StagGCP: A Metashape Plugin for Using STag as Robust Ground Control Points for In-field Agricultural 3D reconstruction

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01

Introduction

Introduction

1.1 3D reconstruction and ground control points

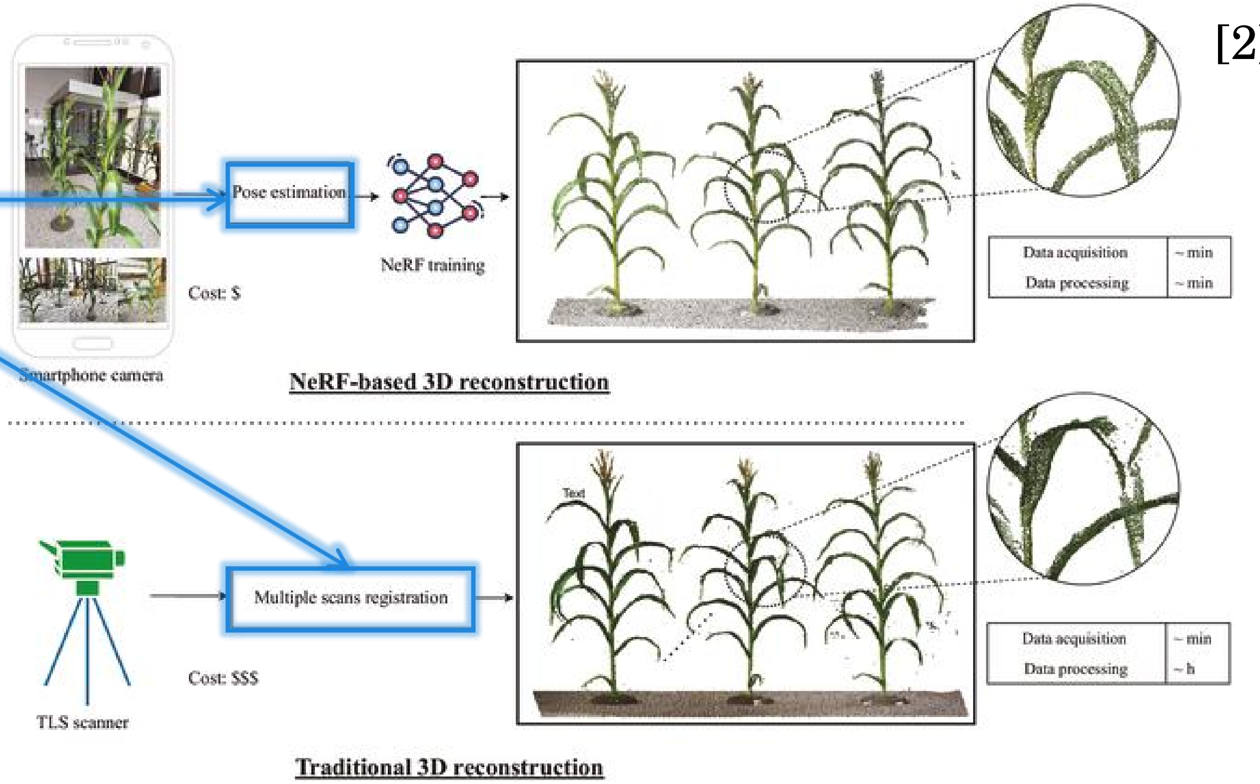
[1]

3D plant structures from multi-view images

camera positions

Important parameters for 3D reconstruction postprocessing

[2]



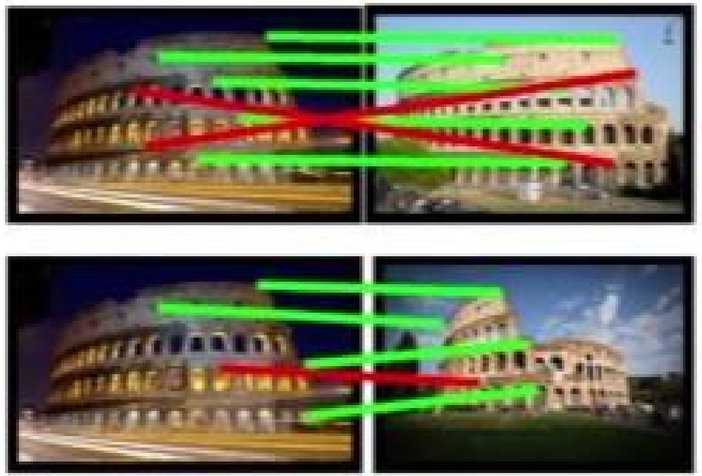
[1] Zhai, R., Wang, Y., Hu, S., Yang, W., 2021. 4DPhenoMVS: A Low-Cost 3D Tomato Phenotyping Pipeline Using a 3D Reconstruction Point Cloud Based on Multiview Images. https://doi.org/10.1101/2021.11.09.467984
[2] Arshad, M.A., Jubery, T., Afful, J., Jignasu, A., Balu, A., Ganapathysubramanian, B., Sarkar, S., Krishnamurthy, A., 2024. Evaluating Neural Radiance Fields for 3D Plant Geometry Reconstruction in Field Conditions. Plant Phenomics 6, 0235. https://doi.org/10.34133/plantphenomics.0235

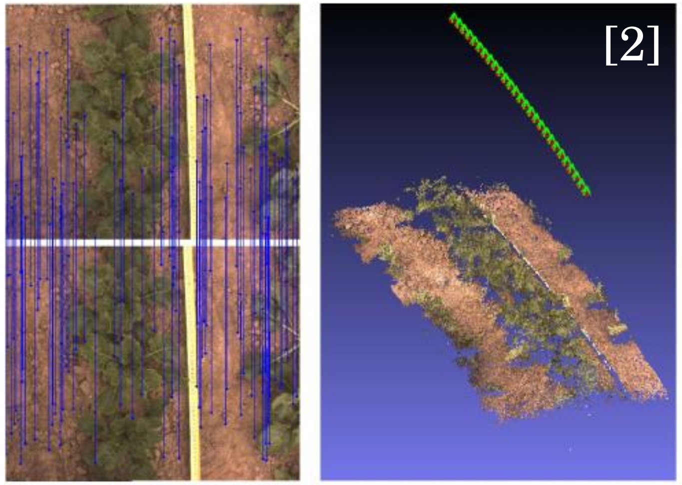
Introduction

1.1 3D reconstruction and ground control points

[1]

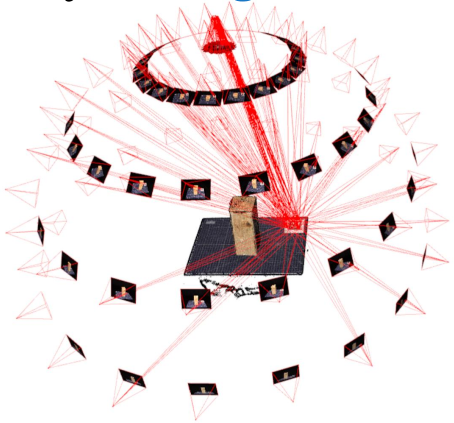
3D plant structures from
multi-view images

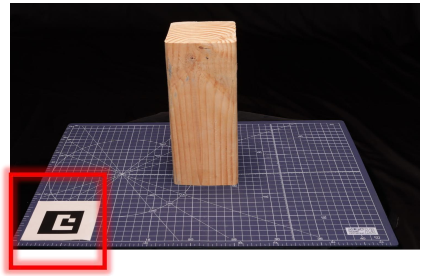




camera positions are estimated by distinguishable point pairs

Ground control points (GCPs) are
manually set as point pairs
to obtain better estimates



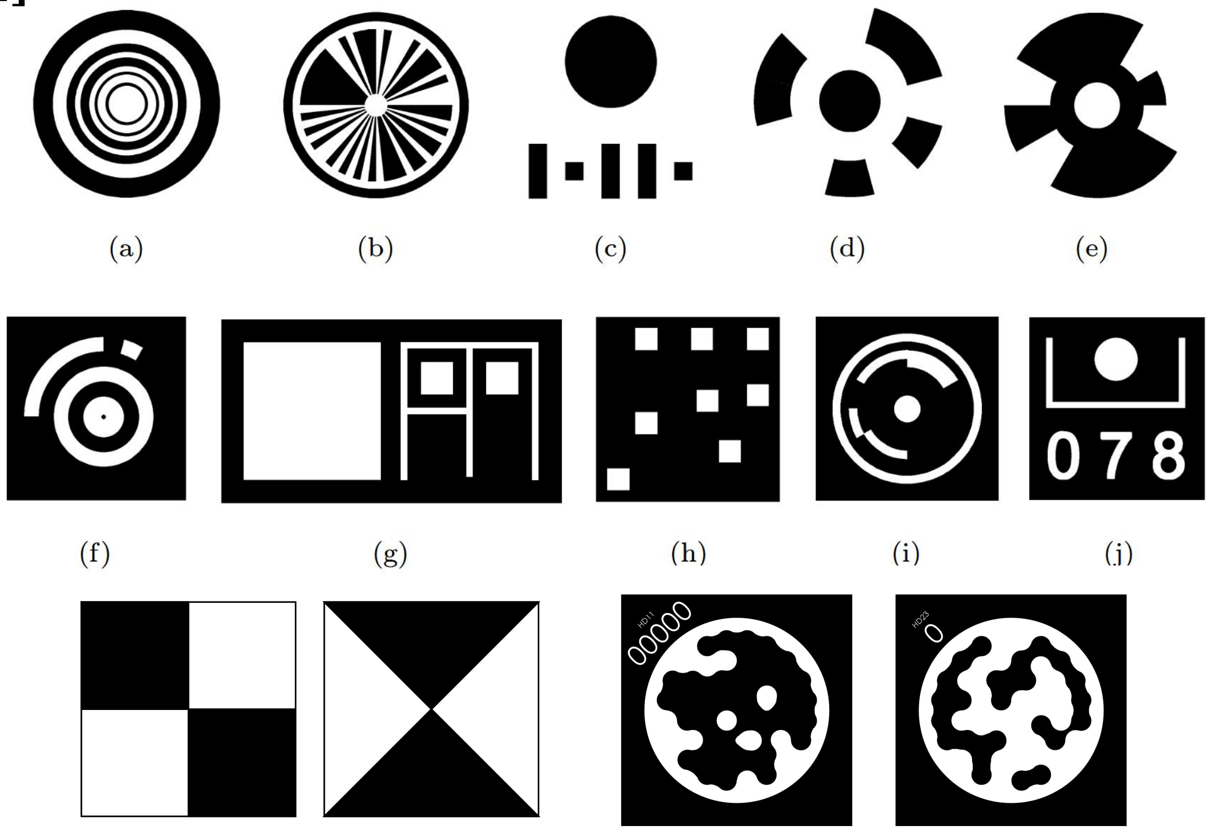


[1] Zhai, R., Wang, Y., Hu, S., Yang, W., 2021. 4DPhenoMVS: A Low-Cost 3D Tomato Phenotyping Pipeline Using a 3D Reconstruction Point Cloud Based on Multiview Images. https://doi.org/10.1101/2021.11.09.467984
[2] Jay, S., Rabatel, G., Hadoux, X., Moura, D., Gorretta, N., 2015. In-field crop row phenotyping from 3D modeling performed using Structure from Motion. Computers and Electronics in Agriculture 110, 70–77. https://doi.org/10.1016/j.compag.2014.09.021

Introduction

1.2 Commonly used GCP tags and tolerance to occlusion

[1]



(a1) Square targets

(a2) Diagonal targets

(c1) Stag HD11 targets

(c2) Stag HD23 targets

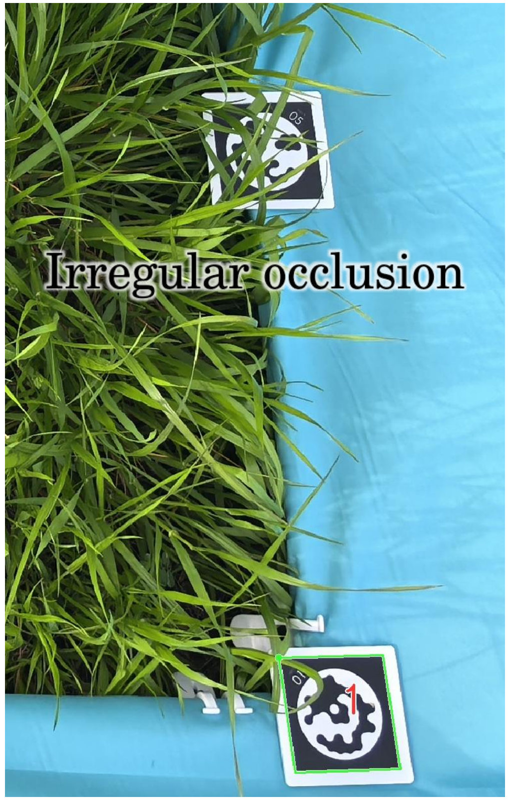
[2]

marker distinguish performance on occlusion

[1] Ahn, S.J., Rauh, W., Kim, S.I., 2001. Circular Coded Target for Automation of Optical 3d-Measurement and Camera Calibration. Int. J. Pattern Recognit. Artif. Intell. 15, 905–919.
[2] https://www.youtube.com/watch?v=vnHI3GzLVrY

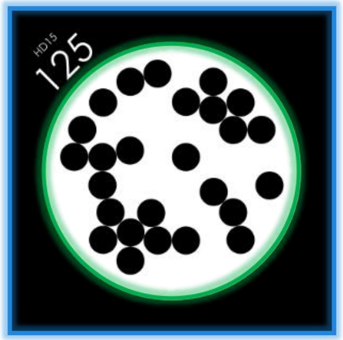
Introduction

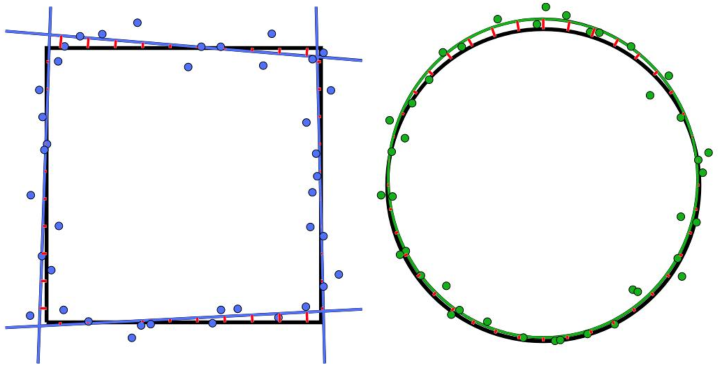
1.4 Challenges



Stag official implementation not performs good on complex outdoor conditions

Reason





(a) Quad localization (b) Ellipse localization

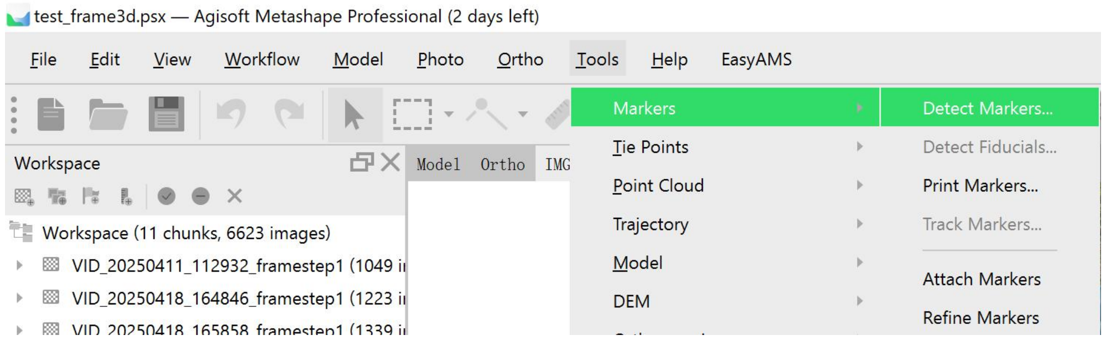
Stag using traditional computer vision approach to detect marker and center regions

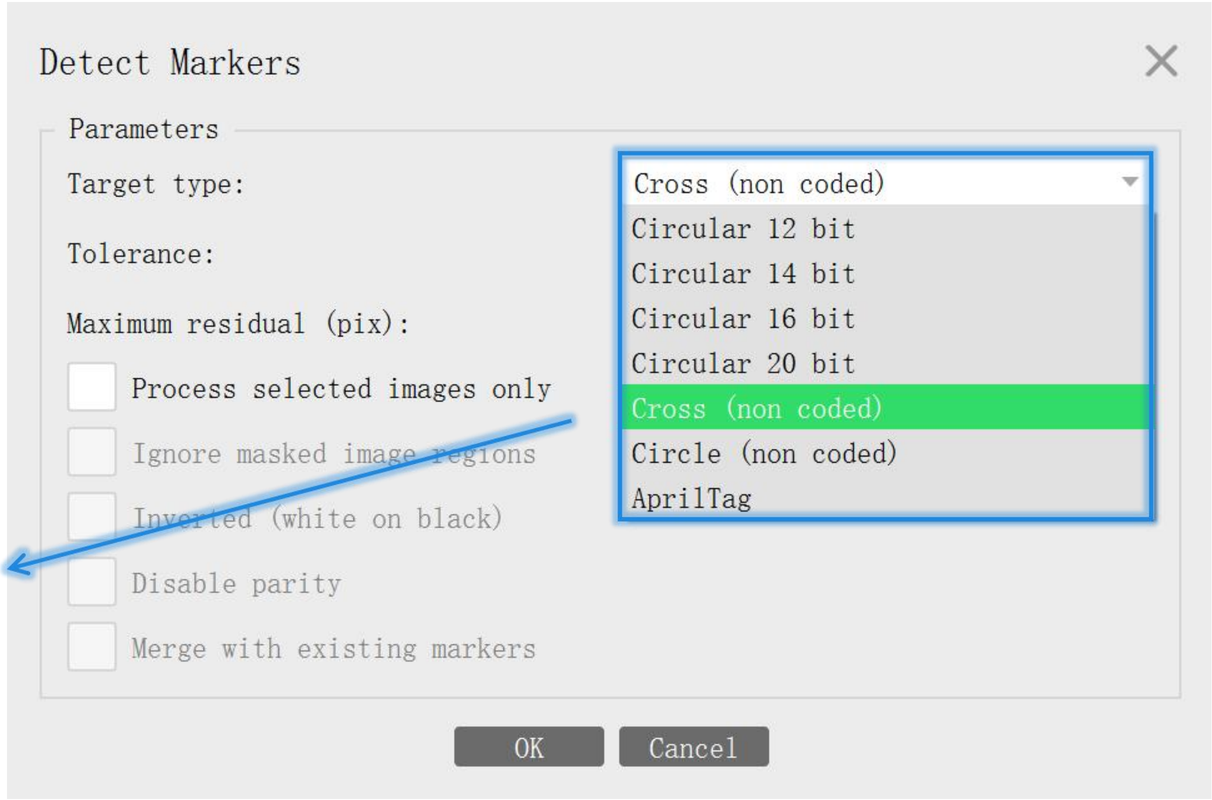
⇩

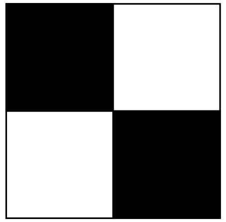
(1) Using deep learning to enhance Stag detection specific for agricultural in-field applications

Introduction

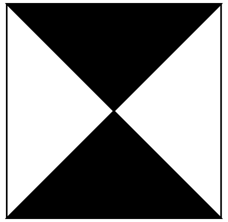
1.4 Challenges



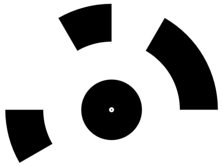




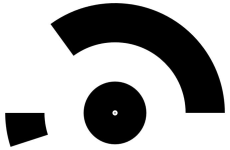
Cross (non coded)



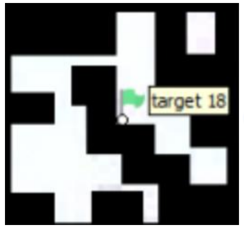
Cross (non coded)



Circular 12bit targets



Circular 20bit targets



AprilTag

Metashape not natively support STags

(2) Make a Metashape plugin to support Stags

Introduction

1.5 Objectives of this study

(1) Using deep learning to enhance Stag detection specific for agricultural in-field applications

(2) Make a Metashape plugin to support Stags and deep learning enhancement

02 Methods and Materials

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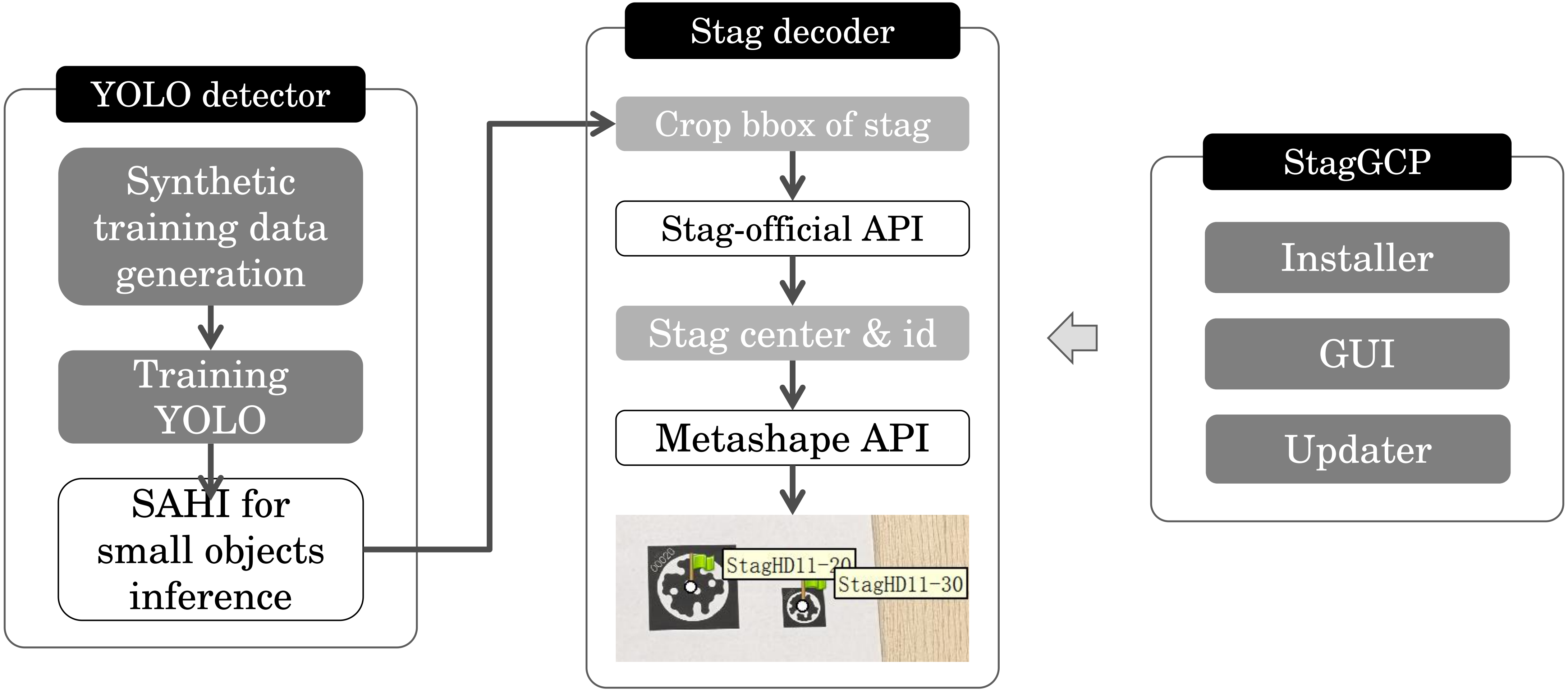
Methods & Materials

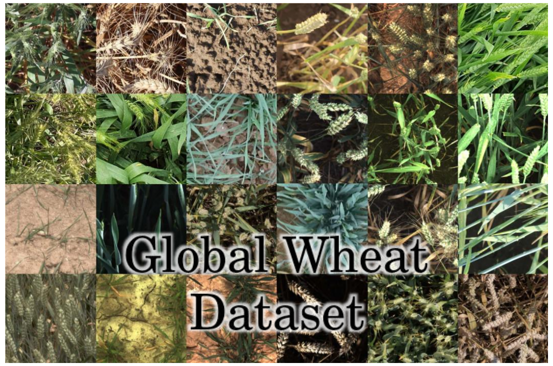
2.1 General workflows



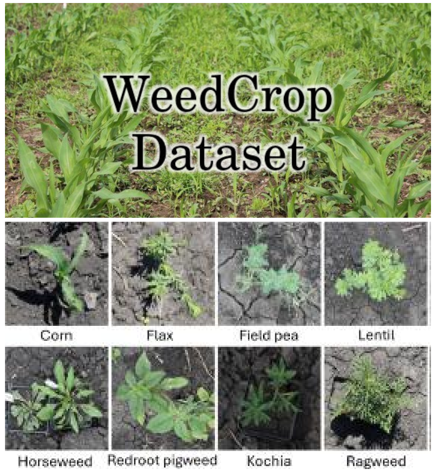
Methods & Materials

2.2 Synthetic training data generation for Yolov11

Method 1: Using public agricultural dataset



PlantDoc
Dataset



Stag marker DB

Marker Visualization (Red: BBox, Green: Corners, Blue: Quad)

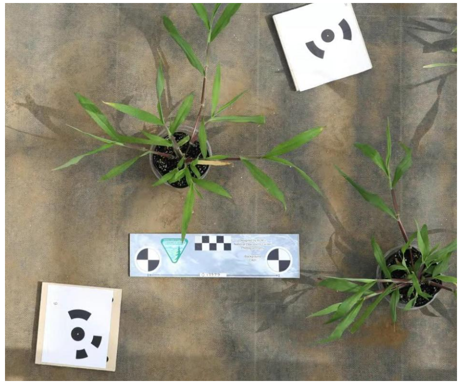
Random size, rotation,
brightness, shadows

Methods & Materials

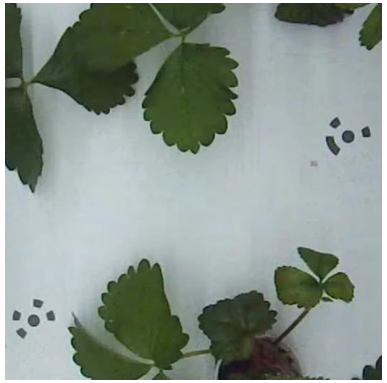
2.2 Synthetic training data generation for Yolov11

Method 2: Converting previous Metashape project with different markers

Indoor

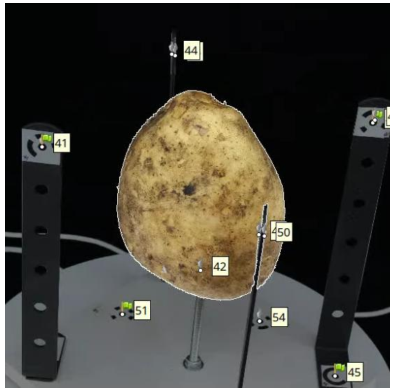


2017_weed



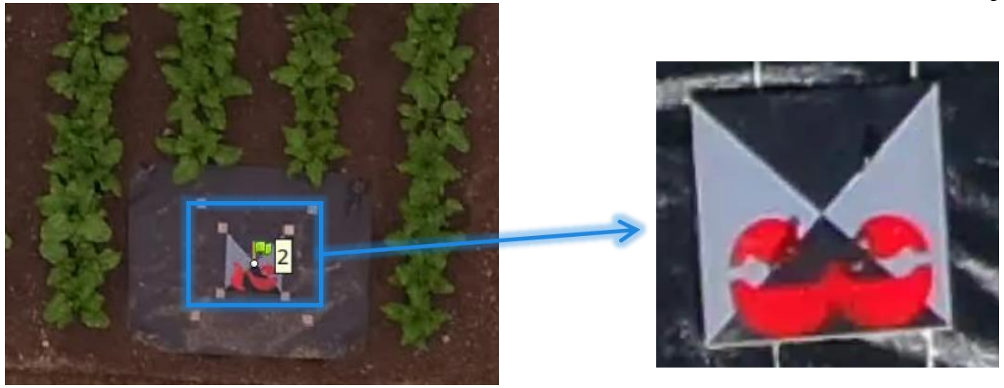
2020_strawberry

2020_kyoto_yoga



Wheat, potato, broccoli, tomato

Outdoor



2018_memuro_sugarbeet

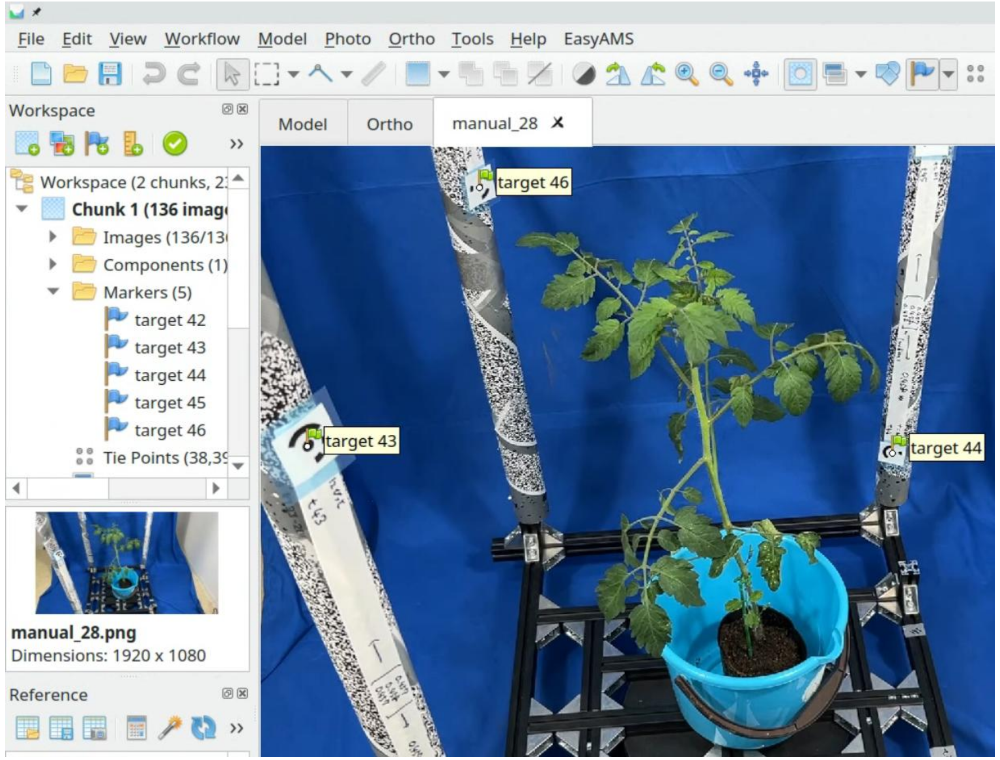
2022_broccoli

2022_paddyrice

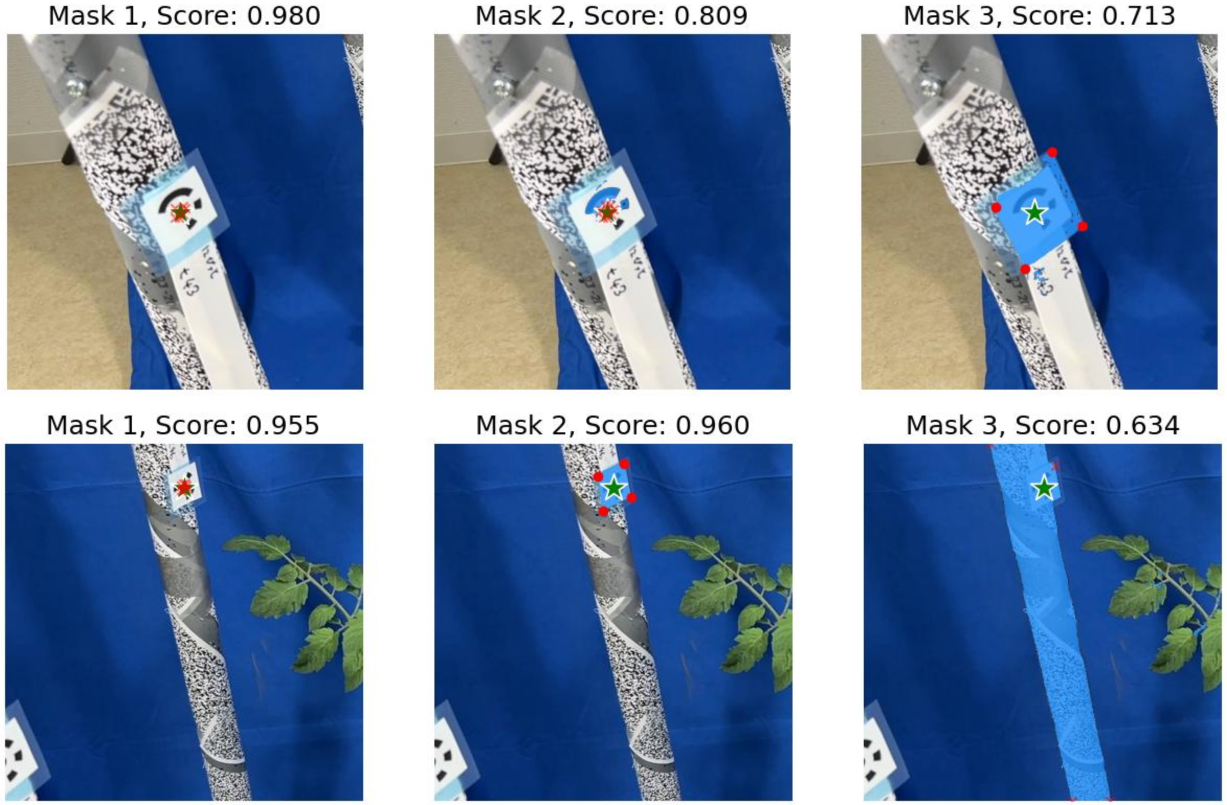
Methods & Materials

2.2 Synthetic training data generation for Yolov11

Method 2: Using metashape project from different markers



(1) Export marker positions from different marker project



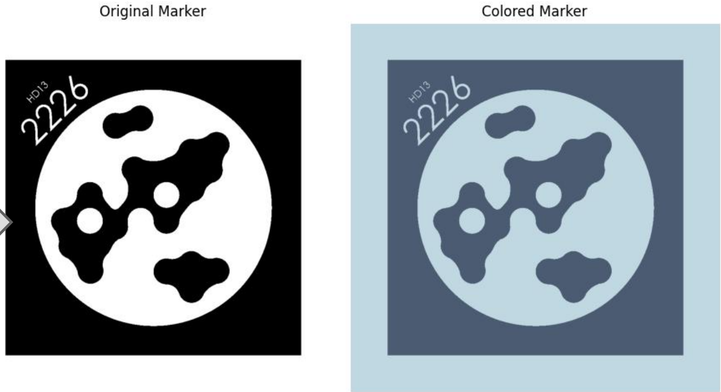
(2) Apply Segment Anything (SAM) to find marker neighbor region

Methods & Materials

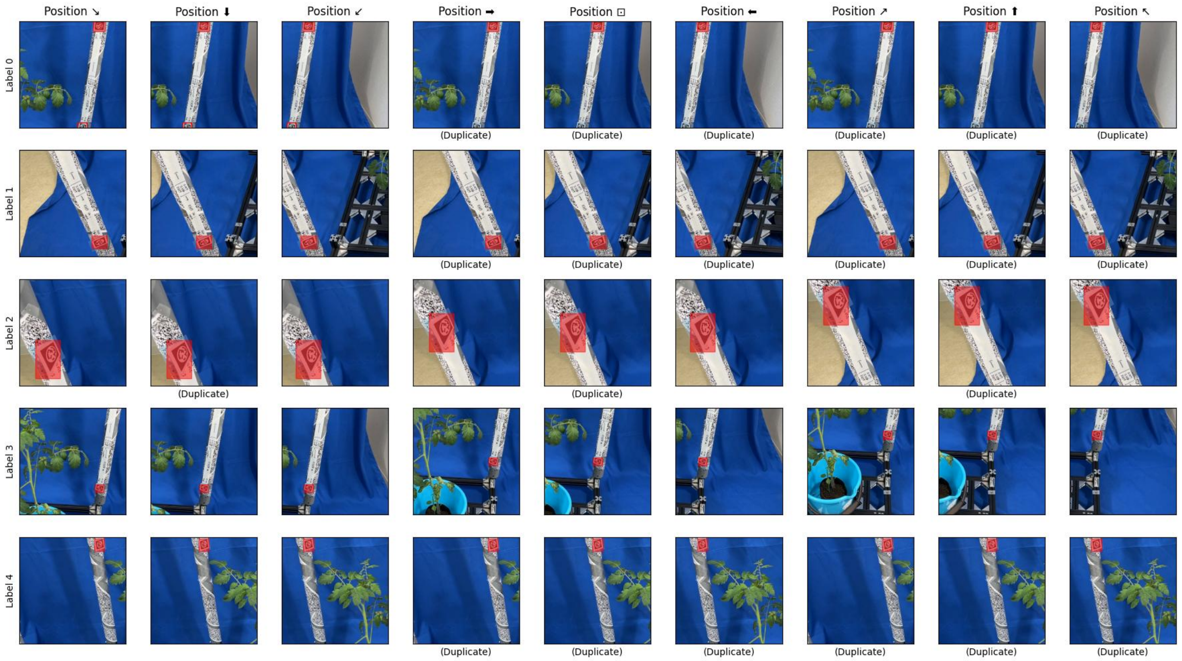
2.2 Synthetic training data generation for Yolov11

Method 2: Using metashape project from different markers

Stag marker DB



(3) Adjust marker’s color to fit with original marker



(4) Generate synthetic training dataset with position augmentation

Methods & Materials

2.3 SAHI framework integration for small objects detection

Flight height 12m

Flight height 30m

Flight height 50m

Marker become small objects on high flight height, often miss detection even with enough resolution

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Methods & Materials

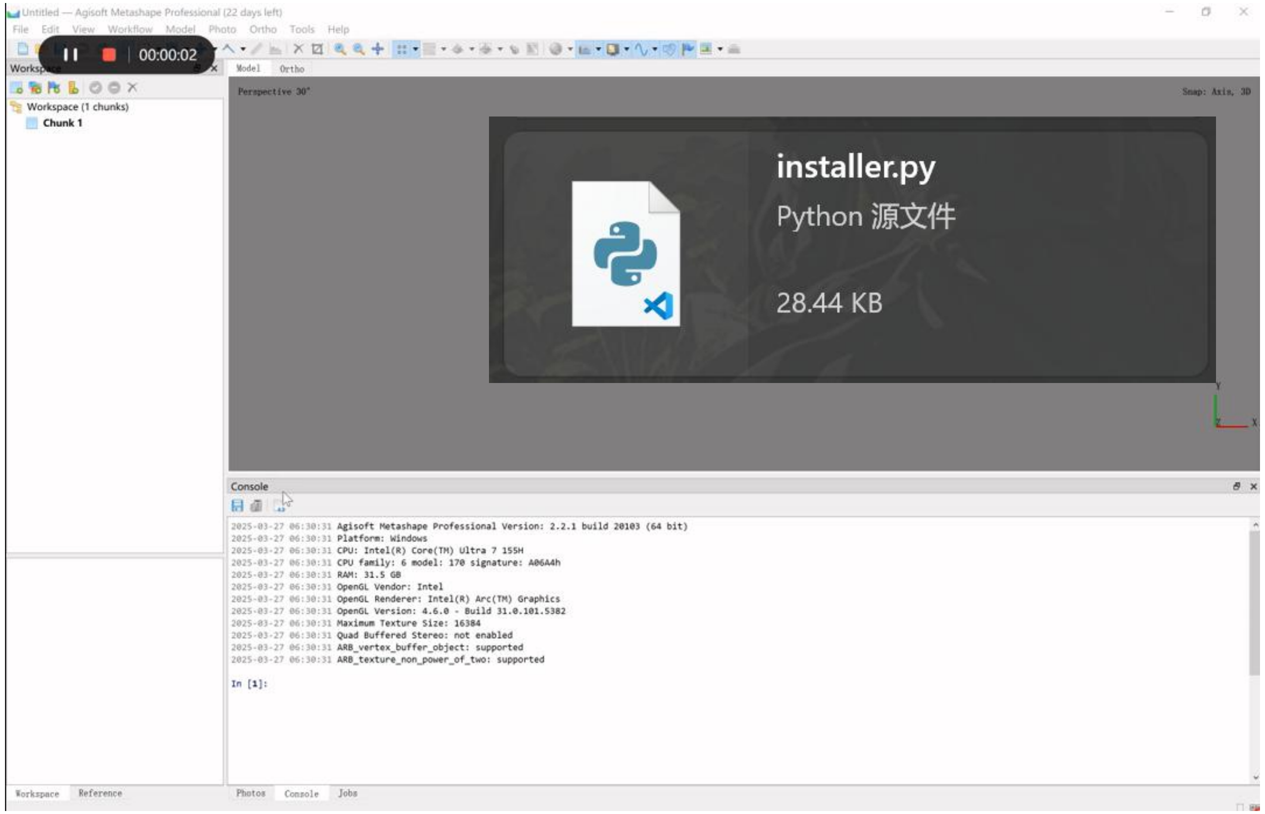
2.3 SAHI framework integration for small objects detection

SAHI framework is an optimized sliding window method to improve the small object detection

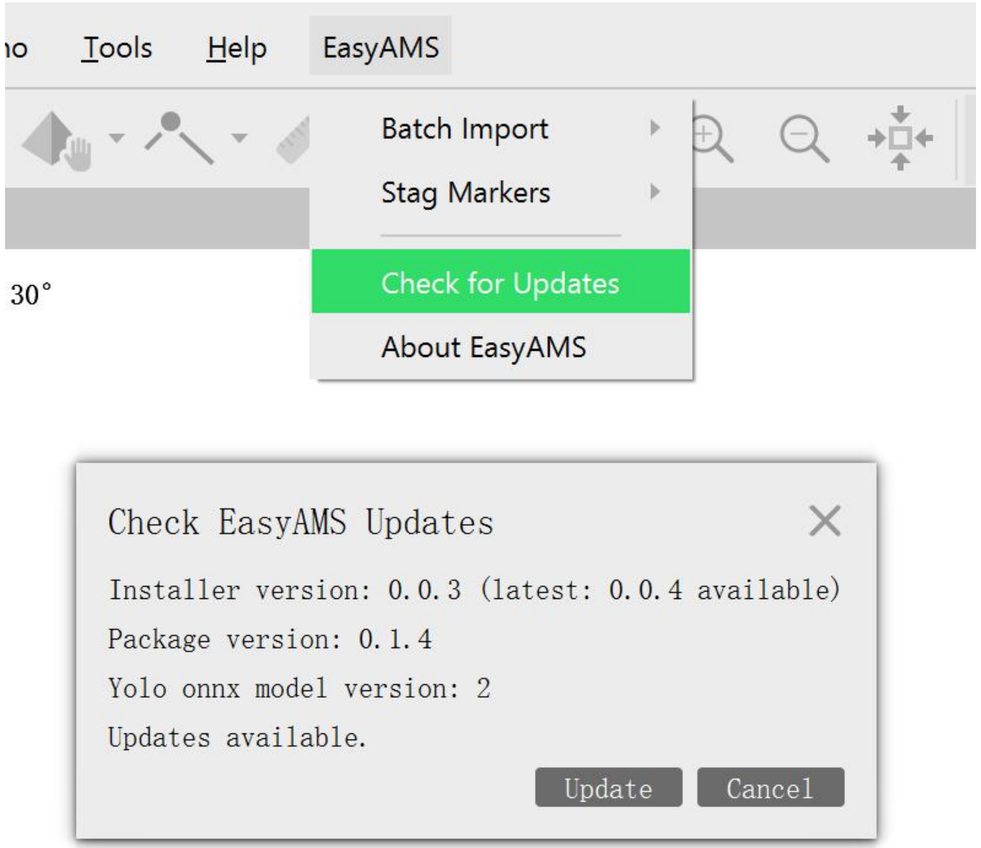
Modified the SAHI source code to remove dependencies on cuda, pytorch and ultralytics (1GB+)
Using ONNX-CPU inference only for the easy of use

Methods & Materials

2.4 Plugin implementation



(1) One-click to install



(2) One-click updates from Github

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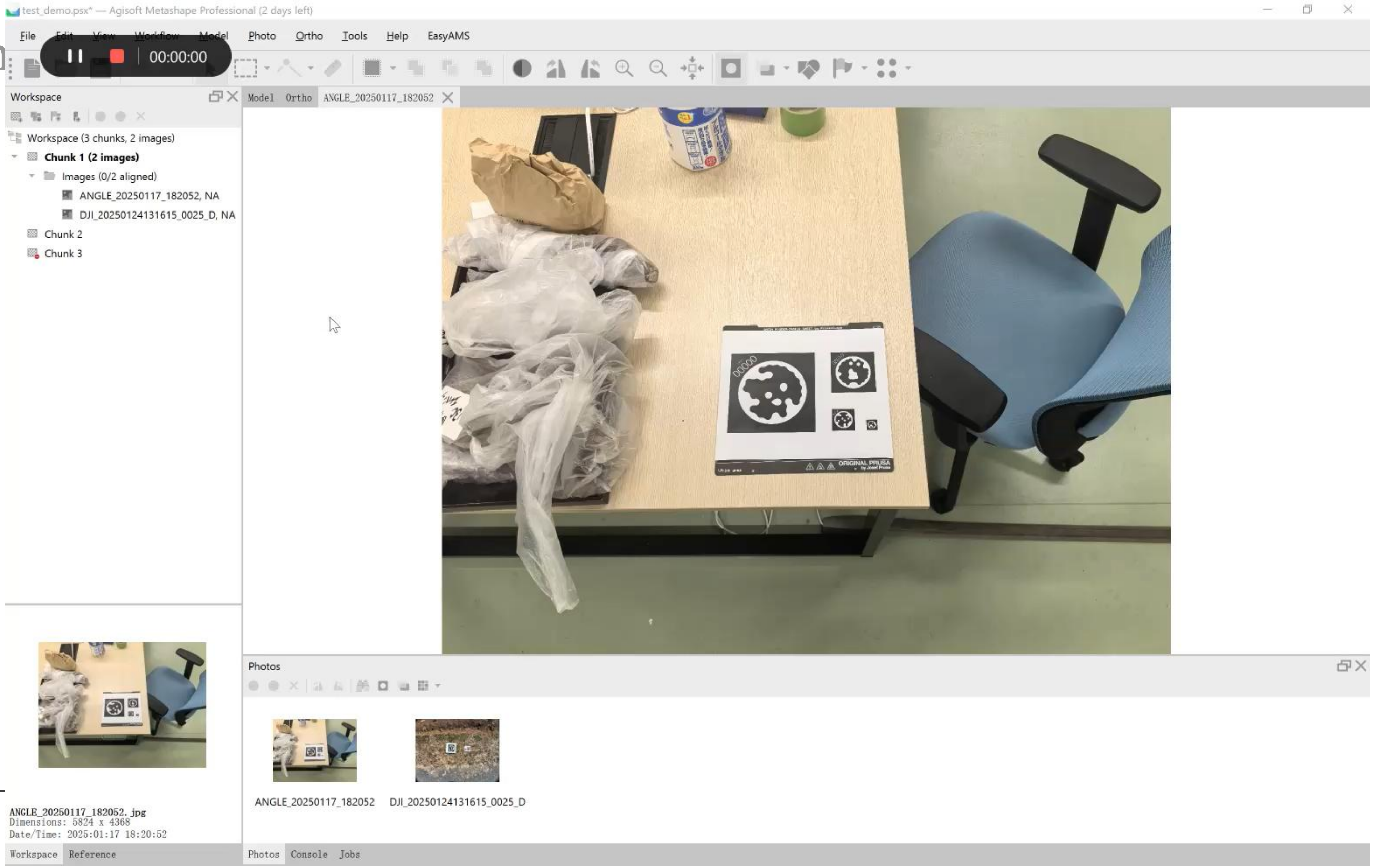
Methods & Materials

2.4 Plugin im

(3) User-friendly
UI for operation



03 Results and Discussion

Results & Discussion

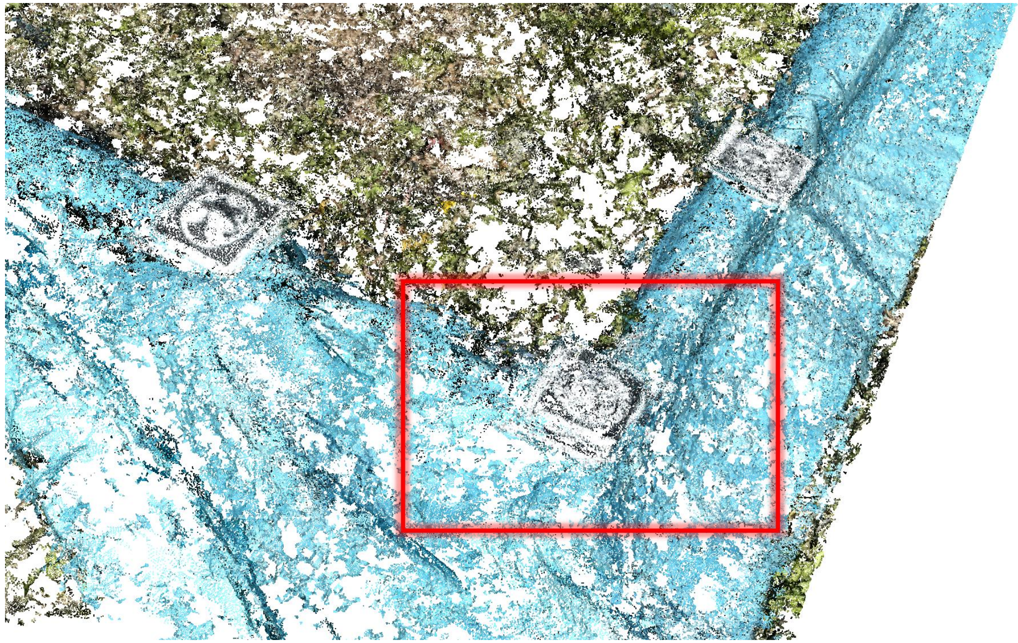
3.1 Detection comparison with Yolov11 detection

By stag official implementation

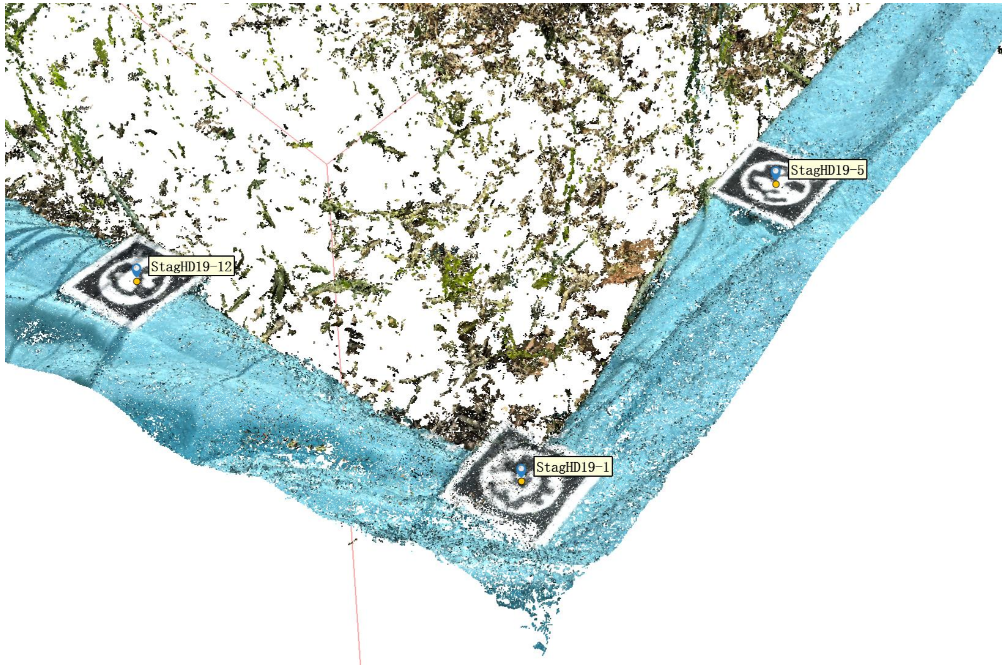
Yolo-detection bbox -> stag official decoding

Results & Discussion

3.2 Reconstruction comparison before & after using stag markers



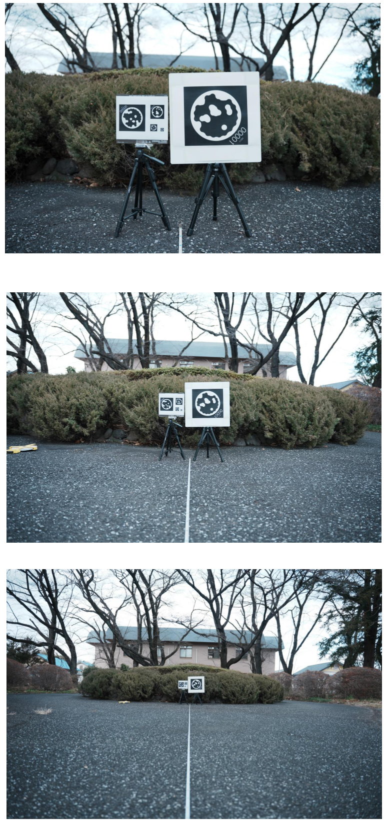
Without Stag markers



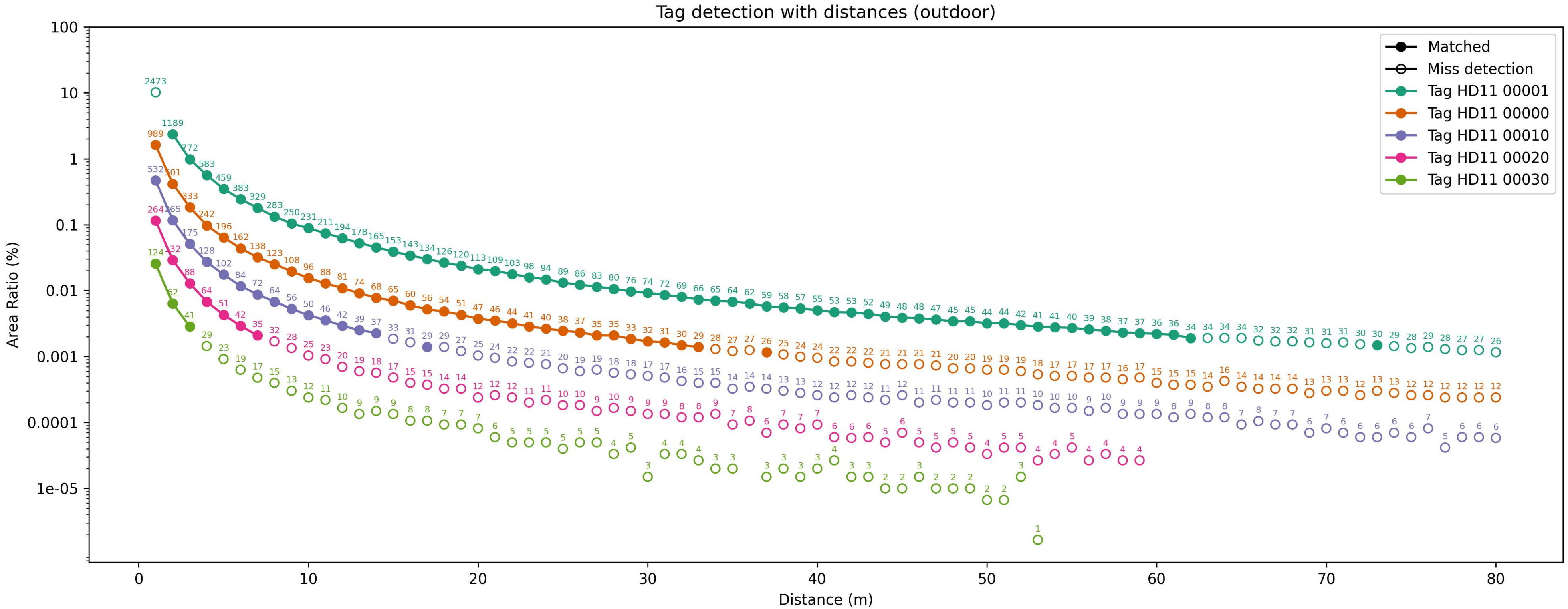
With Stag markers

Results & Discussion

3.3 Distance testing for small objects detection



5 markers from different distances

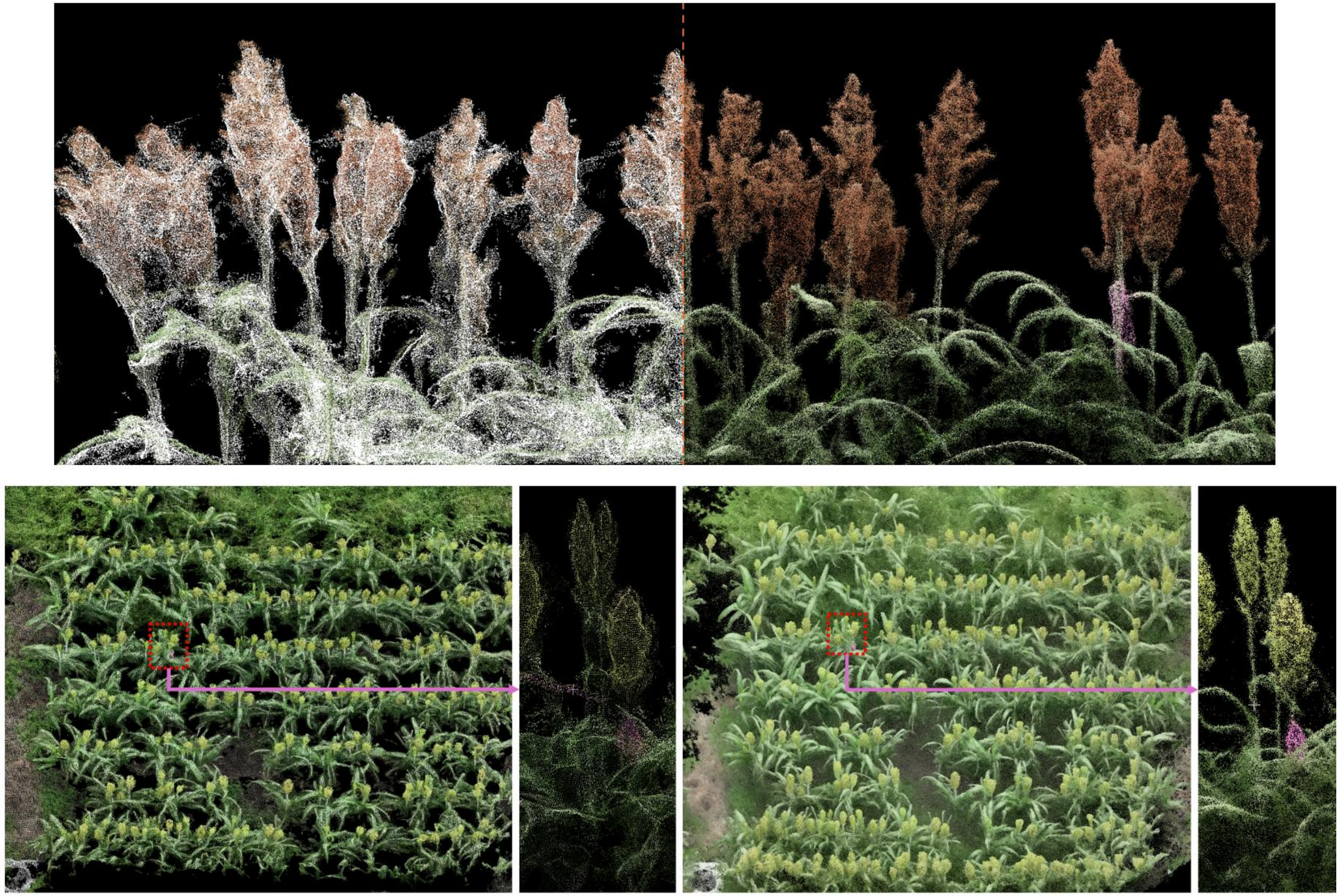


Stag detectable when over 50 pixels width & 0.5% area

Results & Discussion

3.4 Panicle Reconstruction results by Stag & NeRF

[1]



Agisoft point cloud model

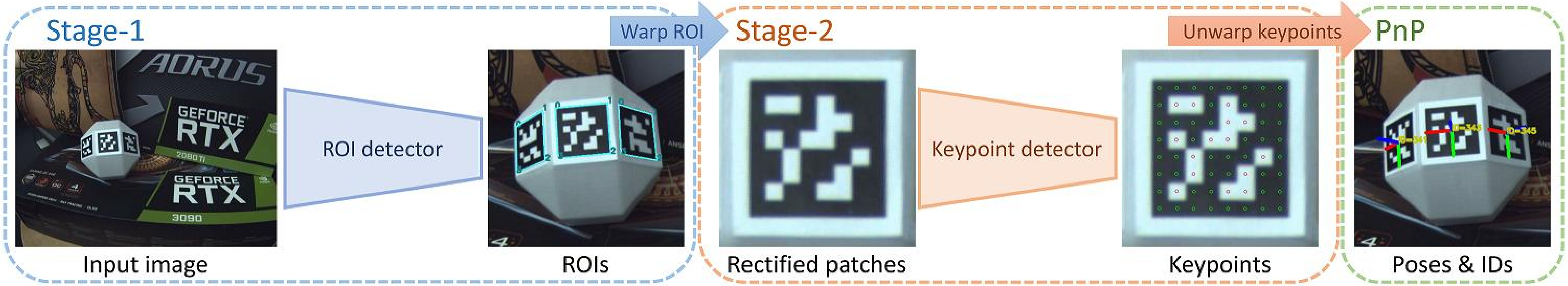
NeRF point cloud model

[1] James, C., Chandra, S.S., Chapman, S.C., 2025. A Scalable and Efficient UAV-based Pipeline and Deep Learning Framework for Phenotyping Sorghum Panicle Morphology from Point Clouds. Plant Phenomics 100050. https://doi.org/10.1016/j.plaphe.2025.100050

Results & Discussion

3.5 Future works

Current just use deep learning for detection, full pipeline can also be implemented in deep learning



DeepTag: A General Framework for Fiducial Marker Design and Detection

Zhuming Zhang Yongtao Hu Guoxing Yu Jingwen Dai

Guangdong Virtual Reality Technology Co., Ltd. (aka. Ximmerse), Guangzhou

IEEE Transactions on Pattern Analysis and Machine Intelligence (IEEE TPAMI 2023)

04 Conclusions

Conclusion

We implemented a Metashape Plugin StagGCP

- Natively support using Stag as GCP in Metashape
- Using deep learning techniques to improve detection
- Easy to install, update, and with user friendly interface.

Github/EasyAMS

https://github.com/UTokyo-FieldPhenomics-Lab/EasyAMS

Acknowledgement

JST Japan Science and Technology Agency

MAFF Ministry of Agriculture, Forestry and Fisheries 農林水産省

CSIRO

Montpellier SupAgro

CAAS

Iowa State University

Indian Institute of Technology Bombay

INRAE la science pour la vie, l'humain, la terre

The University of Queensland Australia

Beijing University of Technology 北京工业大学 1960

Nanjing Agricultural University 1902

Professor Jayashankar Telangana State Agricultural University

International Institute of Information Technology Hyderabad

SoftBank

住友化学 SUMITOMO CHEMICAL

NEC NECソリューションイノベータ

dji

Kubota

木と生きる幸福 住友林業

Thank You !

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