Generic Wheat Disease Segmentation

Shijie Wang[1], Zijian Wang[1], Yadan Luo[1], Scott Chapman[2], Xin Yu[1], Zi Huang[1]
[1]School of Electrical Engineering and Computer Science, The University of Queensland, St Lucia, QLD, Australia, 4072
[2]School of Agriculture and Food Sustainability, The University of Queensland, St Lucia, QLD, Australia, 4072

AAGI
Analytics for the Australian Grains Industry

ABSTRACT

AAGI-UQ developed a semantic-geometric deep learning framework that combines DINOv2 and SAM to accurately segment wheat disease lesions under limited training data, supporting automated disease phenotyping.

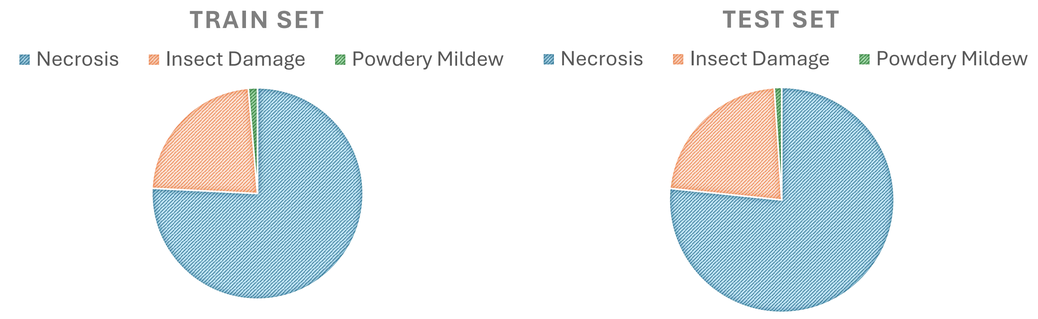
1. The Need

Limited annotated data created an urgent need for accurate and data-efficient automated wheat disease phenotyping. Researchers needed to segment disease lesions across different growth stages, where substantial changes in lesion appearance and morphology made conventional methods less robust. Without this capability, disease assessment relied on extensive manual annotation and was difficult to scale.

2. Challenge

Challenge1: The Long-Tail Challenge in Segmentation

DATA: EFGv2 published by ETH



Necrosis: ~23.35 million pixels
Insect Damage: ~7.03 million pixels
Powdery Mildew: ~426 thousand pixels

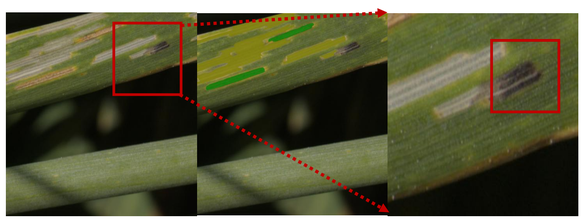
Necrosis: ~5.53 million pixels
Insect Damage: ~1.61 million pixels
Powdery Mildew: ~76 thousand pixels

Hard to identify the disease classes with less training samples!

Challenge2: Professional Knowledge in Annotation



Different scale lesions

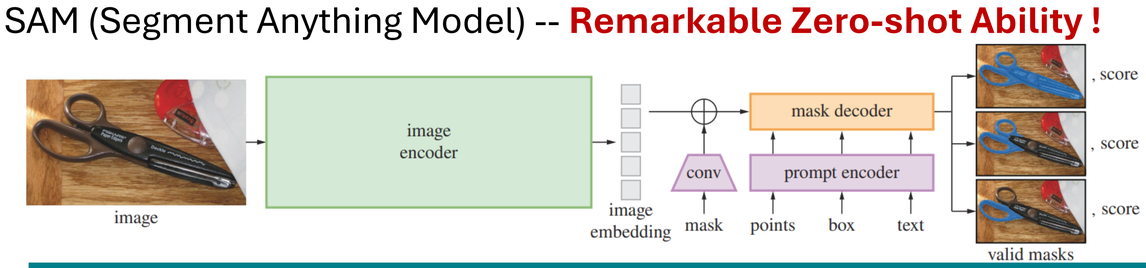


Interference symptoms

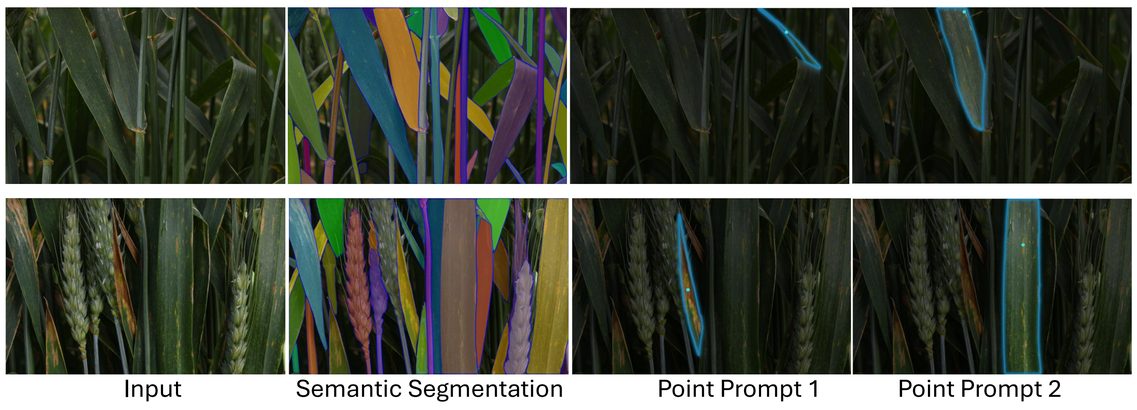
Hard to identify the real disease regions!
Taking more time to provide annotations with accurate boundaries!

3. Motivation

SAM (Segment Anything Model) -- **Remarkable Zero-shot Ability !**



Utilize **11M** diverse, high-resolution images and **1.1B** high-quality **segmentation masks**

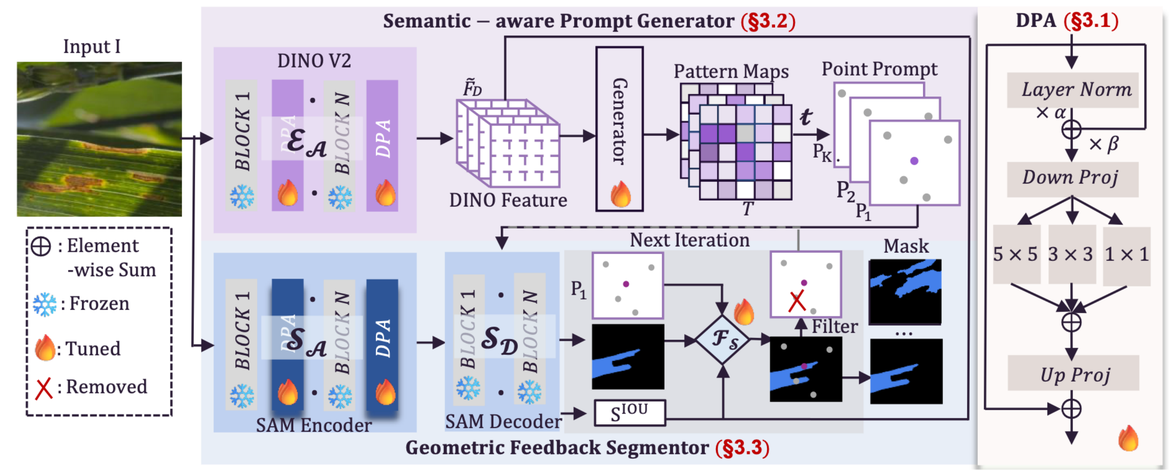


Input | Semantic Segmentation | Point Prompt 1 | Point Prompt 2

SAM segments ***wheat organs*** instead of ***wheat diseases***!

4. Method

Contribution: Propose a semantic-geometric deep learning framework that combines DINOv2 and SAM to accurately segment wheat disease lesions.

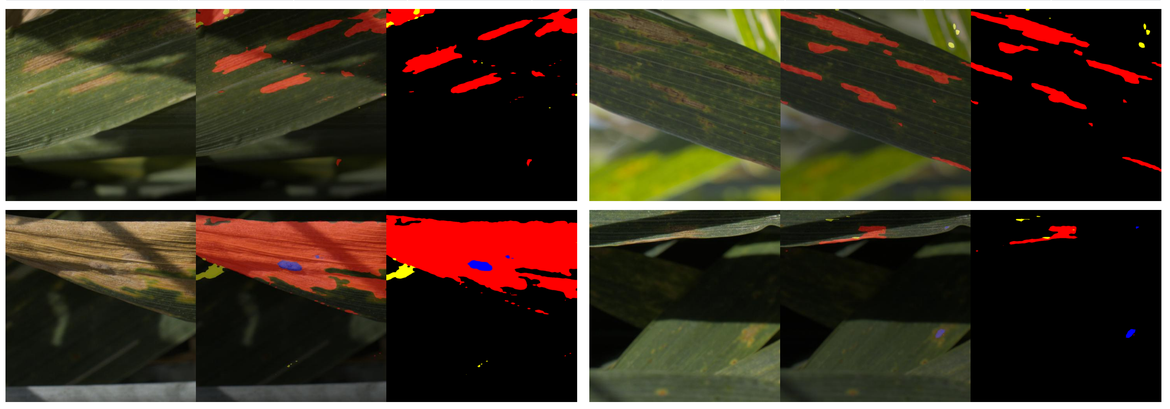


Froze Foundation Models (SAM and Dino V2) and Introduce Less Learnable Parameters (Point Classifier)

5. Results

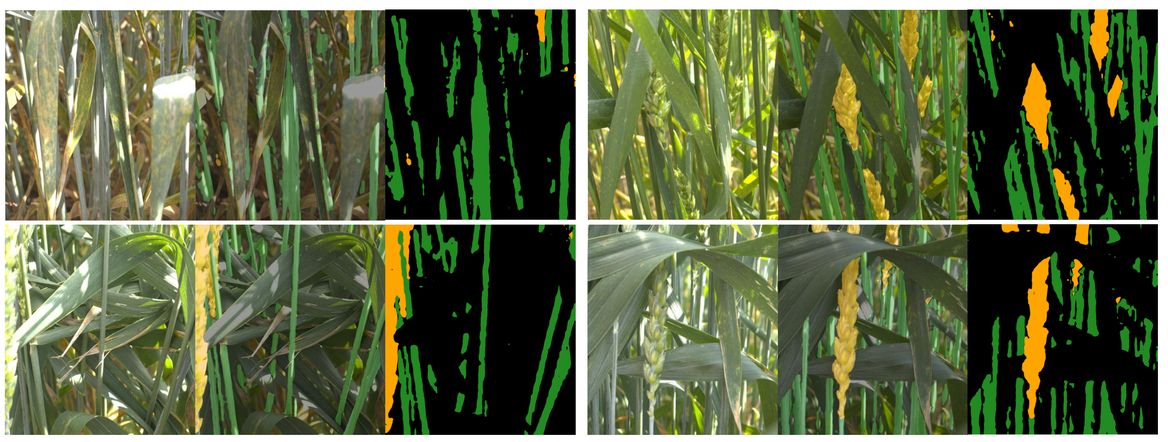
Experiment 1: Wheat Disease Segmentation on EFGv2 Dataset

Method	Necrosis		Insect Damage		Powdery Mildew		Average	
	MIoU	F1	MIoU	F1	MIoU	F1	MIoU	F1
Radek [a]	72.0%	83.7%	58.4%	73.7%	30.3%	46.5%	53.6%	68.0%
Ours	73.7% ($+_{1.7}\uparrow$)	84.8% ($+_{1.1}\uparrow$)	71.7% ($+_{13.3}\uparrow$)	83.5% ($+_{10.2}\uparrow$)	47.4% ($+_{17.1}\uparrow$)	64.3% ($+_{17.8}\uparrow$)	64.2% ($+_{10.6}\uparrow$)	77.5% ($+_{9.5}\uparrow$)



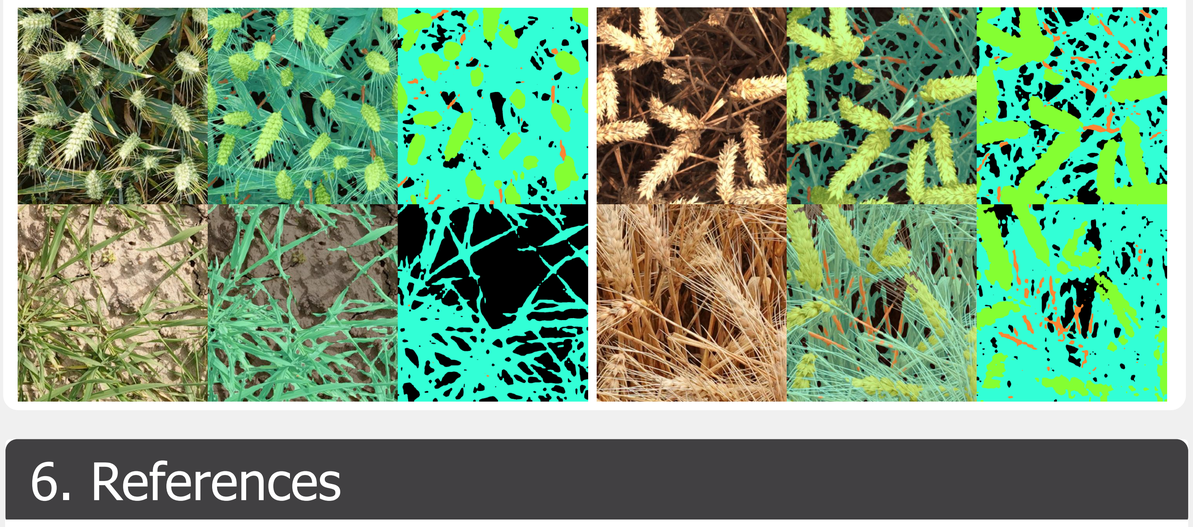
Experiment 2: Wheat Disease Segmentation on OSD Dataset

Method	Ears		Stems		Average	
	MIoU	F1	MIoU	F1	MIoU	F1
Radek [a]	81.9%	90.1%	67.9%	80.7%	74.9%	85.4%
Ours	86.3% ($+_{4.4}\uparrow$)	92.7% ($+_{2.6}\uparrow$)	70.6% ($+_{2.7}\uparrow$)	82.8% ($+_{2.1}\uparrow$)	78.5% ($+_{3.6}\uparrow$)	87.7% ($+_{2.3}\uparrow$)



Experiment 3: Wheat Organ Segmentation on GWFSS Dataset

Method	Background		Head		Stem		Leaf		Average	
	MIoU	F1	MIoU	F1	MIoU	F1	MIoU	F1	MIoU	F1
Ours	77.6%	87.4%	81.9%	90.0%	40.3%	57.5%	83.4%	91.0%	70.8%	81.5%



6. References

[a] *Zenkl Radek, et al*. "From Canopy Images to Organ-Level Disease Assessments: A Scalable Approach to Measure Quantitative Resistance in the Field." *bioRxiv* (2025): 2025-04.

GRDC GRAINS RESEARCH & DEVELOPMENT CORPORATION
Adelaide University
Curtin University
The University Of Queensland AUSTRALIA

The support of the Grains Research and Development Corporation (GRDC) provided through the Analytics for the Australian Grains Industry (AAGI) project is acknowledged.