation indices from uav-based multispectral and digital imagery. *ISPRS Journal of Photogrammetry and Remote Sensing*, 130:246–255, 2017.