Counting heads: How deep learning can simplify tedious agricultural tasks

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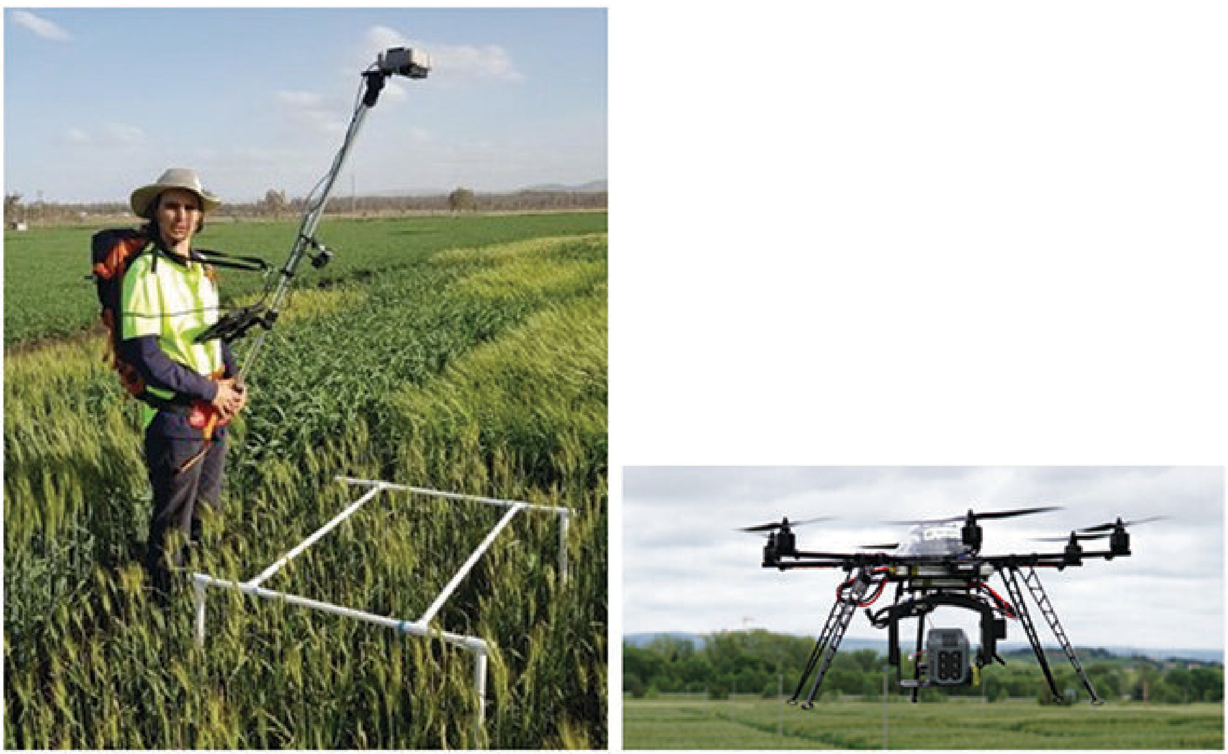
A B

Illustration of 2 image acquisition types. (A) Ground-level acquisition. (B) UAV acquisition. Credit: *Plant Phenomics* (2023). DOI: 10.34133/plantphenomics.0017

The selective breeding of grain crops is one of the main reasons why domesticated plants produce such excellent yields. Selecting the best candidates for breeding is, however, a remarkably complex task. On one hand, it requires a skilled breeder with trained eyes to assess plant resistance to disease and pests, crop growth, and other factors. On the other hand, it also requires precise tool-assisted measurements such as grain size, mass, and quality.

Although all these standard measures are useful, none of them takes into account the number of panicles or 'heads' per plant. Head density is closely related to crop yield in most cases, and it could easily be a staple characteristic to measure in breeding programs. However, estimating the number of heads per plant and per unit area is very time consuming and requires tedious manual work.

To address this issue, many researchers have developed machine learning models that can automatically detect individual heads on grain crops in images taken either at ground level or by drones.

While these models are aimed at simplifying the otherwise manual counting process in the field, the reality is that they are usually trained in limited testing conditions and focus exclusively on head detection without providing more metrics. In other words, using these models outside of the context in which they were developed and trained can be difficult, tedious, and even yield poor results.

Against this backdrop, a research team including Professor Scott Chapman from The University of Queensland, Australia, sought to promote deep-learning models for head counting by providing a detailed pipeline outlining their use. As explained in their paper, which was recently published in *Plant Phenomics*, this pipeline covers most of the quirks and challenges that one could find when using these models.

"We took various real-world variables into consideration, including data preparation, model validation, inference, and how to derive yieldspecific metrics," explains Chapman, "We aimed to outline a practical and end-to-end pipeline for head detection in sorghum."

There are two variants to the proposed pipeline, which are demonstrated by way of two independent illustrative experiments. In the first one, the researchers show how one should proceed if one needed to prepare training, testing, and validation datasets for a given machine learning model from scratch. This is usually the case when publicly available datasets are not suitable for the target field, which can happen, for example, when one is dealing with a different stage in plant development than the available datasets.

In the second experiment, the team showcases the steps required to use various pre-trained deep-learning models for sorghum head detection and/or counting. They demonstrate how the detection results (that is, the output of models that only outline sorghum heads on a set of given images) can be 'stitched together' into larger mosaic images. This enables one to observe and analyze large areas more easily and calculate important metrics, such as head density per tilling row or per square meter.

"Our pipeline produces a high-resolution head density map that can be used for the diagnosis of agronomic variability within a field without relying on commercial software," highlights Chapman.

Overall, this study will be useful to researchers and people involved in the agricultural industry alike. Not only it explains how deep learning models can be leveraged to assess grain crops more efficiently, but it also helps unlock new functionalities for camera-equipped drones in agriculture.

Worth noting, the proposed pipeline could be adapted to other plants besides sorghum, as Chapman remarks: "Although we demonstrated our pipeline in a sorghum field, it can be generalized to other grain species. In future works, we intend to test our pipeline on tasks involving other grain types, such as wheat and maize yield estimation."

More information: Chrisbin James et al, From Prototype to Inference: A Pipeline to Apply Deep Learning in Sorghum Panicle Detection, *Plant Phenomics* (2023). DOI: 10.34133/plantphenomics.0017

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