Development of Workflows for Pavement Distress Segmentation Using 2D Intensity and 3D Range Images

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Introduction

- High-speed 2D intensity and 3D range images support automated pavement assessment.
- Reliable segmentation needs pixel-level masks that preserve cracks, joints, and patches.
- Annotation is the main bottleneck, especially for thin cracks and joint-adjacent distress.

Background

- Model quality depends strongly on label consistency and data preparation.
- Multimodal images help because some features are clearer in intensity and others in range.
- Early project results showed that workflow quality can limit performance as much as model choice.

Objectives

- Develop a faster and more repeatable annotation workflow.
- Compare manual and assisted labeling across distress types.
- Benchmark a real-time baseline and a transformer-based segmentation model.
- Balance annotation effort, mask quality, and deployment relevance.

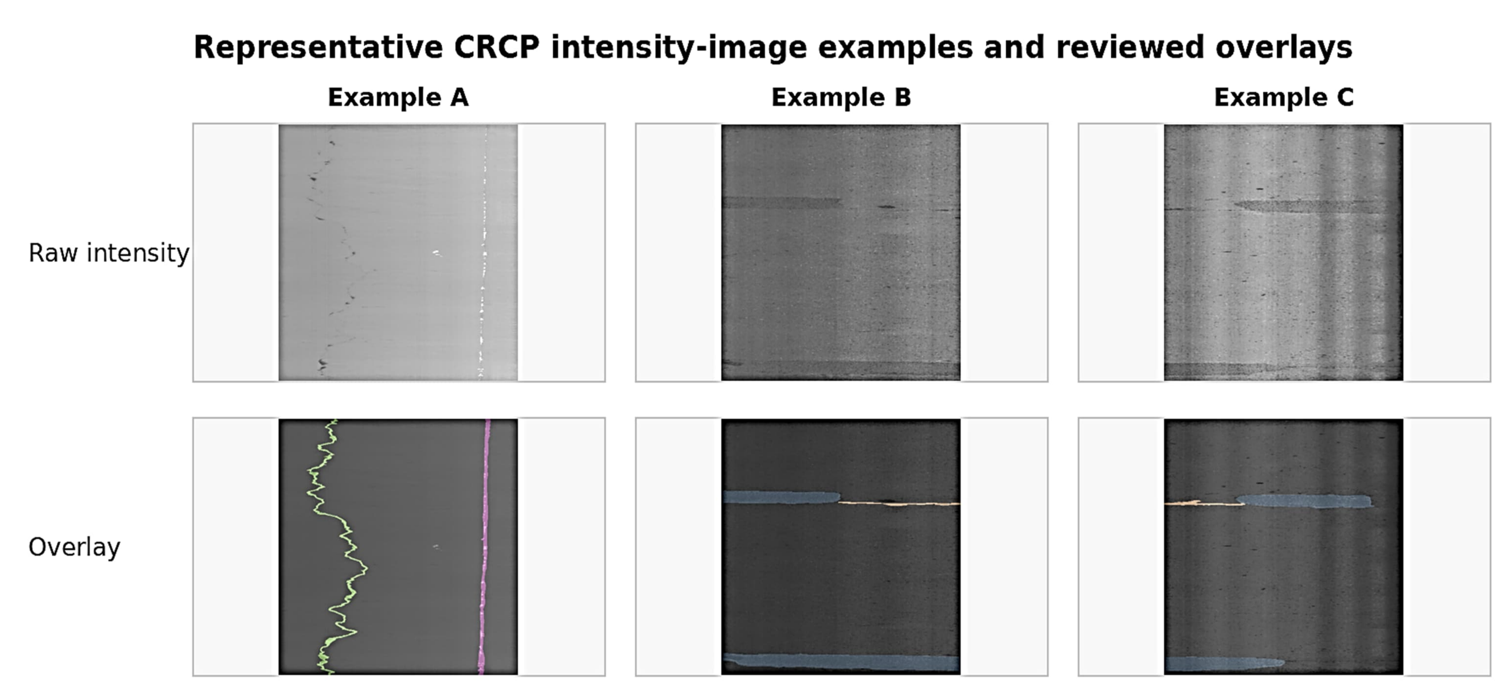
Data

- Paired 2D intensity and 3D range images from concrete pavement sections.
- This poster emphasizes the verified CRCP experiments and current workflow lessons.

Verified source split
141 train / 30 val / 31 test images
6-class CRCP source dataset

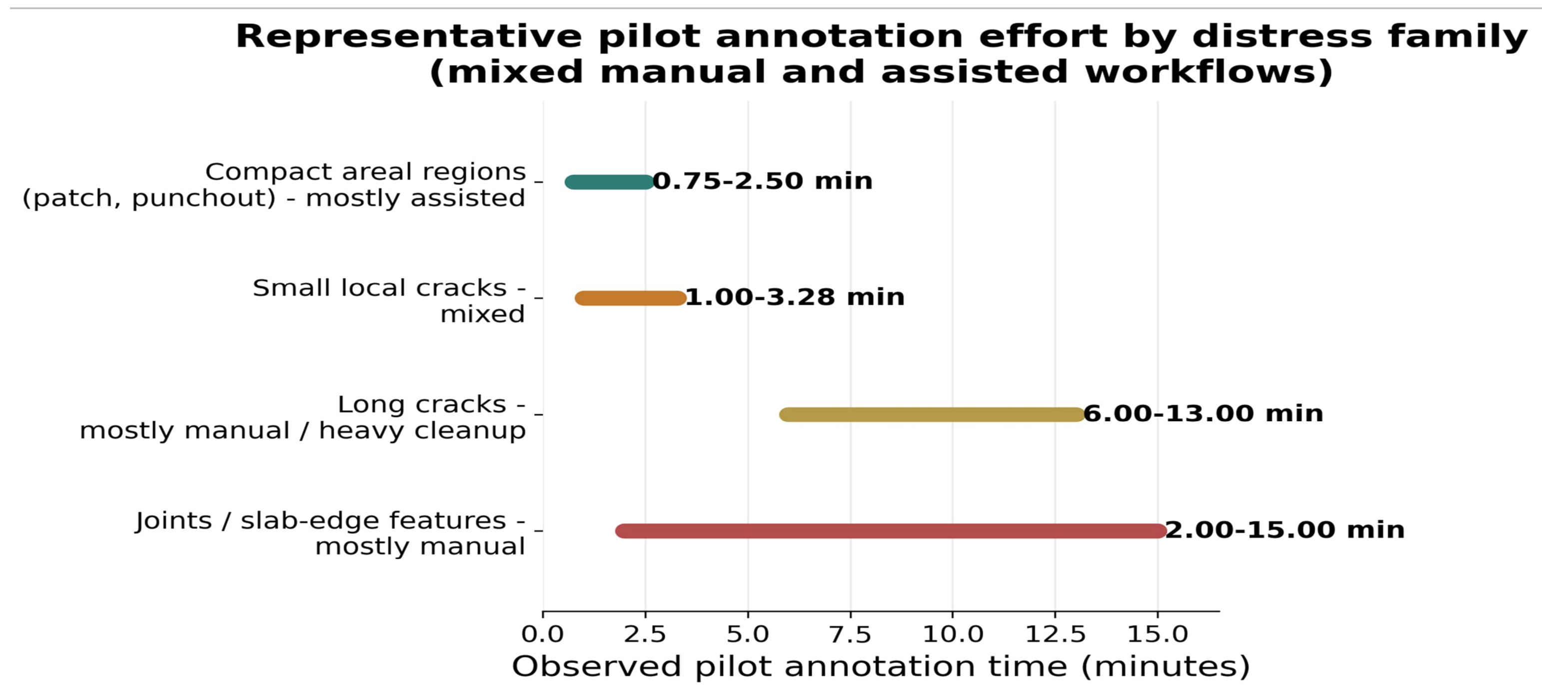
Current crop training
1034 / 440 / 429 crops
train / val / test

Representative Labeling Examples



CRCP examples only; used to illustrate rigid-pavement annotation behavior.

Annotation Effort by Distress Type



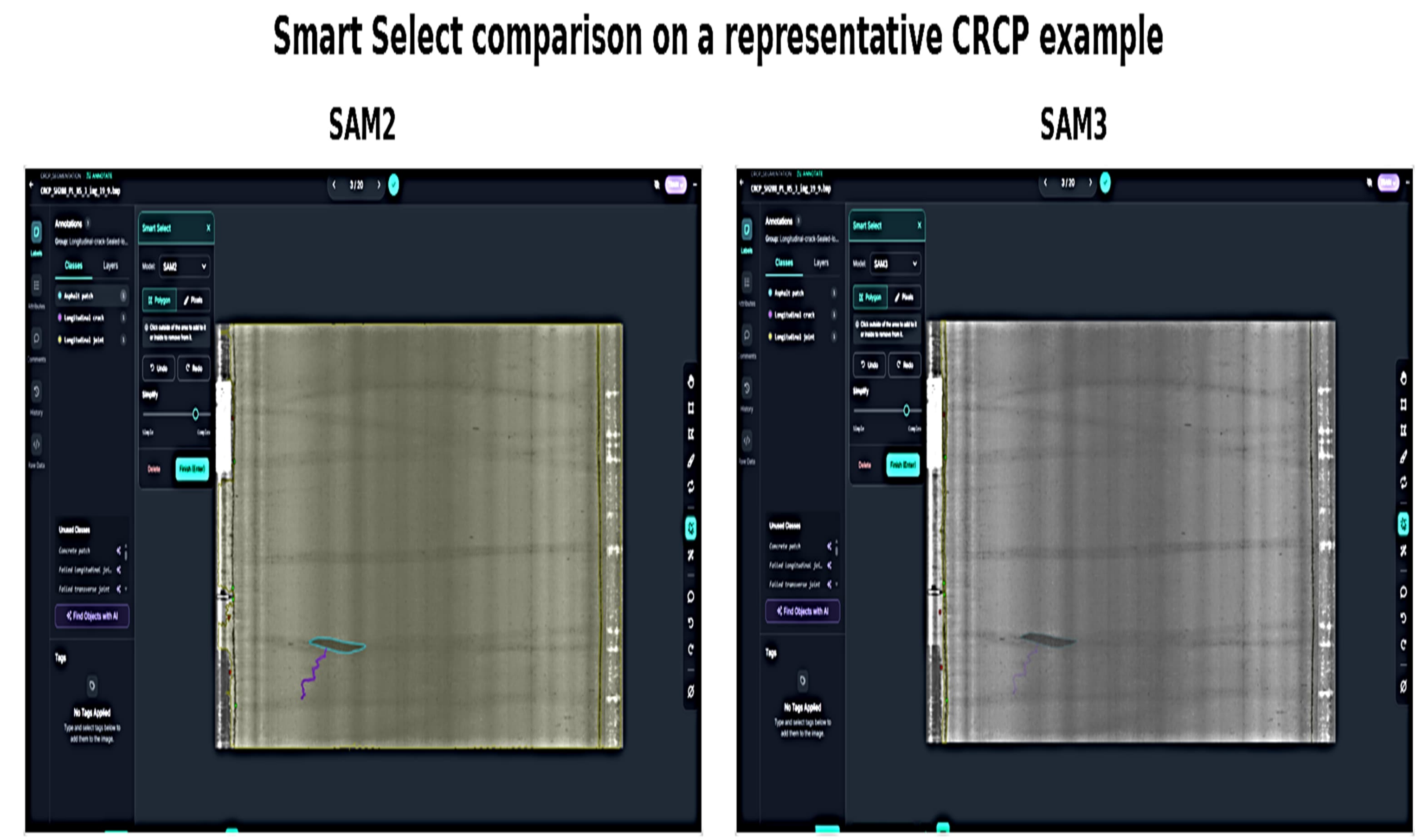
Representative pilot cases mix manual and assisted workflows. Compact areal defects were the best candidates for assisted labeling; long cracks and joints remained the dominant manual burden.

Methods / Workflow

- Standardized labeling rules and repeated review were used to improve repeatability.
- Local contrast sharpening was used only as an annotation aid.

Multimodal image input → ROI selection / local sharpening → Manual or assisted refinement → Quality-control review → Mask export & verification → Model training & feedback

Assisted Labeling Example



Qualitative comparison only; same CRCP longitudinal-joint labeling context. SAM3 appears visually cleaner, but formal time gain still requires controlled benchmarking.

Model Comparison

YOLOv8-seg

Real-time instance-segmentation baseline.

Best pilot result: mAP@0.50 = 0.305

Current evidence is strongest for larger patch-like regions.

SegFormer-B2

Transformer-based semantic-segmentation benchmark.

Best verified result: val mIoU = 0.5349
test mIoU = 0.4984

Workflow Observations

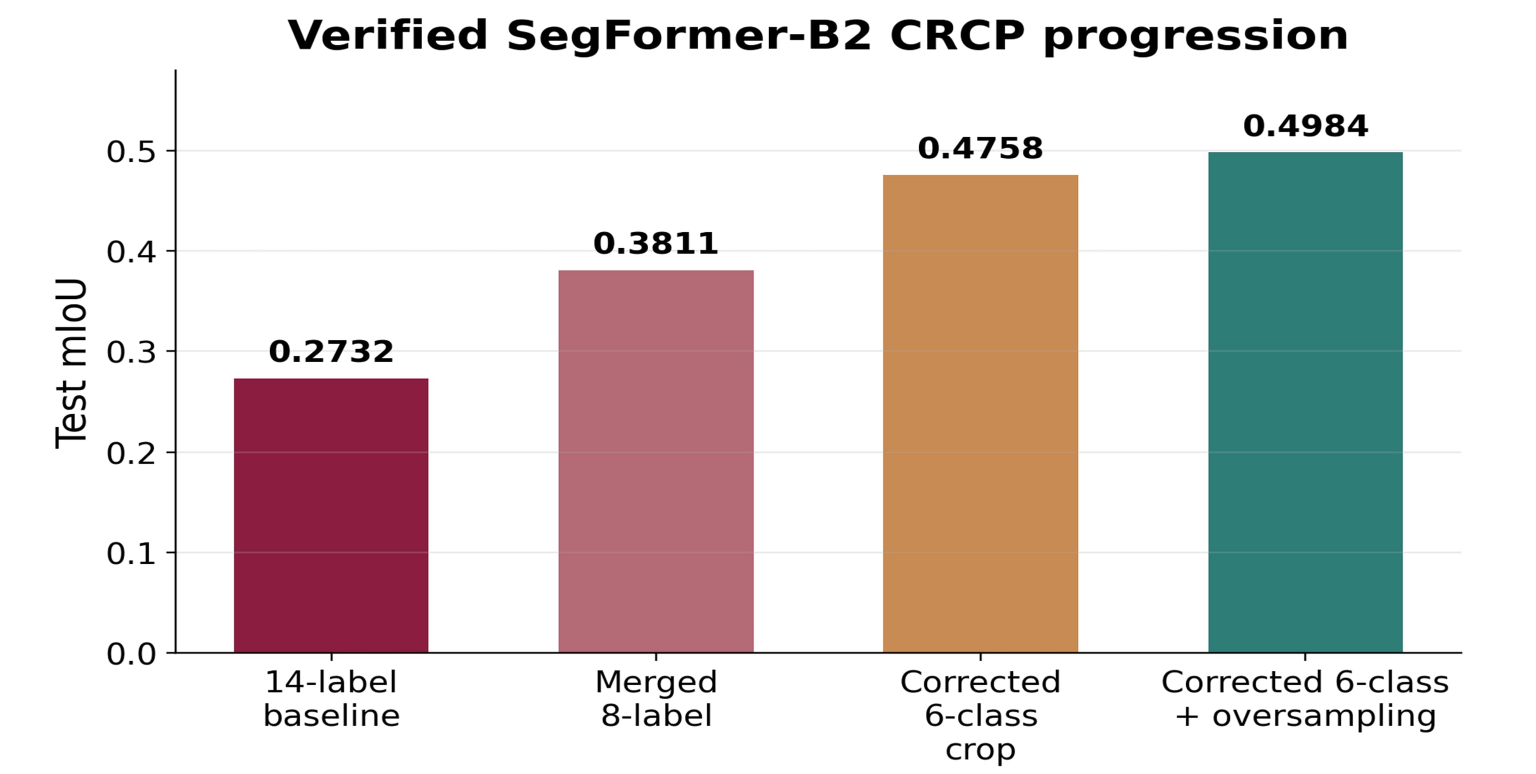
- The largest gains followed improvements in label quality, workflow consistency, and training-data preparation.
- Compact areal defects responded best to assistance; long cracks and joints still needed substantial manual cleanup.
- Multimodal imagery remained important where low contrast or subtle geometry made single-modality interpretation harder.

Practical Takeaway

The strongest gains came from fixing labels, enforcing quality control, and matching the training representation to the evaluation view.

Results & Discussion

Largest gain followed corrected remapping and crop-consistent training. Test mIoU improved from 0.3811 to 0.4984 in the verified SegFormer-B2 chain.



Best verified test mIoU
0.4984
Corrected 6-class + oversampling

Test macro-Dice
0.6155
SegFormer-B2

YOLO mAP@0.50
0.305
Pilot real-time baseline

Key Findings

- Correcting remapped masks and enforcing quality control produced the largest performance improvement.
- Representation-consistent crop training improved segmentation accuracy after the data pipeline was repaired.
- Thin and rare distress types remained more difficult than larger patch-like regions.

Conclusion

- Workflow quality mattered as much as model choice.
- The strongest gains came from fixing labels, enforcing QA, and matching training to evaluation view.

Future Work

- Improve assistance for thin features such as long cracks and joints.
- Extend the QA-first workflow to ACP and other pavement scenes.
- Balance annotation effort, mask quality, and inference speed for practical agency use.

Acknowledgments

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Keywords

Pavement distress; semantic segmentation; multimodal imaging; intensity; range; annotation workflow; quality assurance.

Note: YOLO mAP and SegFormer mIoU summarize different task roles and should not be treated as the same quantity.

Takeaway: workflow quality mattered as much as model choice for current verified CRCP segmentation results.