A Multimodal Fusion Framework for Bridge Defect Detection with Cross-Verification

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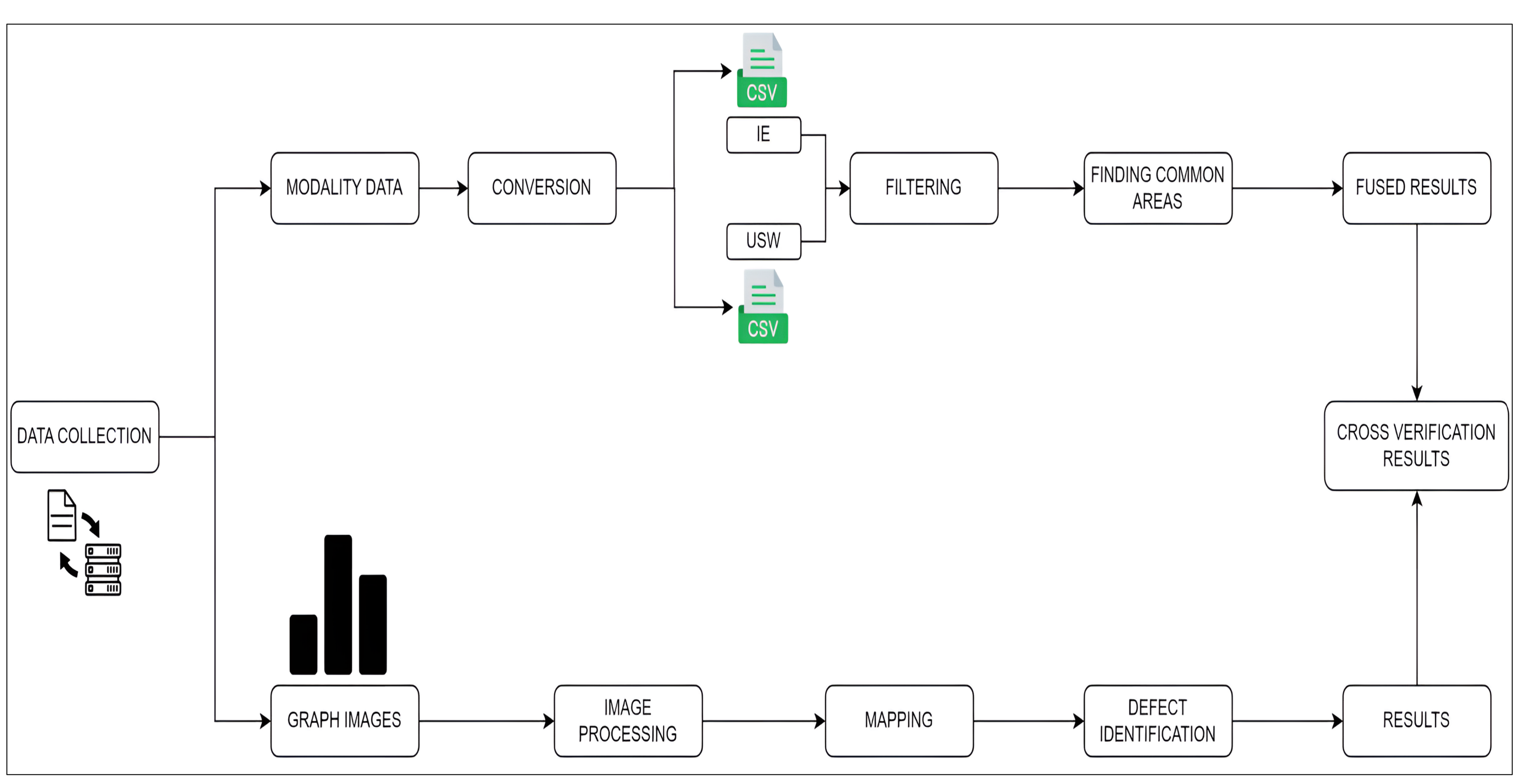
ABSTRACT

Bridges are critical to transportation, yet aging and heavy usage can mask hidden defects like delamination and cracks. Traditional one-method inspections often fall short, risking undetected damage. Our Multimodal Framework for Enhanced Bridge Defect Detection addresses this gap by integrating Non-Destructive Evaluation (NDE) techniques Impact Echo (IE) and Ultrasonic Surface Waves (USW) to pinpoint subsurface anomalies more accurately. Through k-means-based thresholding and Alpha Shape Analysis, we identify overlapping defect zones, then refine these findings with image-based cross-verification (OpenCV contour detection and bounding boxes). This approach significantly reduces false positives and improves localization, achieving an F1-score of 0.83 in pilot studies. The result is a scalable, proactive solution that helps infrastructure owners detect critical issues early, optimize maintenance, and extend the service life of our vital bridges.

PROBLEM & MOTIVATION

- Subsurface flaw detection often leads to lane closures, which in turn cause traffic congestion.
- Emergency repairs can cost up to $90,000 per delaminated slab. By detecting defects early with our fusion framework, total deck rehabilitation costs can be reduced by approximately 40%, based on DOT and research data.
- DOT already collects IE and USW data; our analytics simply *unlocks* their full value.

METHODOLOGY



1 · Data Acquisition & Pre-processing

- Raw NDE data is collected from FHWA InfoBridge and transformed into XML to tidy CSV so every grid point sits in a clean row.

2 · Feature Extraction

- IE data is transformed to peak frequency using Fast Fourier Transform, which indicates voids or delamination.
- USW signals are time-aligned to calculate wave speed, which is subsequently converted into elasticity modulus to identify stiffness loss.

3 · Data-Driven Defect Filtering

- K-means clustering automatically identifies defect thresholds: low-frequency zones in IE for structural anomalies, and low-modulus regions in USW for stiffness loss.

4 · Multimodal Spatial Fusion

- Flexible "blobs" are drawn around defective IE and USW points with Alpha-Shapes ($\alpha = 0.5$), where the overlap of the two blobs marks high-confidence defect zones, tagged by lane.

5 · Image-Based Cross-Verification

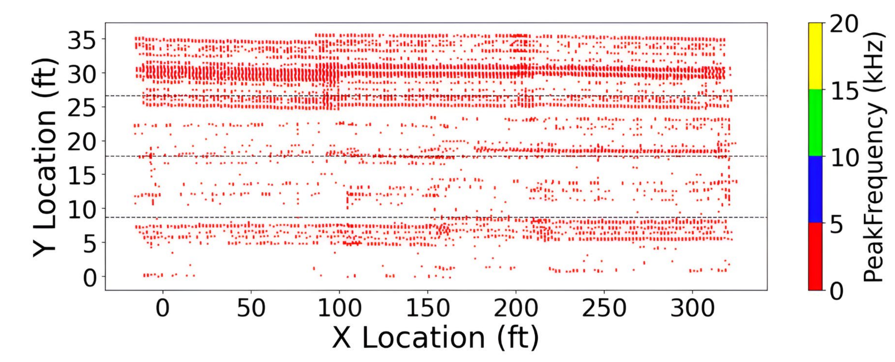
- The IE & USW contour images from InfoBridge are processed using simple HSV filters that pull out red-to-yellow hot spots, then OpenCV boxes them in and are overlaid on the fused map.

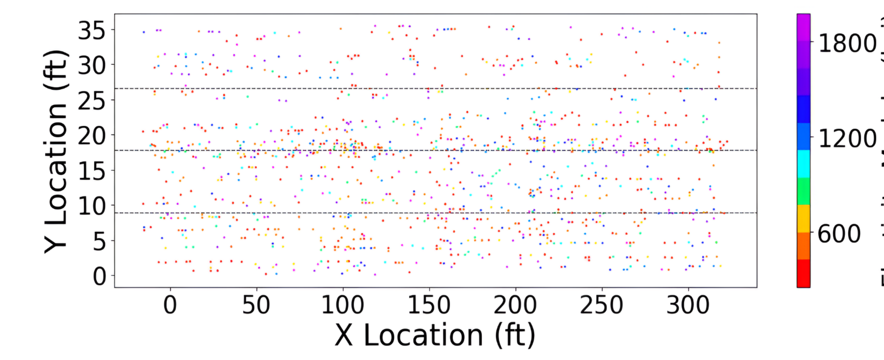
6 · Output & Evaluation

- This framework exports a lane-by-lane risk map and a CSV of coordinates with Precision 0.75, Recall 0.92, F1 0.83, and chopped false alarms down 32 %.

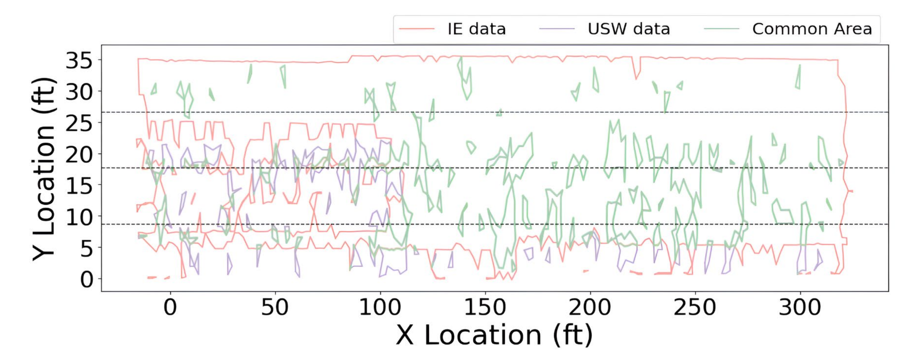
RESULTS & DISCUSSION

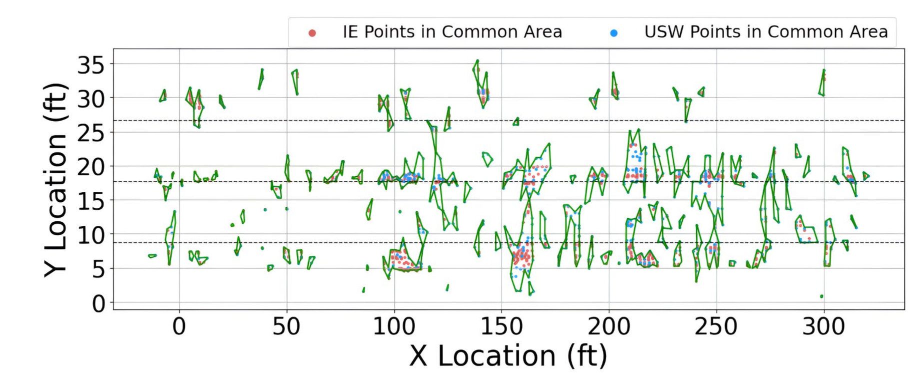
The following figures indicate Scatter plots of IE and USW defective data post filtering.



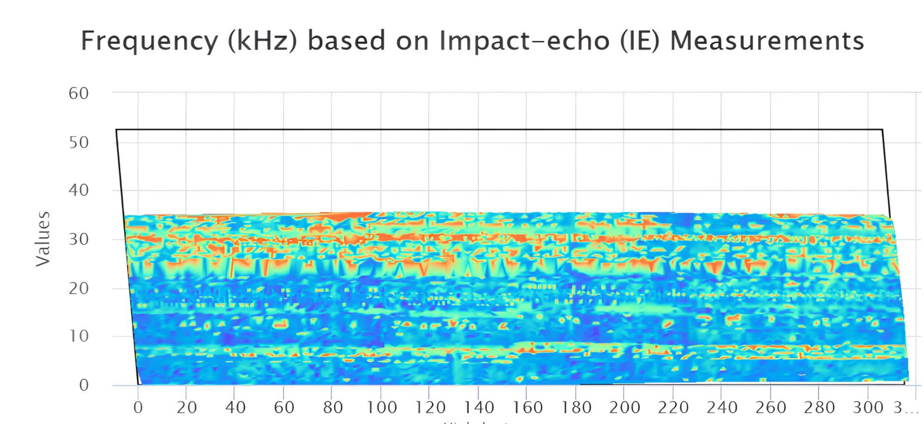


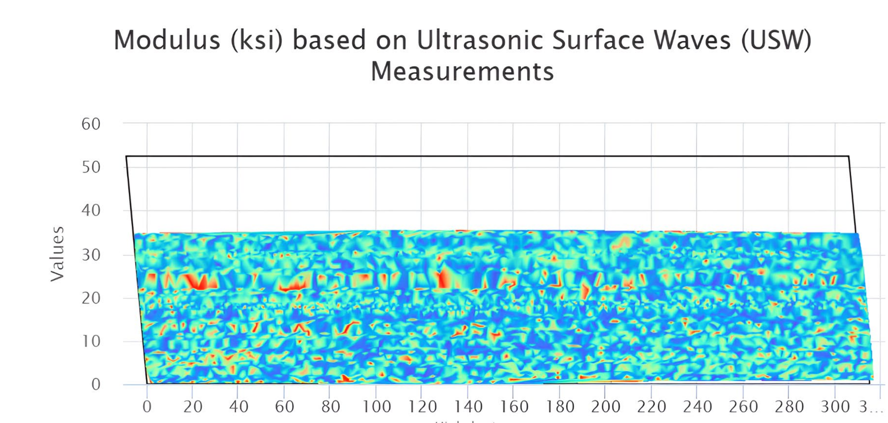
The following figures indicate common areas from IE and USW identified by ASA, with the defective points plotted.



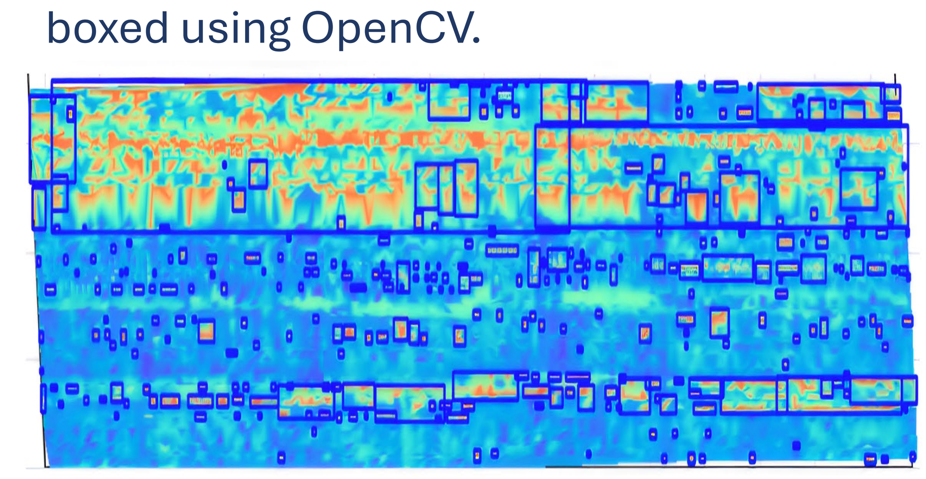


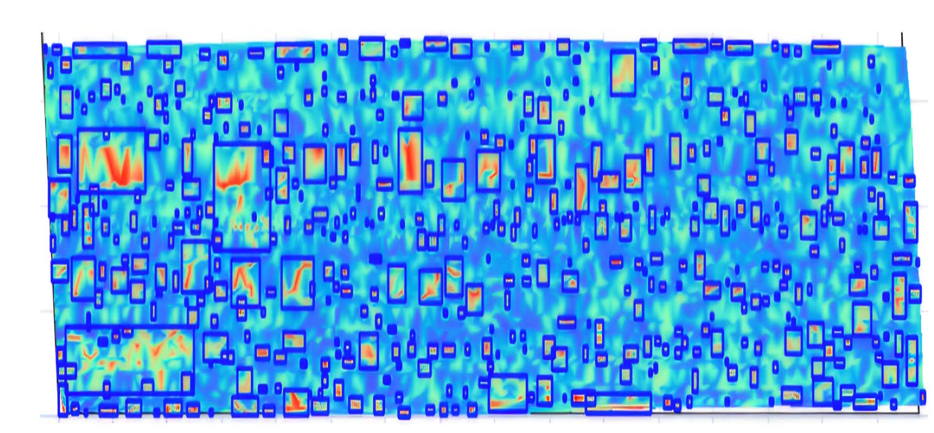
The following figures are IE and USW Contour Images sourced from InfoBridge.



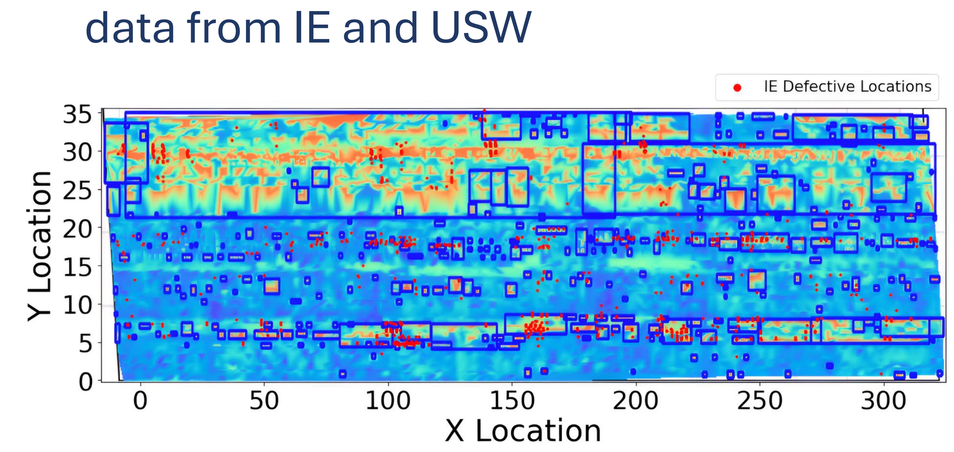


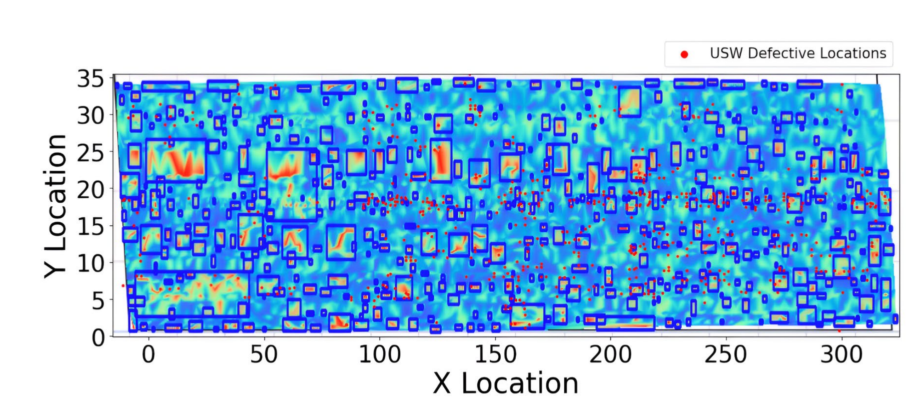
The following figures indicate cropped and processed images using HSV filters and boxed using OpenCV.





The following figures indicate processed images, which are overlayed with defective data from IE and USW





EVALUATION METRICS

Metric	Value
Precision	**0.75**
Recall	**0.92**
F1-score	**0.83**
False-positive reduction	**32 %** vs. best single-modality baseline

The metrics have been calculated using micro-averaged metrics, which aggregate all true positives, false positives, and false negatives across both IE and USW datasets and highlight the overall performance of the framework, demonstrating its capability to detect structural defects.

ACKNOWLEDGMENT

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