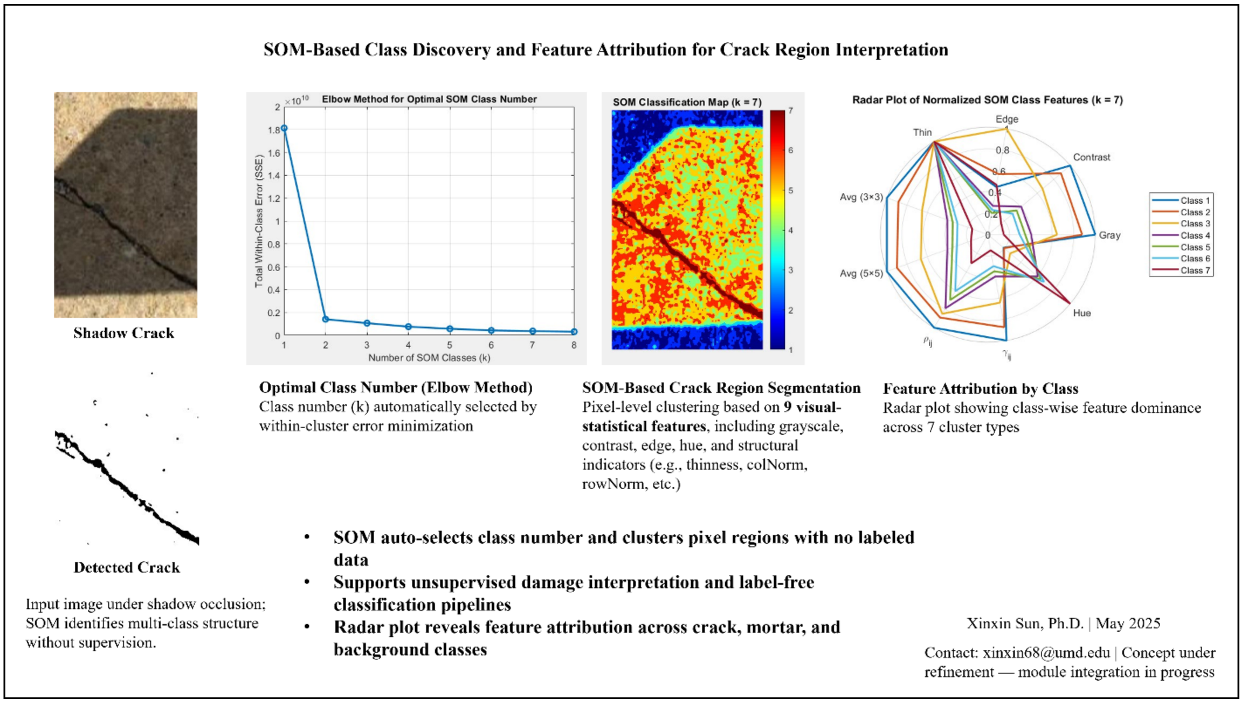
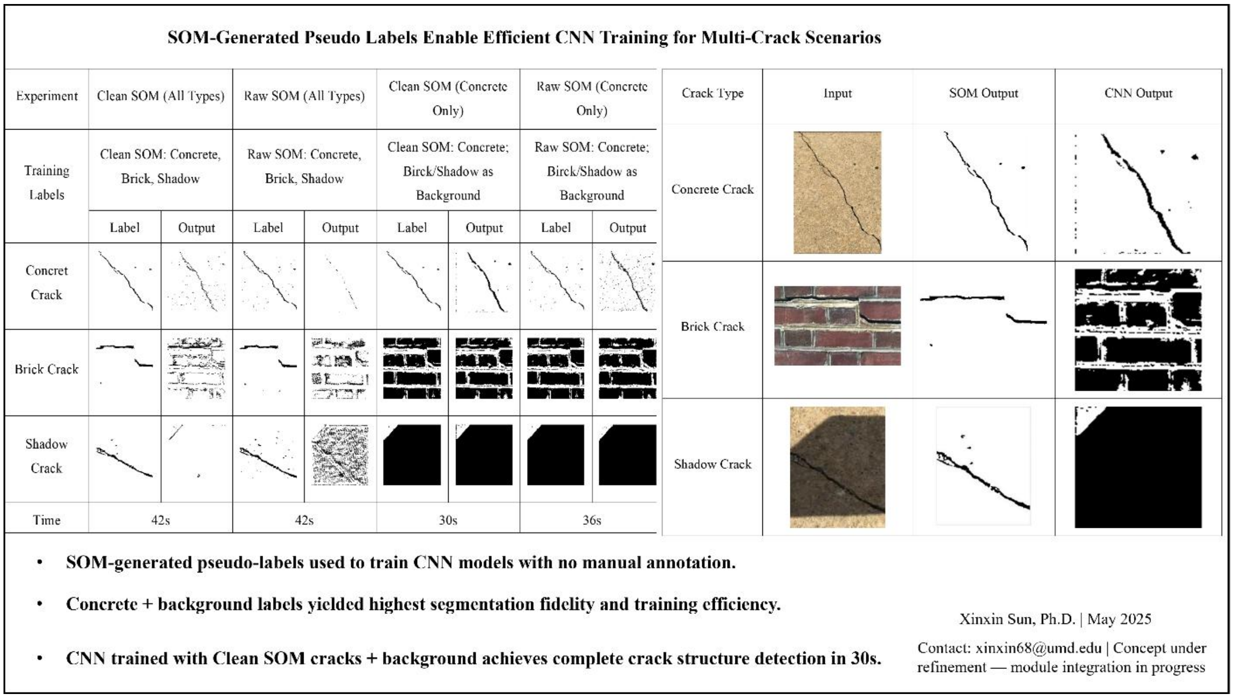


Figure 1: SOM-Based Class Discovery and Feature Attribution for Crack Region Interpretation

This unsupervised AI pipeline enables fully automatic, cost-free, sensor-free, and label-free crack segmentation using only standard RGB images. The SOM clustering process auto-selects class number and generates pixel-level damage classes based on interpretable visual-statistical features (e.g., grayscale, edge, thinness). Feature attribution radar plots reveal class-wise dominance across crack, mortar, and background regions—offering training-free interpretability in safety-critical scenarios.

This workflow offers interpretable AI for crack diagnosis, enabling transparent field deployment and trust in model decisions.



Automatically teaches AI to detect cracks—without needing any labeled examples or expert input.

Figure 2: SOM-Generated Pseudo Labels for Training CNNs Without Manual Annotation

This figure demonstrates how self-organizing maps (SOMs) can be used to automatically generate high-quality pseudo-labels for training convolutional neural networks (CNNs), without any manual annotation. The pipeline segments multiple crack types (concrete, brick, shadow) and evaluates different combinations of class definitions and clustering input. Key findings:

- Clean SOM clusters with crack + background classes yield the highest segmentation fidelity and fastest training (30s).
- CNNs trained on these pseudo-labels can detect complete crack structures across material types.
- This method eliminates the cost and subjectivity of hand-labeling, offering zero-annotation training.
- It also enables rapid model adaptation to new materials and heterogeneous surfaces, supporting generalization in real-world conditions.

This result showcases a scalable framework for building robust crack detectors from unlabeled data—bridging unsupervised discovery with efficient supervised learning.

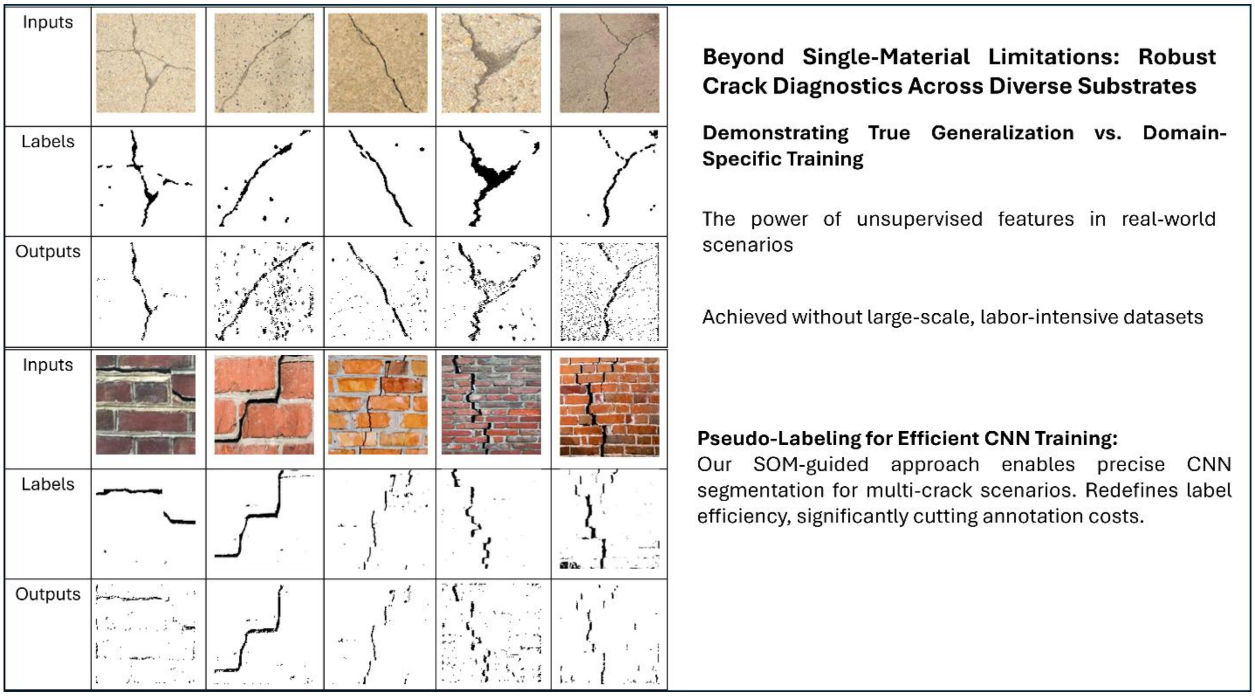


Figure 3: Cross-Material Generalization of Crack Detection via SOM-Guided Pseudo-Labels

This figure demonstrates how crack segmentation models trained with SOM-generated pseudo-labels can generalize to diverse material substrates (e.g., concrete, brick) without material-specific training. Two distinct sets of crack surfaces are shown—concrete (top block) and brick (bottom block). For each surface type, the raw image input, automatically generated labels, and CNN output are presented.

Key insights:

- Robust generalization: The pipeline accurately detects cracks across unseen material textures, proving that the unsupervised SOM features preserve crack semantics over appearance variance.
- No manual annotation required: Labels used for training were automatically clustered, avoiding costly pixel-wise human annotation.
- Broad applicability: Enables practical deployment across heterogeneous infrastructure types (e.g., bridges, walls, pavements) using a single unsupervised core.
- Efficiency and scalability: Demonstrates how minimal supervision can yield rich, transferable representations for safety-critical diagnostics.

This result highlights a critical step toward domain-agnostic, cost-efficient crack detection for real-world civil infrastructure.

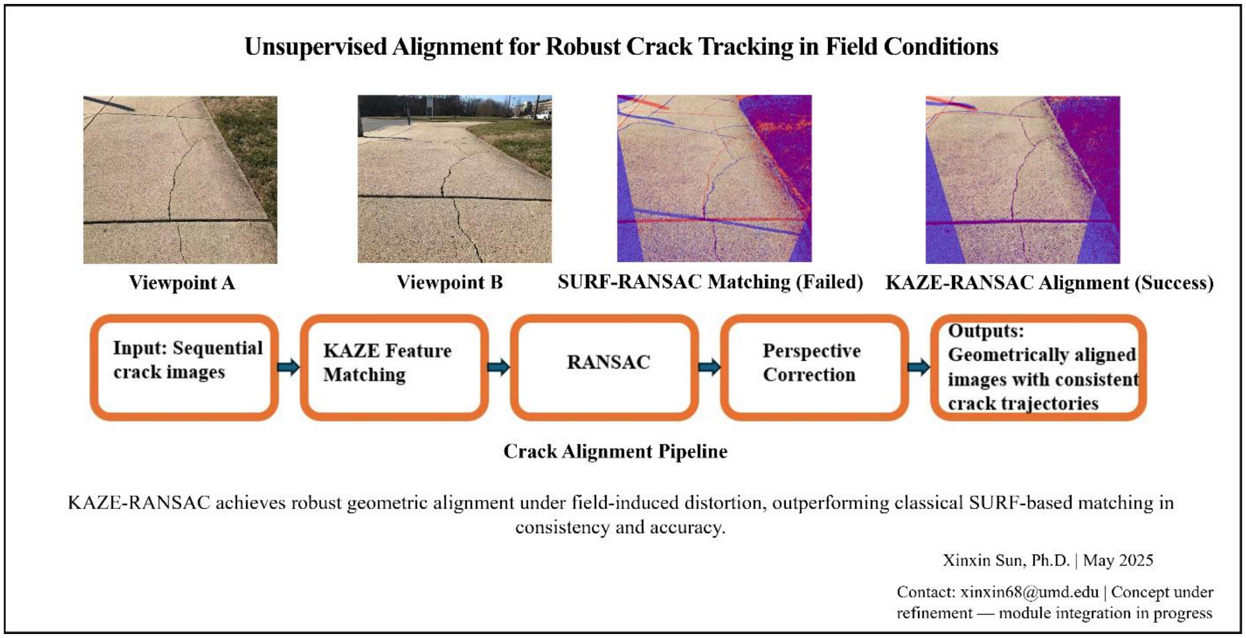


Figure 4: Unsupervised Geometric Alignment for Consistent Crack Tracking in the Field

This figure showcases a novel pipeline for aligning sequential crack images under field conditions with no labeled data or ground-truth control points. Viewpoint shifts (e.g., due to user movement or vehicle motion) often distort the geometry of cracks across frames, making tracking difficult.

- Top row shows images from two viewpoints and the contrast between SURF-RANSAC (failure) and KAZE-RANSAC (success) in alignment performance.
- Bottom flowchart illustrates the end-to-end unsupervised pipeline: starting with raw sequential images, extracting KAZE features, estimating transformations via RANSAC, and applying perspective correction.

Key contributions:

- Field-robust tracking: The method handles real-world distortions such as perspective changes and motion blur.
- Improved geometric consistency: KAZE-RANSAC alignment outperforms traditional methods like SURF, enabling frame-to-frame crack trajectory tracking.
- No supervision required: Alignment is achieved entirely without annotated keypoints or manual calibration.

This alignment strategy supports scalable deployment of crack tracking systems in uncontrolled environments—such as roadside monitoring or mobile SHM platforms like BridgeGuard.

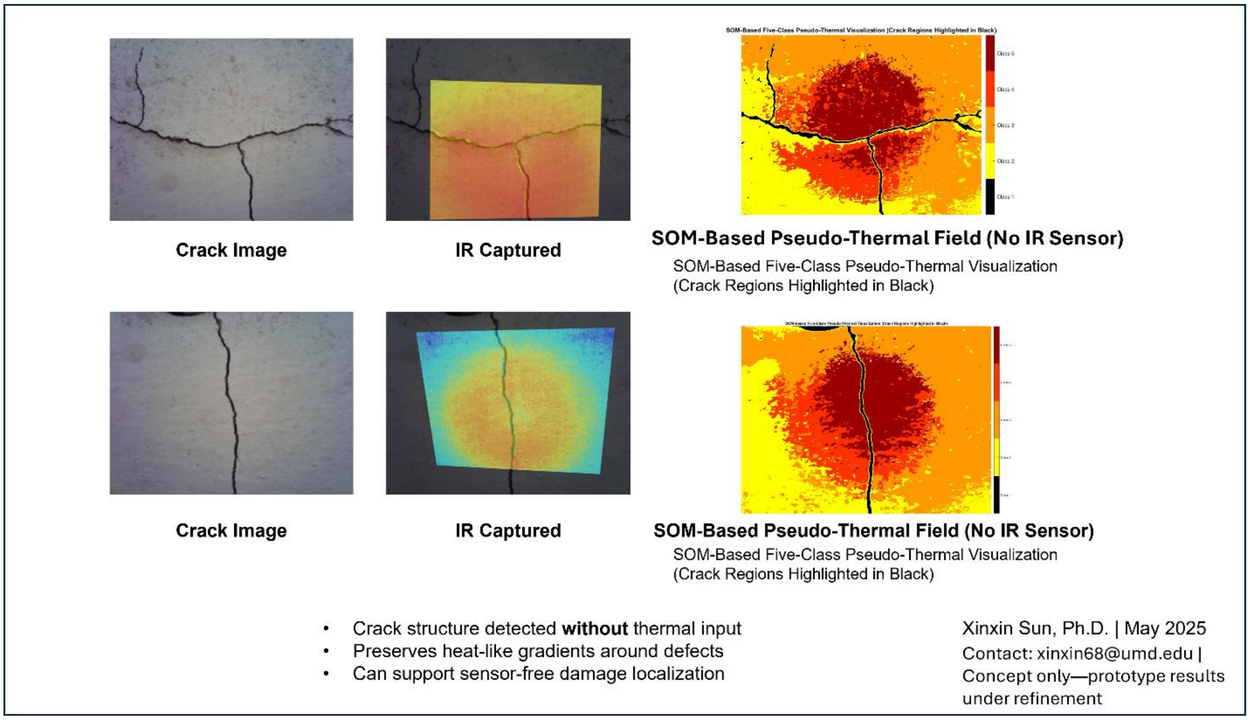


Figure 5: SOM-Based Pseudo-Thermal Visualization Without Infrared Sensing

This method generates thermographic-like fields purely from RGB crack images using SOM-guided unsupervised clustering, without any thermal input.

The pseudo-thermal output mimics IR heat gradients around damage zones and highlights crack regions in black.

This technique enables sensor-free, training-free, and interpretable localization of defects—offering scalable alternatives to hardware-intensive thermal imaging systems.

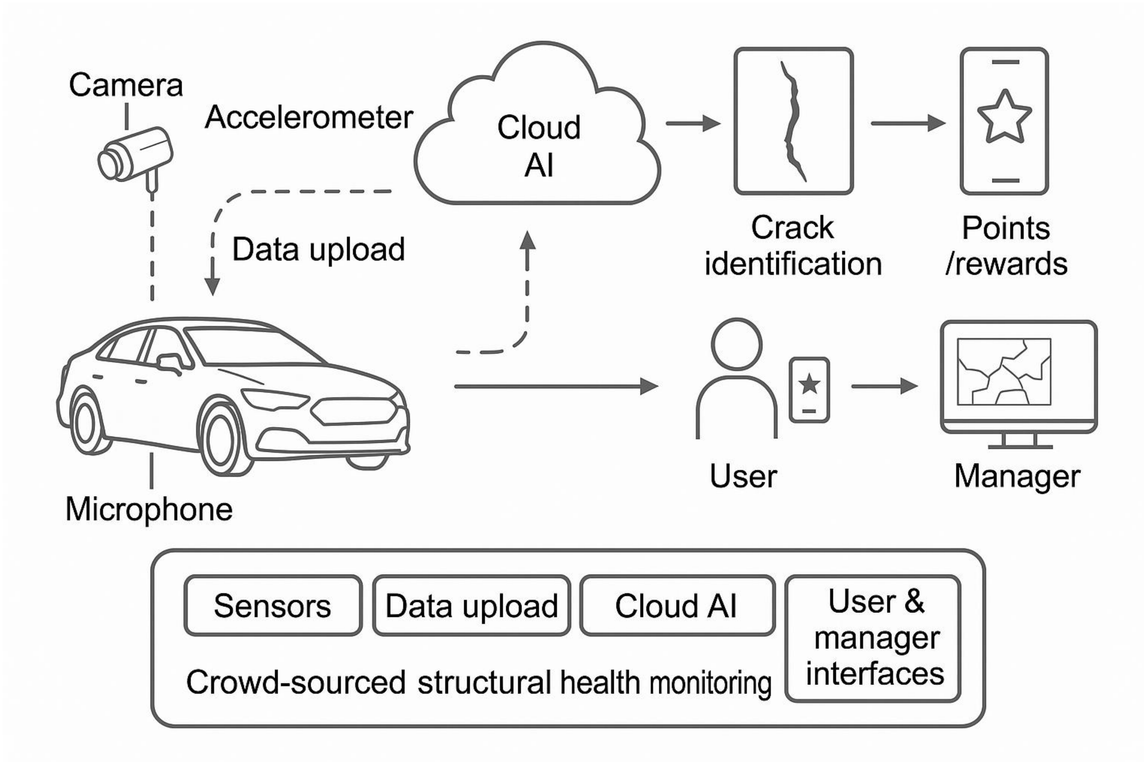


Figure 6. Crowd-sourced Structural Health Monitoring via BridgeGuard

A schematic of *BridgeGuard*, a mobile SHM concept that transforms everyday vehicles into roaming sensor hubs. Vision, vibration, and acoustic signals are uploaded for cloud-based AI inference, enabling large-scale, crowd-powered, training-free infrastructure diagnostics.

Key Contributions of the Unsupervised SHM Pipeline

- Fully automated, label-free crack detection using interpretable AI and self-organizing maps (SOMs).
- Pseudo-label generation for CNN training without human annotation, enabling rapid deployment across unseen materials.
- Domain-agnostic generalization across infrastructure types (e.g., concrete, brick, shadowed surfaces) using one unified model.
- Perspective-robust image alignment using unsupervised keypoint matching (KAZE-RANSAC) for consistent crack tracking under motion.
- Cost-free pseudo-thermal imaging that replaces infrared sensors with SOM-guided clustering of RGB images.
- BridgeGuard: a scalable, mobile SHM system that uses vehicle-mounted sensors for crowd-sourced damage detection and visual diagnostics.
- Field-ready design: interpretable, training-free, and sensor-free deployment compatible with low-resource or hazardous environments.