DOI 10.18699/SBB-2022-351

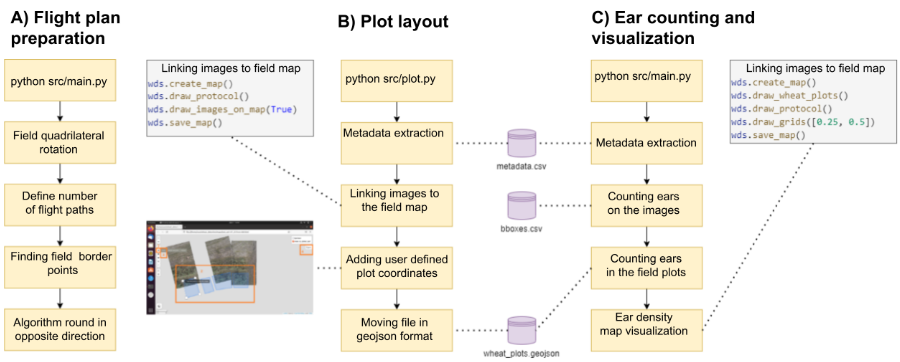
Wheat yield estimation based on analysis of UAV images at low altitude

Kozhekin M.[1, 2]*, Genaev M.[1, 2], Koval V.[1, 2], Slobodchikov A.[3], Afonnikov D.[1, 2]
[1] *Institute of Cytology and Genetics, SB RAS, Novosibirsk, Russia*
[2] *Kurchatov Genomic Center of the Institute of Cytology and Genetics, SB RAS, Novosibirsk, Russia*
[3] *Siberian Research Institute of Plant Production and Breeding – Branch of the Institute of Cytology and Genetics, SB RAS, Novosibirsk, Russia*
* *m.kozhekin@g.nsu.ru*

Key words: wheat detection system, computer vision, UAV

Motivation and Aim: Protocols for manually counting the density of ears in crops have been the only way to estimate yields for a long time. However, this method is labour-intensive and time-consuming. An alternative is the development of automated systems operating in the field [1]. Most of such systems allow to obtain 2D images of crops and use computer vision methods for their automatic processing, in particular, for counting ears in the image. Modern methods of image analysis based on neural network algorithms and deep learning allow ears identification on the image of crops and counting their number with high accuracy [2–4]. The use of these technologies is justified due to the lower cost and acceptable accuracy compared to the labour costs of manual human observation.
Methods and Algorithms: At this research faster rcnn [5] and efficient-det [6] object detection models were trained and evaluated on 3 datasets: GWHD 2020, 2021 [7, 8] and wheat images collected in a field of SibNIIRS on July 29, 2021 at stage of ear formation phase. Manual counting of ears was performed after harvesting from the area of 0.25 m^2. The number of productive stems was counted in four replications.
The ear recognition accuracy estimation was used for neural network prediction results on an additional sample of images that were added to the 2021 GWHD dataset (not used in the network training). The average precision (AP) and mean average precision (mAP) for bounding boxes identified by neural networks with IoU over 50 % were used as described in [9]. After image processing and ear counting in the WDS system, we marked the coordinates of the plots. The system counted the number of ears per plot. Knowing that the area of each plot is equal to 24.75 m^2, we obtain the ear density. Pearson and Spearman correlation coefficients were used to compare the values obtained by manual counting and our system.
Results: The results of testing the models of recognition and spike counting in the image are shown in table below.
Model testing was performed on the 27 sets of images added to GWHD in 2021. Each set is provided by one of 10 institutions. The variability of performance metrics and shooting conditions varies greatly. The best accuracy (73.54 on the mAP metric) is provided by the efficient-det model. The arithmetic mean mAP for these samples is 41.40 for faster rcnn and 37.51 for efficient-det. A comparison of the ear density estimates made using our approach and those made manually showed that the Spearman and Pearson coefficient values between them are 0.6176, p-value = 0.0013 and 0.5405, p-value = 0.0064 respectively. The structure of developed WDS package is shown below: (A) construction of the flight plan on the quadrangular field by 4 points, (B) marking of plot boundaries, (C) counting the number of ears on each plot.

	frcnn	effdet		frcnn	effdet		frcnn	effdet
ARC_1	39.81	34.63	CIMMYT_3	46.72	33.29	Terraref_1	19.29	14.60
Arvalis_10	50.53	69.74	KSU_1	22.03	38.33	Terraref_2	6.89	4.97
Arvalis_11	29.33	35.06	KSU_2	37.49	39.99	Ukyoto_1	34.25	36.62
Arvalis_12	51.37	40.97	KSU_3	30.52	37.33	ULiège-GxABT_1	25.14	33.68
Arvalis_7	62.79	43.13	KSU_4	13.61	26.00	UQ_10	49.70	39.84
Arvalis_8	57.31	47.16	NAU_2	72.45	69.98	UQ_11	30.18	24.95
Arvalis_9	44.60	36.09	NAU_3	73.26	73.54	UQ_7	50.64	46.49
CIMMYT_1	37.84	20.91	NMBU_1	55.72	37.84	UQ_8	41.23	32.99
CIMMYT_2	63.66	42.13	NMBU_2	33.13	22.17	UQ_9	38.28	30.33



Software package, instructions and scripts for installation are available at https://github.com/Sl07h/wheat_detection.

Conclusion: We have developed a software package to estimate wheat yield based on counting the number of ears in UAV images of wheat crops, which does not require image stitching. The software package allows to form a flight plan for low altitude flying over the crops (~3 m), to count the number of ears on each image by a deep learning neural network, to link the obtained images to the crop map, and to visualize the density of ears for the studied crops.

Acknowledgements: The study is supported by the Kurchatov Genomic Centre of the Institute of Cytology and Genetics, SB RAS (075-15-2019-1662).

References

1. Jin X. et al. *IEEE Geosci*. 2020;9(1):200-231.
2. Khaki S. et al. Wheatnet: A lightweight convolutional neural network for high-throughput image-based wheat head detection and counting. arXiv preprint arXiv:2103.09408. 2021.
3. Md Mehedi et al. *Plant Methods*. 2018;14(100).
4. Zhao J. et al. *Remote Sensing*. 2021;13(16):3095.
5. Ren S. et al. Faster r-cnn: Towards real-time object detection with region proposal networks. In: Proceedings of the 28th International Conference on Neural Information Processing Systems, NIPS'15, 7-12 Dec 2015, Montreal, Canada. 2015.
6. Tan M., Pang R., Le Q.V. Efficientdet: Scalable and efficient object detection. In: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, CVPR, 14-19 Jun 2020, remote. 2020.
7. David E. et al. *Plant Phenomics*. 2020;2020:3521852.
8. David E. et al. *Plant Phenomics*. 2021;2021:9846158.
9. Yu J., Zhang W. *Sensors*. 2021;21(9):3263.