Mungbean Root Phenotyping UOQ2403-012RTX

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AAGI Analytics for the Australian Grains Industry

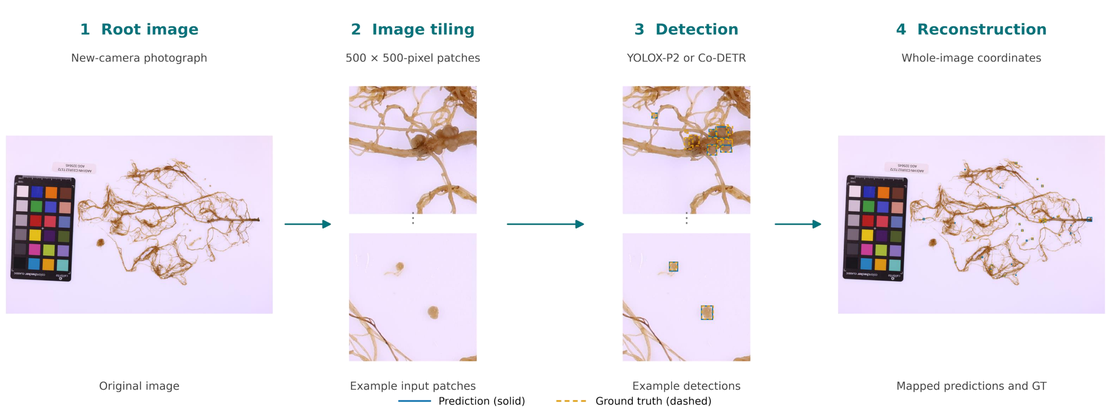
ABSTRACT

Accurate nodule detection supports mungbean root phenotyping. We developed a patch-based workflow and compared different detection models, including YOLOX-P2 with Co-DETR. On an external test image, Co-DETR achieved 75.57% AP50, compared with 59.05% for YOLOX-P2. Small, overlapping nodules and limited old-nodule samples remain key challenges. Further validation across plants and imaging conditions is needed.

1. Background

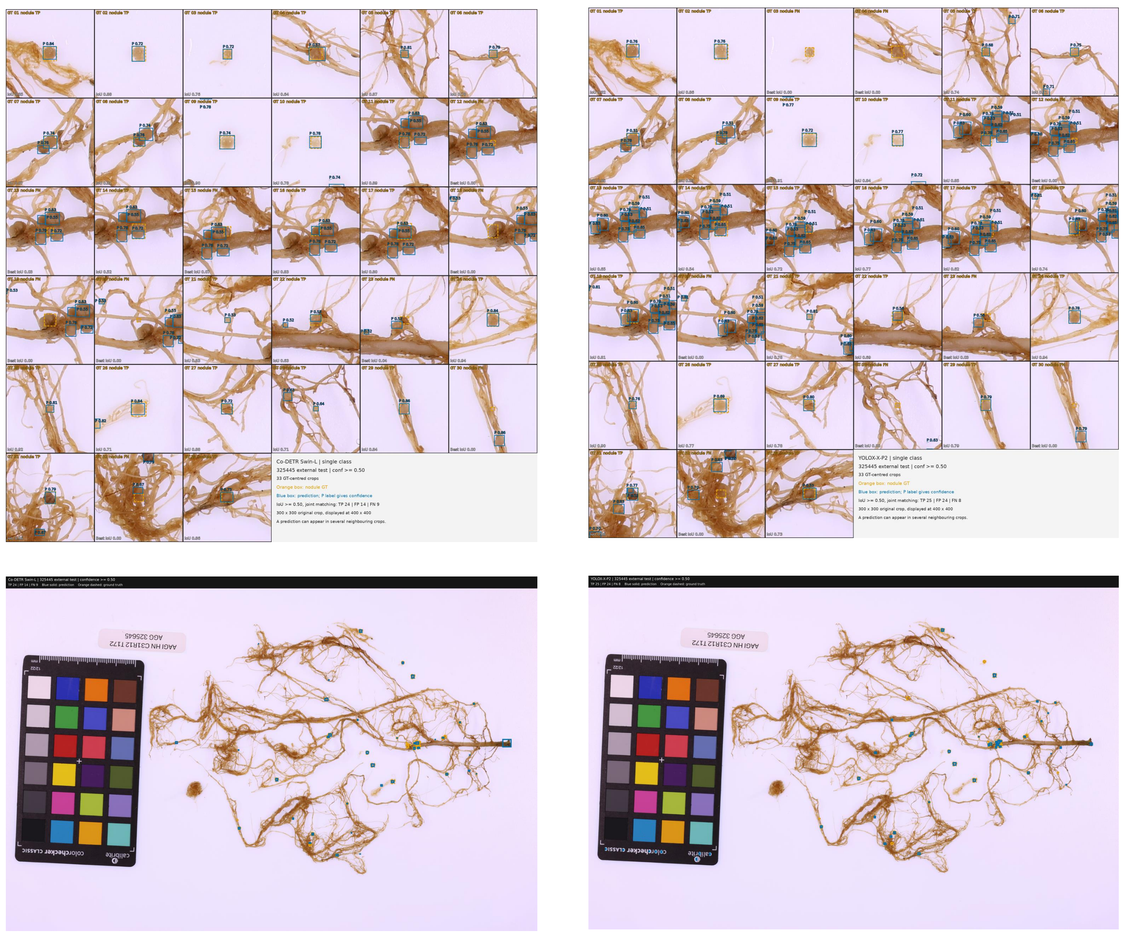
This project supports a genetic initiative to improve symbiotic nitrogen fixation in Australian pulse crops. It aims to develop automated analysis of 2D mungbean root images to quantify nodule number, size distribution and spectral characteristics, with a target of phenotyping up to 2,000 plants. The current work focuses on reliable nodule detection as a foundation for these measurements. Small, overlapping nodules and variation in image quality present key challenges.

2. Detection Workflow



Root images are split into 500 × 500-pixel patches. A detection model identifies nodules in each patch, then patch-level boxes are mapped back to the full image.

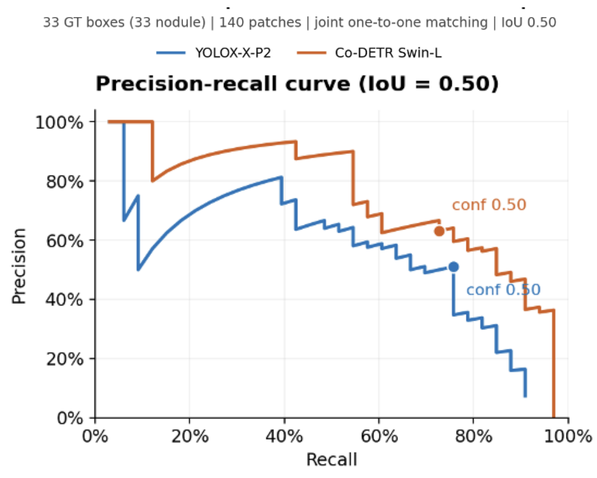
3. Model Performance



Co-DETR Swin-L and YOLOX-X-P2 detections at confidence 0.5. Montages show nodule-level predictions; stitched views show full-image results. Blue: predictions; orange: ground truth.

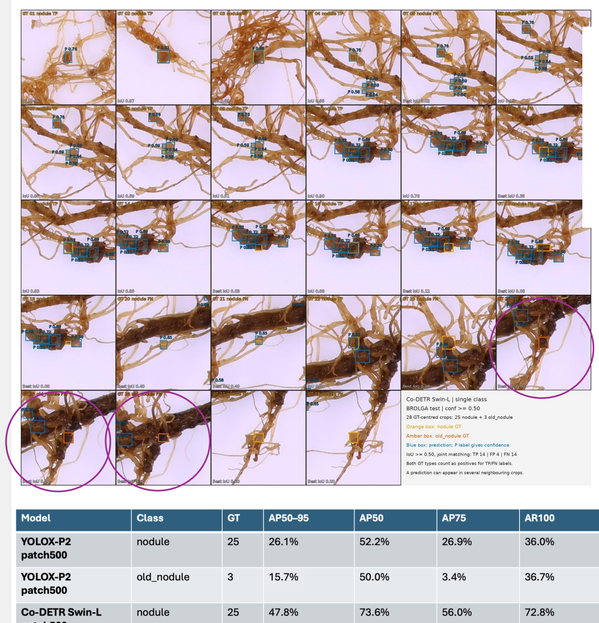
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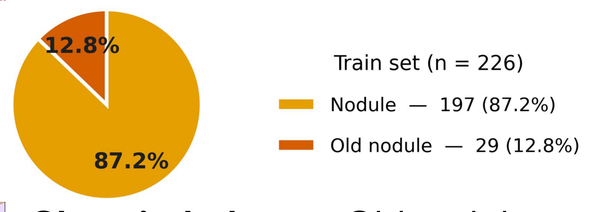
model	AP50:95	AP50	AP75	AR@100
YOLOX-P2 patch500	33.3%	59.05%	37.89%	53.33%
Co-DETR Large patch500	46.23%	75.57%	54.02%	69.09%



The table summarises overall model performance, while the figure shows the precision–recall curves. Co-DETR outperformed YOLOX-P2 across all reported metrics, and its curve maintained higher precision across most recall levels.

4. Detection Challenge





Model	Class	GT	AP50–95	AP50	AP75	AR100
YOLOX-P2 patch500	nodule	25	26.1%	52.2%	26.9%	36.0%
YOLOX-P2 patch500	old_nodule	3	15.7%	50.0%	3.4%	36.7%
Co-DETR Swin-L patch500	nodule	25	47.8%	73.6%	56.0%	72.8%
Co-DETR Swin-L patch500	old_nodule	3	4.2%	6.9%	6.4%	56.7%

Class imbalance: Old nodules account for only 12.8% of training annotations (29 of 226 boxes), compared with 197 nodule boxes. The examples and table highlighted in purple show that the model also detects old nodules less reliably.

5. Conclusion and Future Work

Conclusion: Co-DETR outperformed YOLOX-P2 across the reported performance metrics, showing promise for automated mungbean nodule detection. However, old nodules were underrepresented in the training data and were detected less reliably, highlighting the effect of class imbalance on model performance.

Future work: Increase the number and diversity of old-nodule examples through additional annotation and targeted data augmentation. Evaluate both models on a broader range of root images and imaging conditions, then refine the detection workflow. Once detection is reliable across nodule types, extend the pipeline to quantify nodule number, size distribution and spectral characteristics for larger-scale root phenotyping.

6. References

Yolo: Ge, Z., Liu, S., Wang, F., Li, Z., & Sun, J. (2021). *YOLOX: Exceeding YOLO Series in 2021*. arXiv:2107.08430.

CoDETR: Zong, Z., Song, G., & Liu, Y. (2023). *DETRs with Collaborative Hybrid Assignments Training*. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)* (pp. 6748–6758).

QAAFI Queensland Alliance for Agriculture and Food Innovation · appn Australian Plant Phenomics Network · NCRIS National Research Infrastructure for Australia, An Australian Government Initiative · The University Of Queensland AUSTRALIA

GRDC Grains Research & Development Corporation · Adelaide University · Curtin University · The University Of Queensland AUSTRALIA

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