

Alexandre Boyer¹

Jing Wang²
 Geoff Bull¹
 Jamie Scarrow¹
 Julianne Lilley¹
 Jeremy Whish²
 Alexander Zwart¹
 Shannon Dillon¹
 Chris Helliwell¹

¹ CSIRO Agriculture & Food,
 Canberra, Australia

² CSIRO Agriculture & Food,
 St. Lucia, Australia

Background:

Assessment of phenology is critical for optimising varietal flowering time and increased productivity and profitability of canola. The growth stages of canola are defined by key visual characteristics, such as leaf number, and the appearance of buds and inflorescences. Phenotyping plants in the field is currently performed manually, which is expensive and time consuming for both researchers and breeding companies.

Objective:

Modern phenomics using drones equipped with high resolution cameras allows rapid acquisition of trait data at the plant, plot or field scale in agricultural trials. The availability of 'big data' analysis techniques using high performance computing and deep learning has achieved great success recognising patterns from images. We aimed to develop a workflow that combines these technologies to automate canola phenology detection.

Methods:

From plant emergence to flowering, twice-weekly manual observations of plant growth stage were made on a field experiment with 350 canola varieties and two times of sowing at Boorowa, NSW. High resolution RGB images were captured by twice weekly drone flights with a DJI M600 drone equipped with a Sony A7iii camera and a 50mm lens. An image dataset with organ and plot level annotations for developmental stage categories mapped to trial design was established. Deep object detection networks, pretrained on the ImageNet dataset, were designed, trained, and fine-tuned on the canola image dataset.

Results:

More than 60,000 drone images were collected spanning key growth stages of canola. An acquisition and pre-processing workflow was implemented to deliver quality images and an accurately annotated MS COCO dataset. An organ level detection model with 9 phenology classes was trained on a total of 19231 labelled bounding boxes. Model evaluation using images held-out of the training set achieved a mAP of 0.603. Plot level phenotyping was subsequently performed by mapping predictions obtained with the previously trained model to individual plots in the trial design for each flight. Correlation between the extracted and manual measurements show promising results. Lastly, a separate plot level classification model was trained on a data set of paired manual plot level observations and segmented plot images. Various challenges were resolved to develop the plot segmentation pre-processing workflow, and preliminary results are encouraging.

Conclusions:

We have developed a phenomics framework that delivers automated canola phenology detection at multiple scales and provides a high-throughput alternative to traditional assessment of phenology, which can be expensive, time-consuming and prone to human error. By combining high-resolution images, expert led annotation of image datasets linked with plot coordinates and manual observations of key phenology stages, we demonstrate that deep learning models can be leveraged to detect canola phenology at the plant and plot scale in field experiments. The comparison with manual observations reveals that detection networks deliver comparable levels of accuracy to on ground scoring for seedling leaf number, and the appearance of buds and inflorescences on canola crops. Such tools and technology will have potential for immediate application in research and commercial settings, to improve the cost and rate at which detailed non-destructive phenology measures can be obtained.