

Resolution-Standardized Bamboo-Pole Counting

from Multi-Resolution UAV Imagery for Coastal Monitoring.

A collaborative research project



DMCR

Department of Marine
and Coastal Resources



NECTEC

National Electronics and
Computer Technology Center



SIIT

Sirindhorn International
Institute of Technology

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Coastal Erosion in Thailand

Why coastal protection matters

3,151 km

Thailand coastline

Gulf of Thailand +
Andaman Sea

861 km

Affected by erosion

Including coastlines
already protected

27.3%

Of total coastline

DMCR 2024 assessment



Coastal Protection Measures

Examples of common approaches used in Thailand



Built barriers

Hard structures help reduce wave impact.



Mangrove restoration

Mangroves help protect and stabilize the coast.



Bamboo fences

Bamboo fences are used in muddy coastal areas.

Why DMCR Needs Bamboo-Pole Counts

Government bamboo fences need regular inspection and maintenance

Government assets

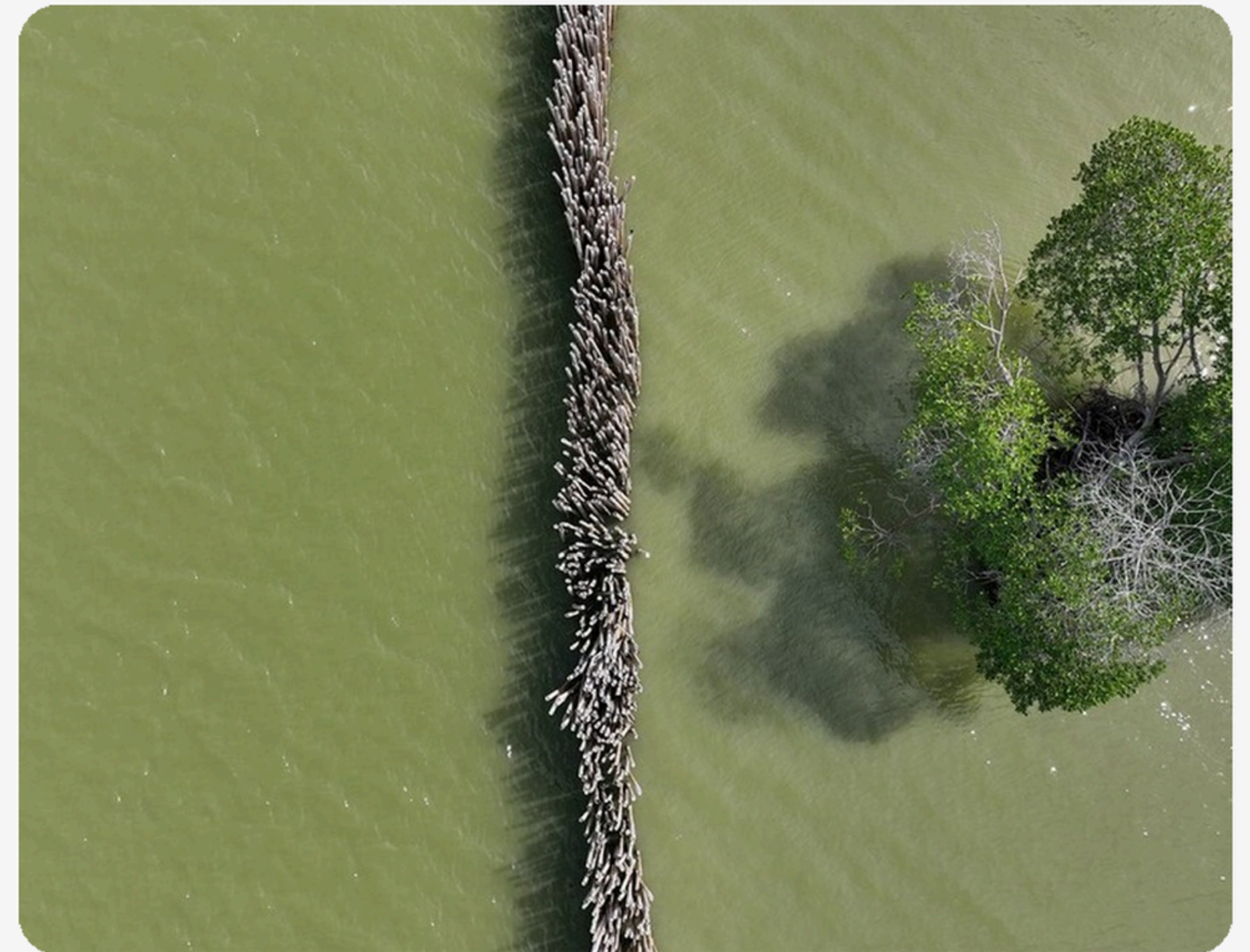
DMCR manages bamboo-fence projects for coastal protection.

Yearly inspection

Teams take drone photos and manually count visible bamboo poles.

Time-consuming work

Counting many poles in many images takes time and effort.



UAV image of a bamboo fence

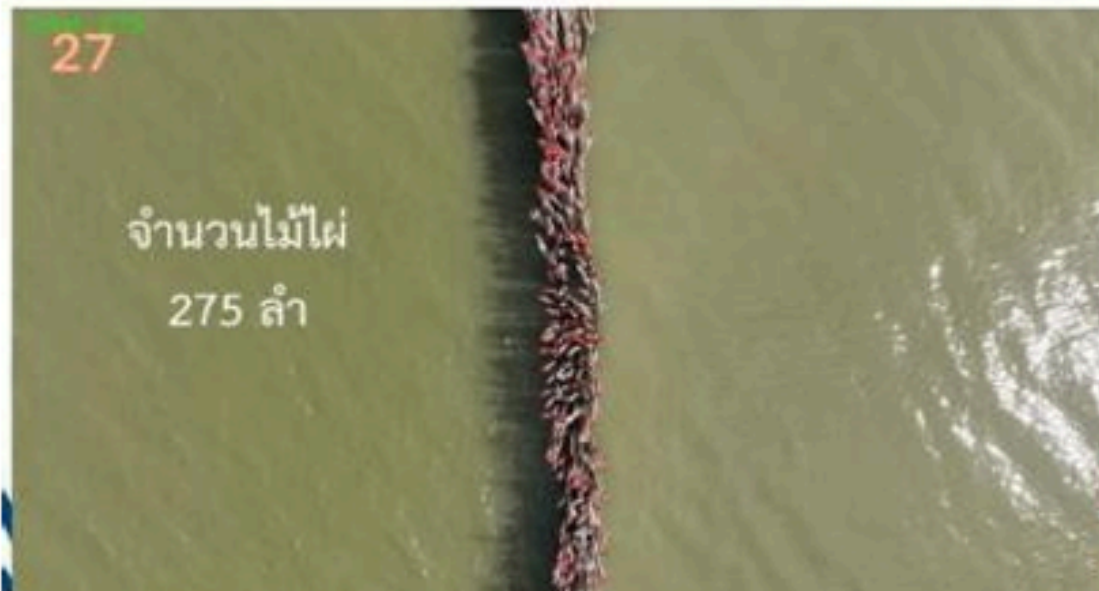
DMCR + NECTEC + SIIT → AI-assisted counting

The same scene led to different reported counts

Field testing motivated a controlled investigation of input resolution.

คอมพิวเตอร์

โทรศัพท์ ระบบปฏิบัติการ iOS



Example from
DMCR Testing

266 PC

146 iOS

Research Objectives

What did we want to find out?

01

Resolution effect

Evaluate how input image resolution affects bamboo-pole counting accuracy.

02

Standardization

Investigate whether resizing inputs to 4K improves counting consistency.

03

Fine-tuned detector

Assess the fine-tuned detector across different input resolutions.

What was inherited — and what we changed

The earlier two-stage segmentation–detection architecture was retained.

INHERITED FROM PREVIOUS WORK

1. Bamboo-region segmentation
2. ROI extraction + sliced inference
3. Existing high-resolution detector

CONTRIBUTIONS OF THIS STUDY

1. Fine-tune the pole detector
2. Standardize input image resolution
3. Evaluate paired resolutions

System Workflow



INHERITED Segmentation + sliced detection

THIS STUDY Standardization + detector fine-tuning

The system counts visible bamboo-pole ends—not entire physical poles.

Image Preparation

LANCZOS interpolation aligns the processing scale used by the detector.

4K

3840 × 2160

Already at 4K

2K

2560 × 1440

Resize to 4K

1080p

1920 × 1080

Resize to 4K

Detector Fine-Tuning

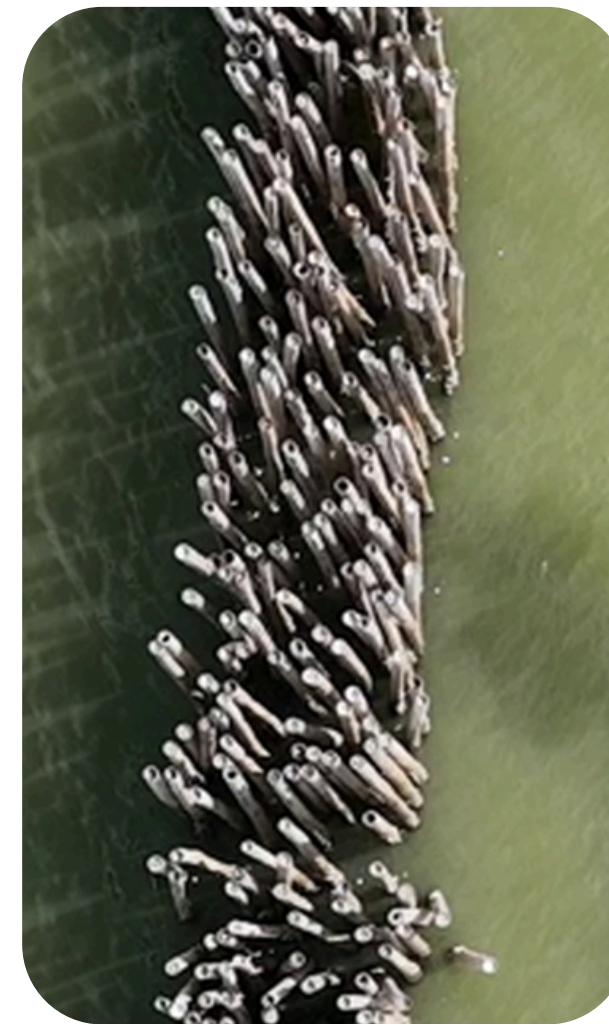
Training across image-quality variations

One original image was used to create six modified versions.

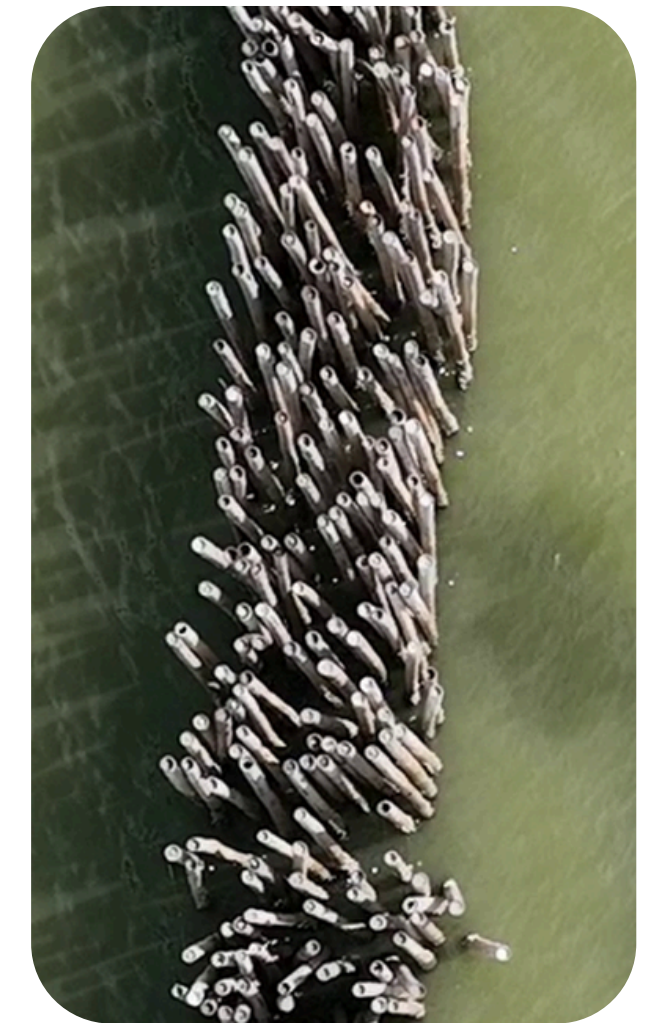
Original Image



Resolution Degradation



50% degradation

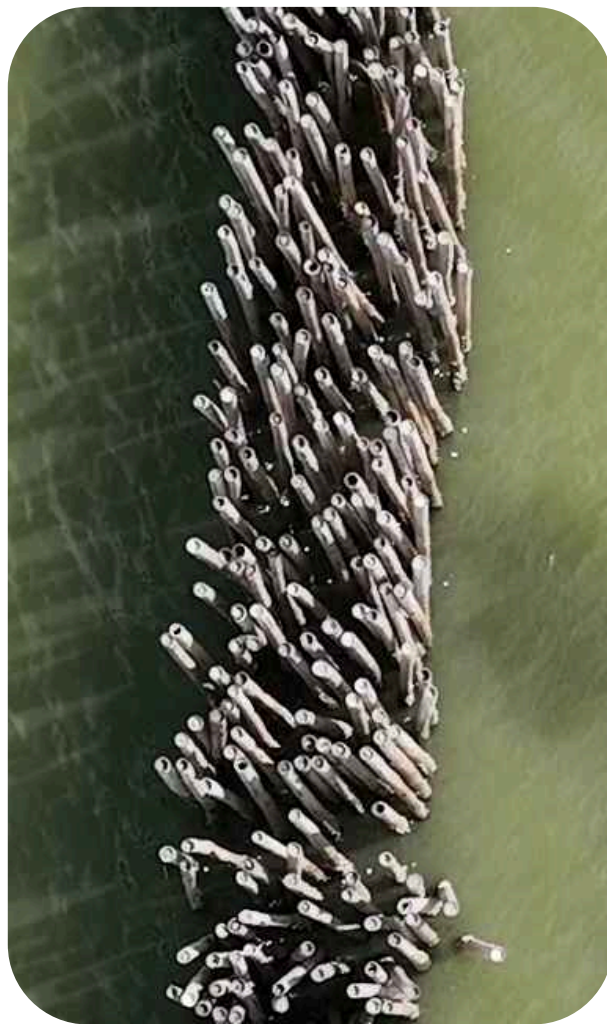


75% degradation

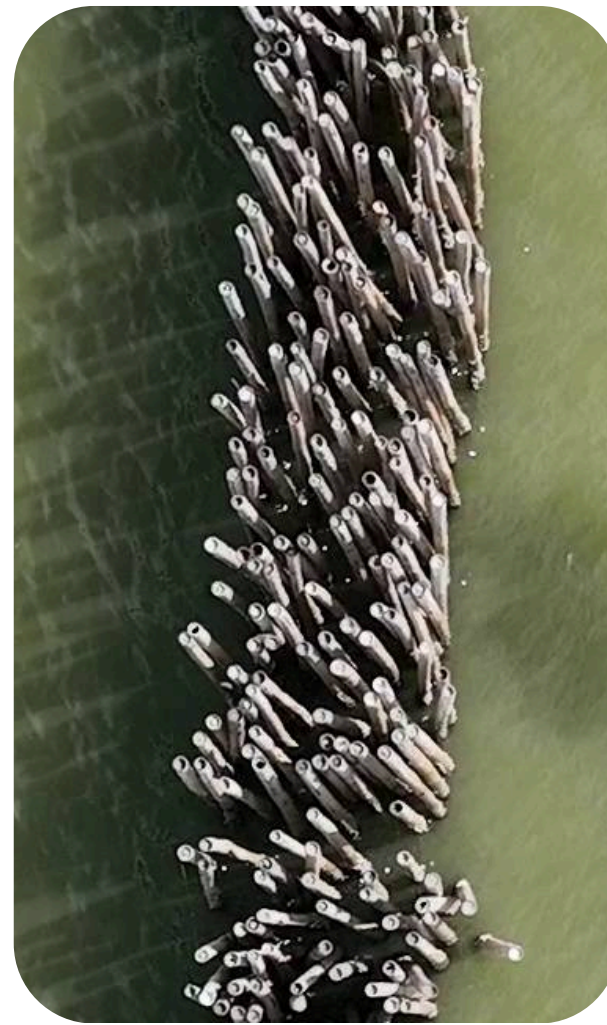
Image-Quality Variations (Continued)

Additional training images created using JPEG compression and sharpness adjustment.

JPEG Compression

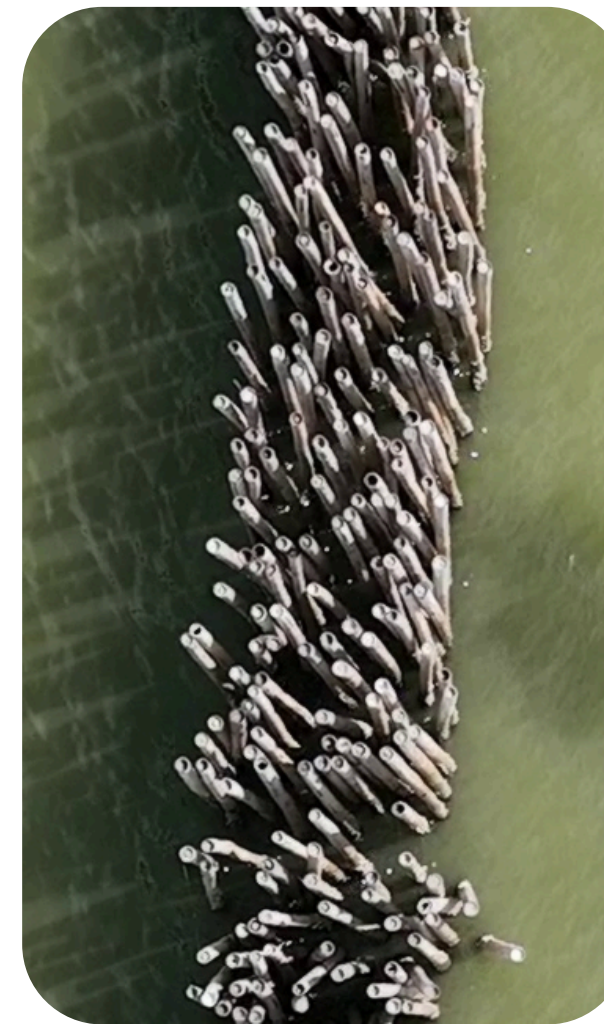


Quality 40

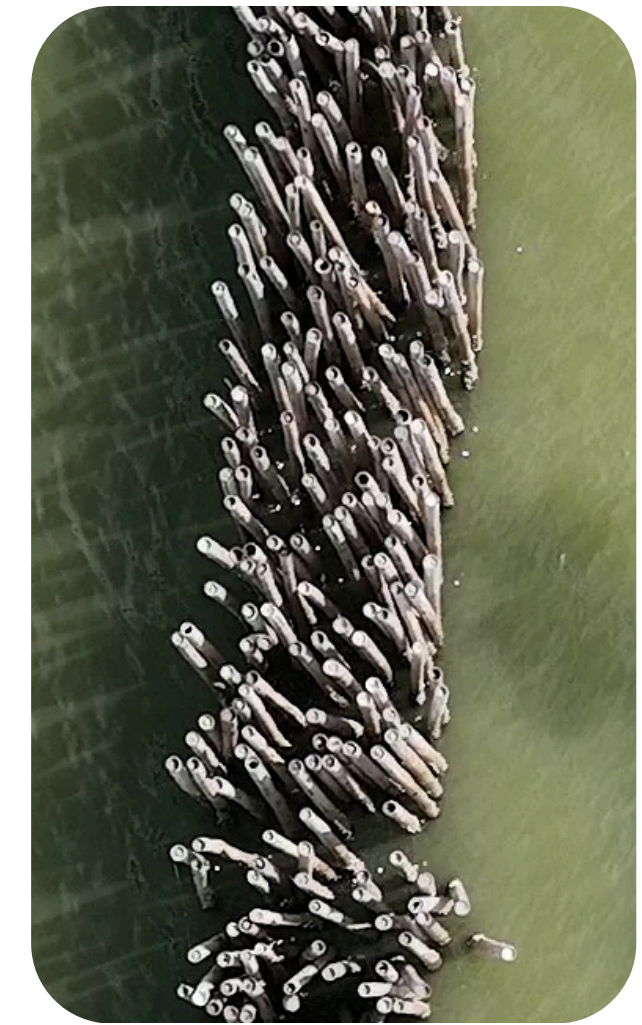


Quality 70

Sharpness Adjustment



Factor 0.50



Factor 1.50

Detector Fine-Tuning

Training Dataset After Augmentation

One original image was used to create six modified versions.

1,164

original training images

×

For each original image

1 original

+ 6 augmented versions

= 7 total versions

=

8,148

total training images
after augmentation

Resolution

2 variants: 50% and 75% degradation

JPEG

2 variants: quality 40 and 70

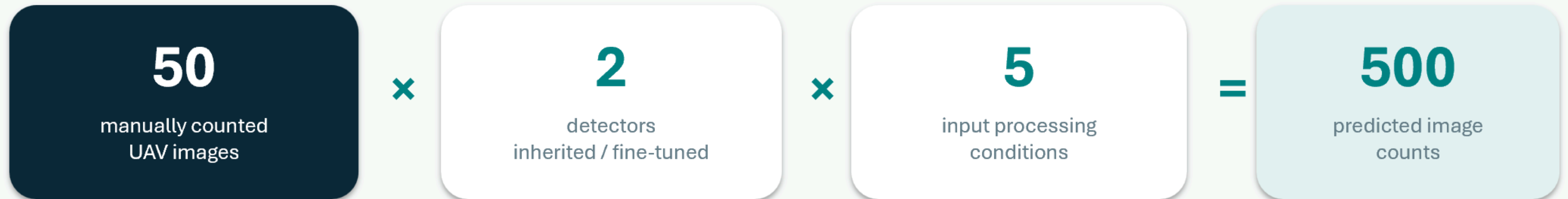
Sharpness

2 variants: factors 0.50 and 1.50

Experimental Design

A controlled paired-resolution benchmark

The same 50 scenes were tested using two detectors and five resolution conditions.



The five input-processing conditions

4K (1 condition)

4K resized

2K (2 conditions)

2K, without standardization

2K → 4K standardized

1080p (2 conditions)

1080p, without standardization

1080p → 4K standardized

1 + 2 + 2 = 5 conditions

Main metric: MAE (lower is better) · Also reported: RMSE, MAPE, Bias

Counting Error Across Resolutions

Mean Absolute Error (MAE) in poles - lower is better

Input condition	Inherited detector	Fine-tuned detector
4K resized	64.40	19.60
2K, without standardization	89.26	63.64
2K → 4K standardized	53.52	18.90
1080p, without standardization	211.84	253.60
1080p → 4K standardized	68.30	19.04

Standardized = resized to 4K before processing

Key takeaway: Standardized 4K, 2K and 1080p inputs had similar MAE (about 19 poles).

Main Finding

At 1080p, standardization reduced MAE by 92.5%

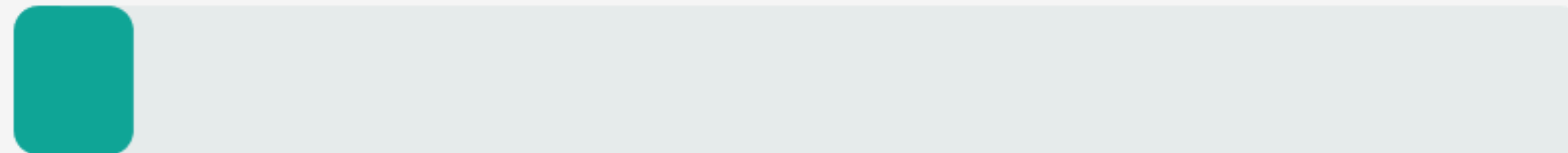
Fine-tuned detector · paired 50 images · lower MAE is better.

1080p, without standardization



253.60 poles

1080p, standardized to 4K



19.04 poles

–92.5% mean absolute error

Across Resolutions

Three standardized conditions had similar errors

Mean Absolute Error (MAE) — lower is better

2K → 4K

18.90

MAE (poles)

1080p → 4K

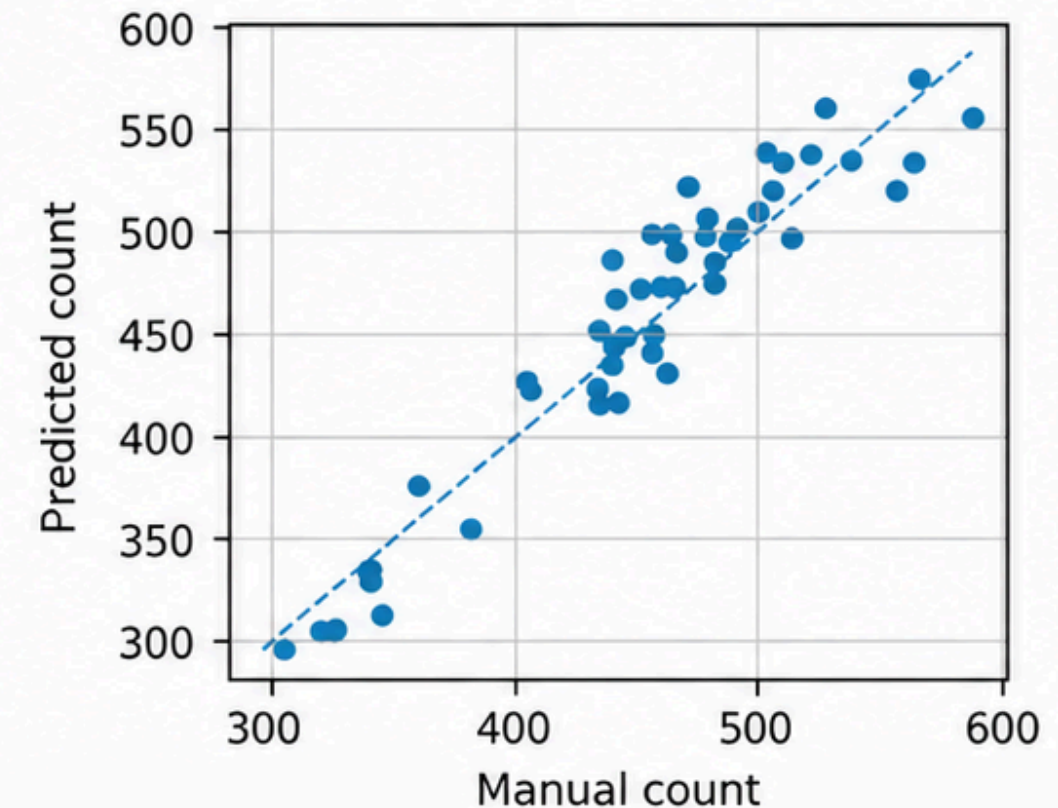
19.04

MAE (poles)

4K resized

19.60

MAE (poles)



Manual vs predicted counts (2K → 4K)

All three standardized conditions produced about 19 poles of average counting error.

What the evidence supports — and what it does not

The study tests a combined pipeline under controlled image-resolution changes.

Supported by the experiment

- Lower counting errors after standardization
- Similar errors across tested resolutions

Not yet demonstrated

- Consistency after deployment
- Different drone conditions
- Real-world impact

Conclusion

What we learned from the controlled experiments

- 01 Image resolution matters**
Counting accuracy changed substantially with input resolution.
- 02 Standardization helps**
4K standardization combined with fine-tuning reduced counting errors under the tested conditions.
- 03 Similar standardized results**
Standardized 4K, 2K, and 1080p inputs all had MAEs close to 19 poles.
- 04 More validation is needed**
Future tests should include different UAV flights, cameras, and field conditions.

Thank You

Any Questions?



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Research Collaboration



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