Spike App: Automated Image Analysis of Grain Spikes In Greenhouse

High throughput Cereal Crop Analysis with Advanced Spike Detection Toolbox

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Overview

This study addresses the challenge of detecting grain spikes in RGB images originating from high-throughput phenotyping platforms for crop yield assessment. Grain spikes are crucial but difficult to discern due to their minimal presence and similarity to surrounding leaves, posing a challenge even for advanced deep-learning networks. Testing on diverse European wheat varieties, including complex bushy types, our modified FRCNN (FRCNN-A) outperforms the standard model, achieving a mean Average Precision (mAP) increase from 76.0 % to 81.0 %. Compared to the Swin Transformer's 83.0 % mAP, our model shows competitive performance. We also tested Yolov8 and Yolov4 models, achieving 0.79 and 0.78 mAP, respectively. The Spike APP model is deployed on the PlantScreen™ Analyzer SW to extract phenotypes such as awn detection and spike count in late reproductive stage plants. We show high linear correlation between virtual spike number count detected by Spike APP and the ground truth manual count of spike number among the nine genotypes (R2 = 0.74) of barley plants cultivated under control and drought conditions in greenhouse environment.

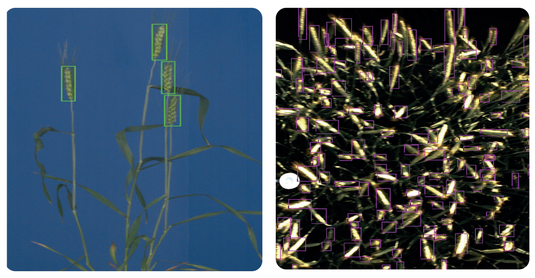

Fig.1. Spike detection in RGB images from greenhouse and field grown wheat plants.

Methodology

Dataset preparation

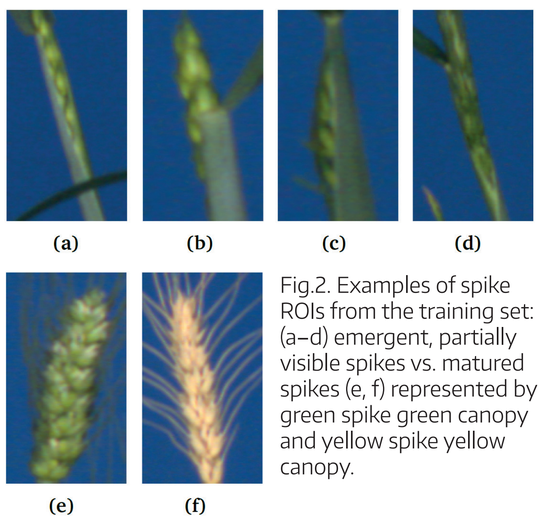

Fig.2. Examples of spike ROIs from the training set: (a–d) emergent, partially visible spikes vs. matured spikes (e, f) represented by green spike green canopy and yellow spike yellow canopy.

Optical plant/background appearance varies upon

- Developmental stage
- Environmental conditions
- Illumination, reflections

Image Augmentation with FastGAN

To generate synthetic images for training, we used FastGAN architecture. The model was trained in PyTorch with an input of resolution 1,024 × 1,024. The input for FastGAN is optimized for 1,024 × 1,024; therefore, we have cropped the right and left sides adjacent to the plant, and the region directly above the plant's canopy. The average resolution of images after the cropping is 1,200 × 2,800.

Fig.3. Examples of synthetic images of greenhouse-grown plants generated by FastGAN (selected from the epoch 80k)

Spike detection toolbox

YOLOv4 and YOLOv8x were trained on datasets of varying sizes and utilized for spike detection in both barley and wheat. The dataset of 1010 images was divided into training and test sets in the proportion 80:20, regardless of the spike numbers, spatial position, and orientation. All images were manually annotated for the training and testing of the spike detection. ROI boxes were evaluated with mean average precision (mAP).

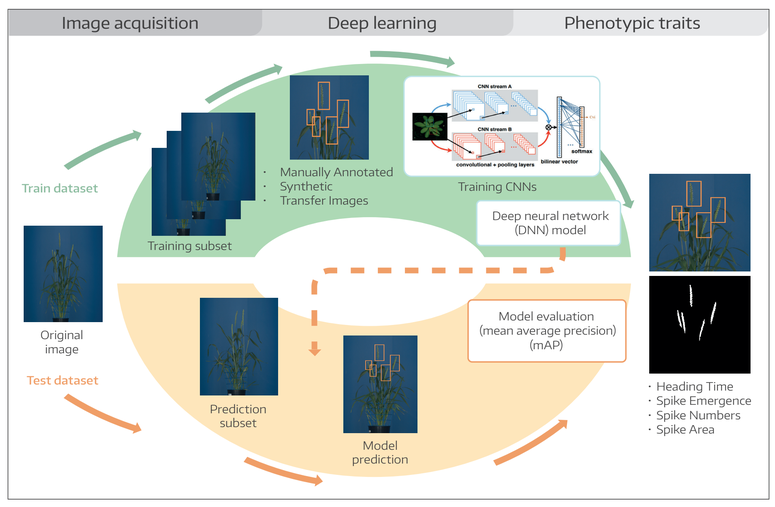

Fig.4. Overall scheme of supervised spike detection

Results

1. YOLOv8x outperforms on the barley dataset

Evaluation of spike detection DNN models :Yolov4 and Yolov8x (1.3% increase) on mAP (0.5).

Training set	Test set	
810	200	
Spike Detection DNNs	Backbone	Average precision ($AP_{0.5}$)
Yolov4	CSPDarknet53	0.78
Yolov8x	CSP Dark Net	0.79

2. Case study

The impact drought stress on yield of nine spring barley *(Hordeum vulgare L)* genotypes was assessed throughout all developmental stages. During the reproductive phase the heading time (when spikes begin to emerge) and the development rate of spikes was analyzed with Spike APP. Hundreds of RGB images from PlantScreen™ high-throughput phenotyping system were analyzed to extract traits related to spike development from the initiation of the heading stage (late reproductive stage) to the grain ripening stage.

· Spike count during the development

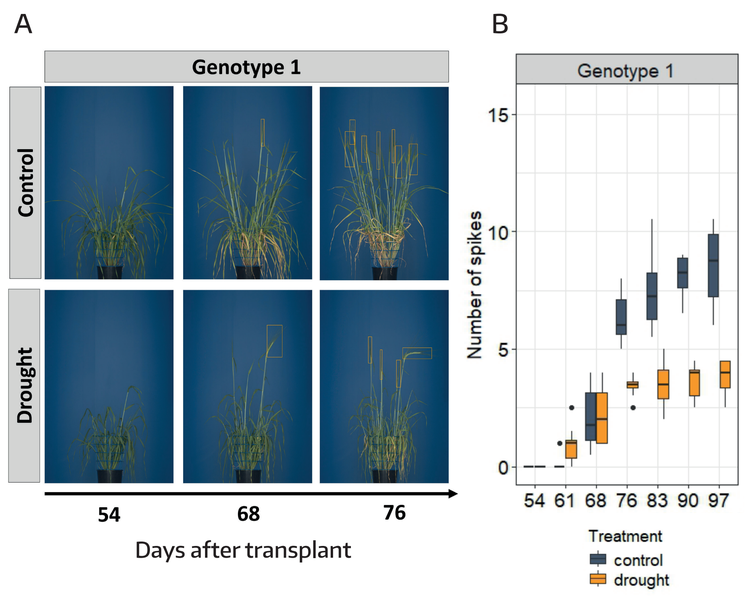

Fig. 5. (A) RGB side view images in one barley genotype under control and drought stress selected from three-time points. (B) Modelbased counting of spike number during late reproductive stage till grain filling stage.

· Spike count in late reproductive stage stage

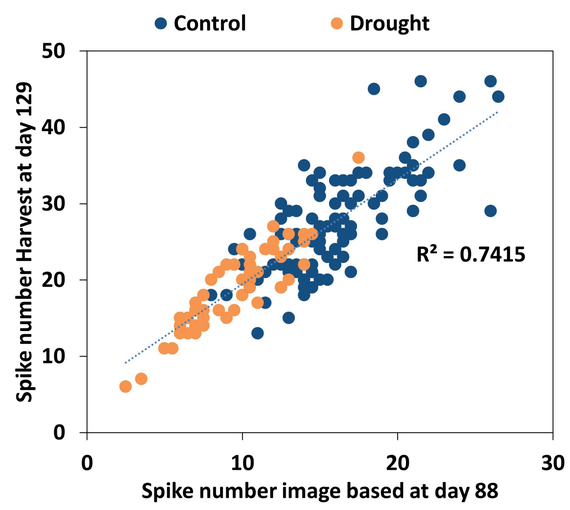

Fig. 6 Correlation between virtual spike number count (RGB images acquired 87 days after transplantation) and the ground truth manual count of spike number (harvested 129 days after transplant)

Spike APP

Spike APP is configured to communicate with the PlantScreen™ Data Analyzer through a dedicated database setup to facilitate seamless data exchange and processing including spike localization, extraction of essential phenotypes, and the generation of Region of Interest (ROI) boxes.

Key Extracted Traits

- Spike detection and counting
- Identification of growth stages associated with heading time
- Spike development during late reproductive and grain-filling phases
- Single spike morphological analysis including spike area

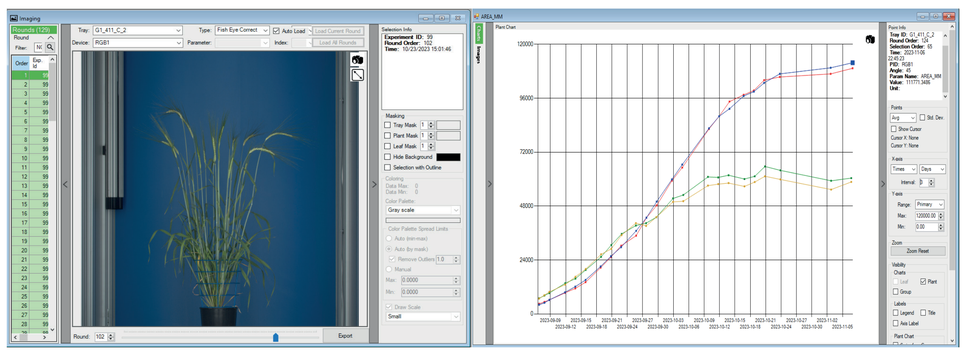

Fig. 8. Visualization of the extracted traits in PlantScreen™ Analyzer SW

Conclusion

- YOLOv4/v8 offer faster and more efficient training for smaller datasets
- Spike APP : shows significant accuracy for the detection of the spike number and its distribution changes over time
- Spike APP model robustly identifies spike emergence and heading time

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