

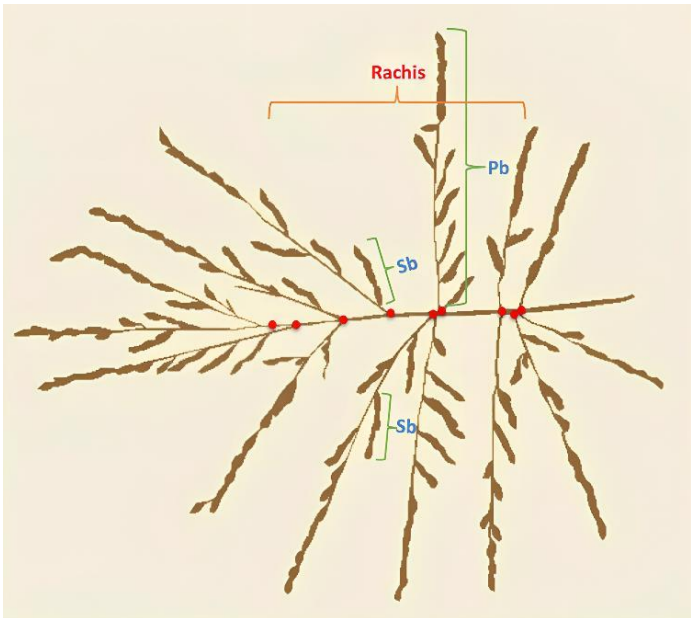
Structural Analysis of Asian and African Rice Panicles via Transfer Learning

Cong Hieu Le, Lam Thai Nguyen, Trung Kien Pham, Tran Hiep Dinh*, Le Khanh Nguyen, Stefan Jouannic, Helene Adam, Pierre Duhammel, Nguyen Linh Trung, and Hoang Trong Minh

*Corresponding author: Tran Hiep Dinh (tranhiep.dinh@vnu.edu.vn)

Motivation

- In the face of continuous climate change, sustainable genetic improvement through breeding is essential for maintaining rice yield and quality.
- However, breeding progress is **hindered** by manual, low-throughput phenotyping activities, which are **inaccurate and non-repeatable** [1].
- By leveraging the visual similarities between **pavement cracks and rice panicles**, we propose a cross-domain method to fully automate the **junction detection process**.
- Comprehensive experiments are conducted to test whether a general approach is applicable to both **Asian and African rice panicles**.



Structure of a rice panicle.

Method

Step 1 (Segmentation)

Seven pre-trained segmentation models on CFD dataset [2] are fine-tuned with our dataset.

Step 2 (Skeletonization)

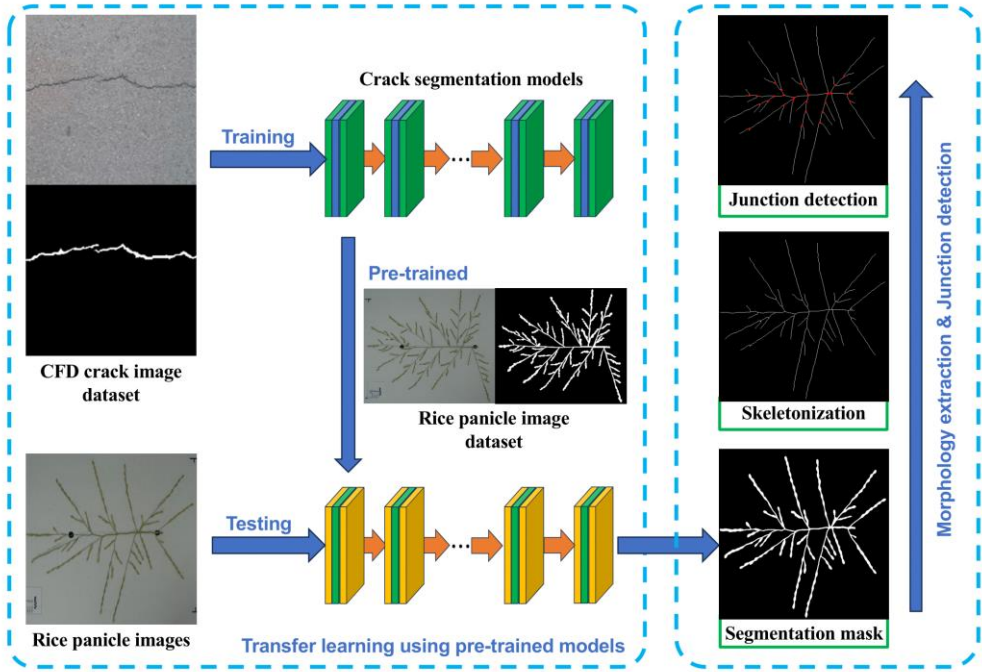
Resulting binary images are transformed into unitary thickness skeletons.

Step 3 (Junction detection)

Various clustering algorithms are used to locate junction positions.

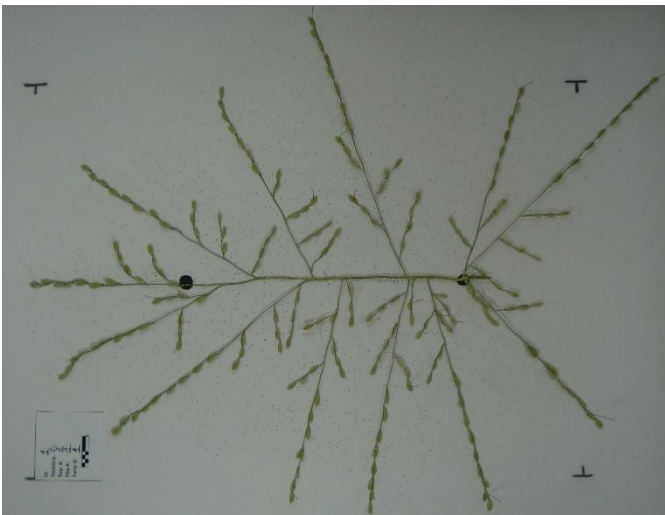
Step 4 (Evaluation)

Located junctions are compared to pre-labelled junctions for evaluation.



The proposed pipeline.

Data



Asian rice panicle.

- Asian panicles: 100 images.
- African panicles: 100 images.
- Settings: Laboratory, secured in place against a white background.
- Format: RGB.

Results

Segmentation

- U-net** [5] achieves the highest average $F1$ score across 3 datasets, reaching nearly **90%** accuracy.
- SegNet** [6] excels in Recall (R_c) but underperforms in Precision (Pr), indicating possible **over-segmentation**.
- U²CrackNet** [7] showcases strong performance, particularly in Precision (Pr).

For balanced performance, **U-Net** is the best choice.

Performance (%) of fine-tuned models.

Model	DeepCrack	FCN	SegNet	U-Net	U ² CrackNet	ACS	RUC-Net
Asian rice panicles							
Pr	89.46	86.80	77.78	89.60	91.61	88.21	86.02
R_c	89.73	88.35	94.95	90.18	86.81	90.23	92.07
F_1	89.53	87.41	85.26	89.85	89.10	89.18	88.89
African rice panicles							
Pr	89.14	86.09	77.18	89.26	90.93	87.95	86.00
R_c	89.24	88.49	94.72	89.78	86.72	89.89	91.40
F_1	89.08	87.04	84.84	89.42	88.69	88.83	88.52
Mixed Asian and African rice panicles							
Pr	90.10	86.95	77.80	89.05	91.72	88.26	86.38
R_c	88.73	89.13	95.41	90.91	86.66	90.22	91.68
F_1	89.34	87.86	85.51	89.91	89.05	89.17	88.88

Junction Detection

Performance in $F1$ score (%) of different algorithm combinations.

Skeletonization Clustering	ZS			GBO		
	DBSCAN	FINCH	CN	DBSCAN	FINCH	CN
Main axis junctions						
Asian	73.94	41.71	82.02	77.16	49.96	82.56
African	68.17	44.43	78.61	73.79	54.20	81.44
Combined	69.27	34.62	78.85	72.75	41.23	78.63
High-order junctions						
Asian	53.18	13.48	54.63	51.64	13.64	52.23
African	72.25	11.10	72.54	66.68	11.88	67.79
Combined	59.58	12.18	60.61	56.58	13.19	57.11
All junctions						
Asian	60.09	16.91	62.60	59.01	18.78	60.59
African	72.04	14.68	75.31	69.54	16.67	72.59
Combined	64.49	15.78	67.91	63.21	18.11	65.45

- The combination of **Zhang-Suen** thinning [3] and **Crossing Number** [4] (ZS-CN) consistently detects main axis junctions with approximately **80%** accuracy.
- Further refinements are needed to enhance the accuracy of high-order junction detection, particularly in complex structures like Asian's.

Conclusion

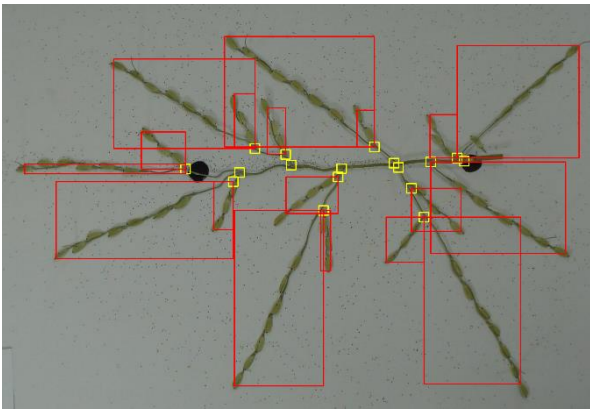
Contributions

- A novel method to **fully automate** the detection of rice panicle junctions.
- Comprehensive experiments to test whether a **general approach** is applicable to both Asian and African rice panicles.

U-Net – Zhang-Suen – Crossing Number can serve as a general approach for panicles structural analysis.

Future Works

- Develop a robust method with fewer steps.
- Employ detection models for grain and junction identification.



Bounding boxes for rice panicle grains and junctions.

References

- [1] F. Al-Tam, H. Adam, A. d. Anjos, *et al.*, “P-trap: A panicle trait phenotyping tool,” *BMC Plant Biol.*, vol. 13, pp. 1–14, 2013.
- [2] Y. Shi, L. Cui, Z. Qi, F. Meng, and Z. Chen, “Automatic road crack detection using random structured forests,” *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 12, pp. 3434–3445, 2016.
- [3] T. Y. Zhang and C. Y. Suen, “A fast parallel algorithm for thinning digital patterns,” *Commun. ACM*, vol. 27, no. 3, pp. 236–239, 1984.
- [4] R. Bansal, P. Sehgal, and P. Bedi, “Minutiae extraction from fingerprint images-a review,” *Int. J. Comput. Sci. Issues (IJCSI)*, vol. 8, no. 5, p. 74, 2011.
- [5] O. Ronneberger, P. Fischer, and T. Brox, “U-net: Convolutional networks for biomedical image segmentation,” in *Med. Image Comput. Computer-assisted Intervention–MICCAI 2015: 18th Int. Conf., Munich, Germany, October 5-9, 2015, Proc., part III* 18, Springer, 2015, pp. 234–241.
- [6] V. Badrinarayanan, A. Kendall, and R. Cipolla, “Segnet: A deep convolutional encoder-decoder architecture for image segmentation,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 39, no. 12, pp. 2481–2495, 2017.
- [7] P. Shi, F. Zhu, Y. Xin, and S. Shao, “U2cracknet: A deeper structure with two-level nested u-structure for pavement crack detection,” *Struct. Health Monit.*, vol. 22, no. 4, pp. 2910–2921, 2023.