Artificial Intelligence in Condition Assessment of Concrete Structures

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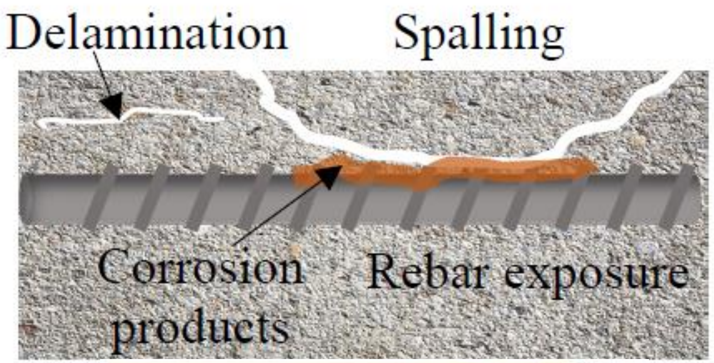
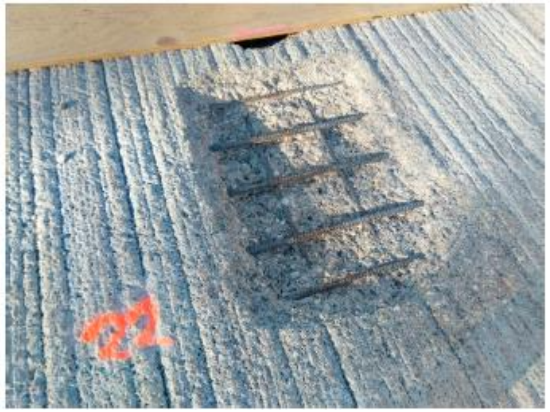
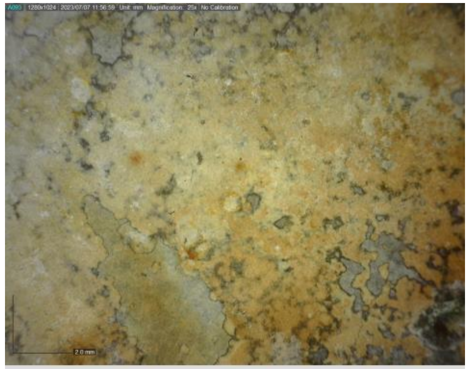
Defects in Concrete Structures

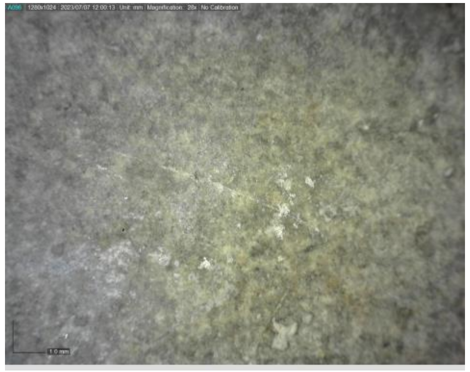
- Surface
  - **Crack**
    - Spalling





- Subsurface
  - Rebar corrosion
  - Delamination





- Subsurface and subsurface
  - Carbonation

Dorafshan, S., Thomas, R. J., & Maguire, M. (2018). SDNET2018: An annotated image dataset for non-contact concrete crack detection using deep convolutional neural networks. Data in brief, 21, 1664-1668.
Lavadiya, D. N., & Dorafshan, S. (2022). Deep learning models for analysis of non-destructive evaluation data to evaluate reinforced concrete bridge decks: A survey. *Engineering Reports*, e12608.

Condition Assessment

- **Detection and quantification of symptoms in structure (defects)**
- Incorporated other parameters (age, ADT, environmental)
- Rate structural member (quantitative, qualitative)

Use sensing

- Human Sensing (conventional)
  - Visual inspection for surface (vision)
  - Chain dragging for delamination (hearing)

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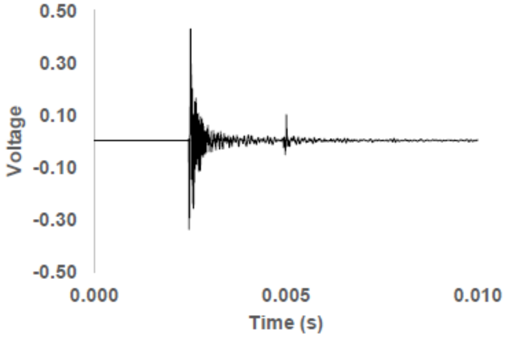
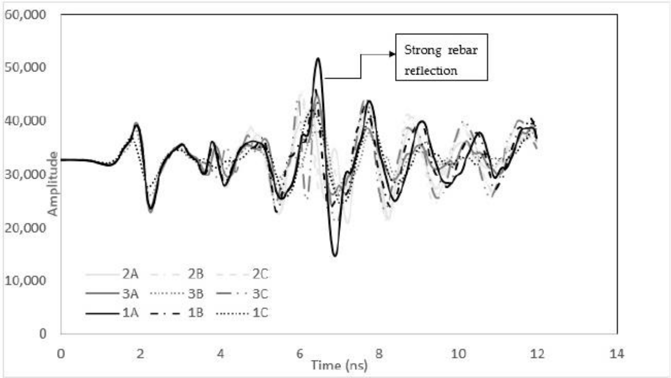
Incentives for autonomy

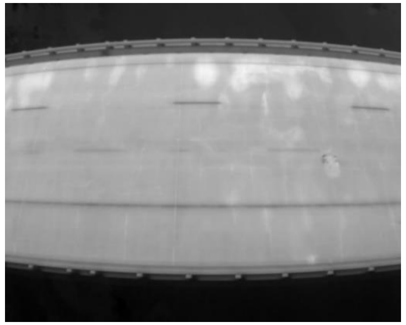
- Aging infrastructure
  - More data required for assessment beyond service life
- Human bias
  - Inconsistent condition assessment of the same infrastructure
- Abundance of data
  - Applications of NDE
  - Introduction of noncontact sensing
    - Allows assessment of hard to reach regions
    - No need for being within arms reach
- Reducing cost and safety risks associated with conventional condition assessment
  - Robotics (data collection)
  - **Artificial Intelligence (conditions assessment)**

Advanced sensing for condition assessment

- One dimensional data (Signals)
  - Impact Echo (subsurface defects)
  - Ground Penetrating Radar (corrosion, material properties)
- Two dimensional data (Images)
  - Visual
  - Infrared thermography
  - Two dimensional representation of signals (time-frequency)







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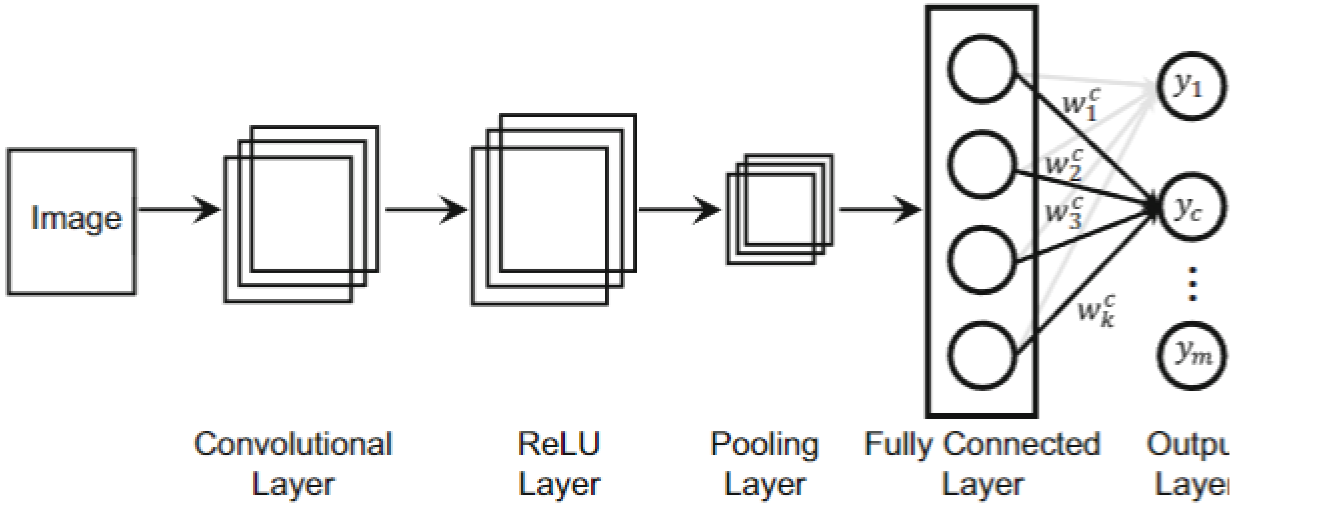
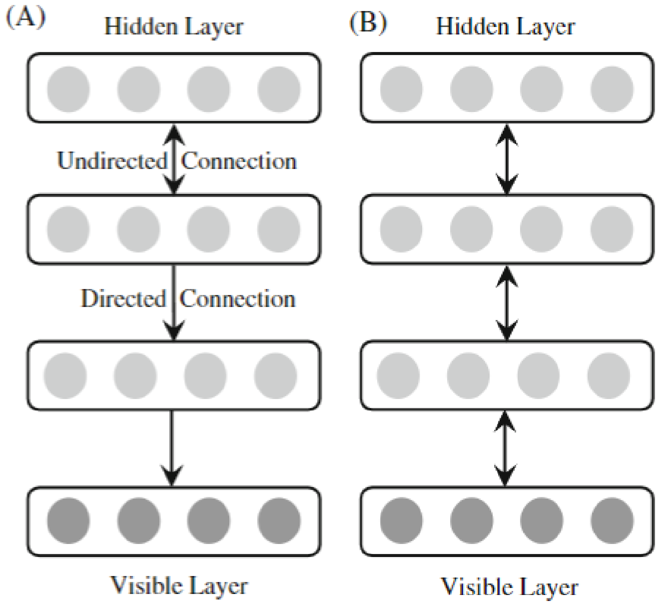
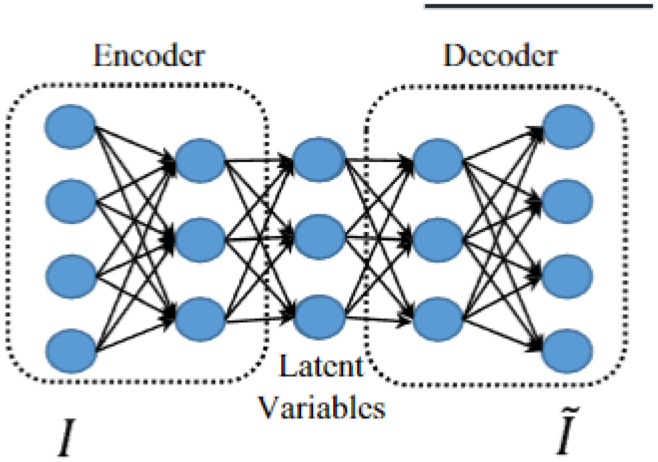
AI Models

- Supervised learning
  - User-defined features
    - Simplest one is correlation
    - Support Vector Machines
    - Image segmentation
    - Clustering
  - Less expensive to implement
  - Less generic in general

- Unsupervised learning
  - Training on annotated dataset used to find features
    - CNN
    - Boltzmann machine
  - More generic
  - Requires annotated dataset



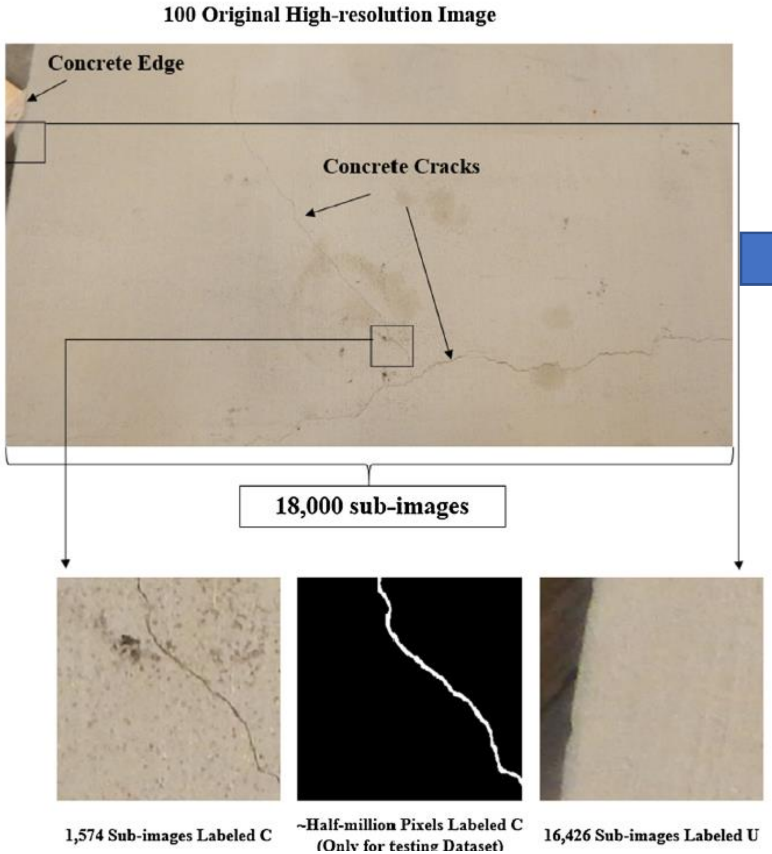


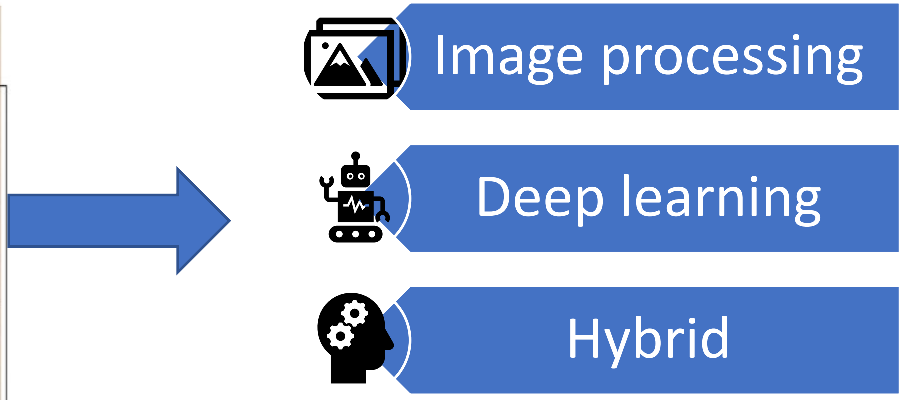


Crack detection

- Cracks can be presented as a series of features
  - Edges
  - Darker

- Images are matrices
  - Find what feature correlates with actual location of crack





Number of cracked and sound sub-images in training, validation, and testing datasets.

Dataset	No of Original Images	C	U	Total
Training	81	1129	11,680	12,809
Validation		125	1646	1771
Testing	19	319	3101	3420

Dorafshan, S., Thomas, R. J., & Maguire, M. (2018). Comparison of deep convolutional neural networks and edge detectors for image-based crack detection in concrete. Construction and Building Materials, 186, 1031-1045.

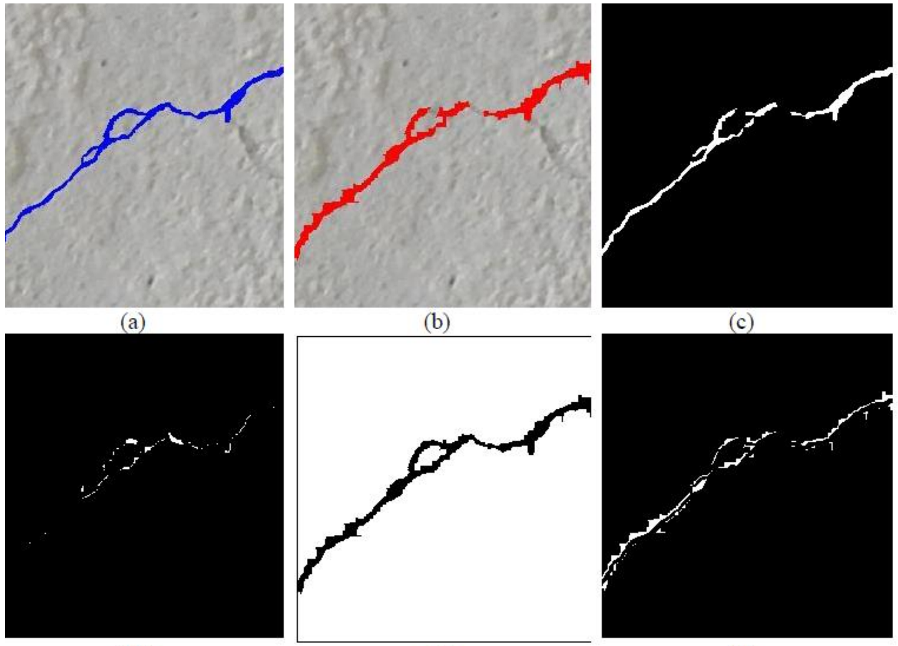
Crack detection (cont'd)

Using edge detection (difference between pixel intensities is

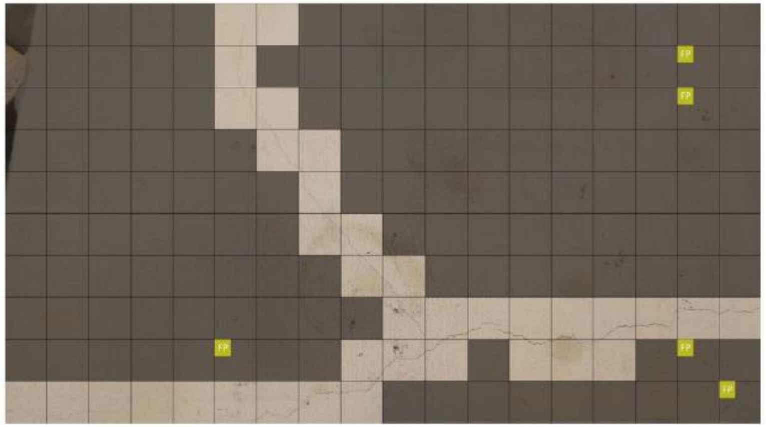
defined by user/developer

y.

166	164	166	164
161	162	160	160
166	166	165	162
169	165	170	162
172	171	169	168
173	171	168	165
172	170	166	162



ig. 6-7 Examples of metric, (a) ground truth, Cp=1,582 px, Up=63,954 px, (b) final binary nage using Roberts edge detector, Cp=2276 px, Up=63,260 px (c) TP=1367 px, (d) FN=215 px, (e) TN=63,045 px, (f) FP=909 px (Robersts edge detector)



- Using Deep learning to find the difference autonomously through learning on annotated dataset

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NDE methods for condition assessment

TABLE 1 Potential sensors and their limitations for bridge subsurface inspection[25]

Sensor	Standard	Potential	Limitations
Impact echo	ASTM C 1383	Detects delamination, voids, honeycombing, elastic modulus, and rebars	Less reliable in the presence of asphalt overlays and requires experienced operator and analyzing expert.
GPR	ASTM D 6087	Deck thickness, delamination, corrosive environment, and rebar detection	Presence of moisture content introduces inconsistent results and cannot provide information about mechanical properties of concrete.
Infrared Thermography	ASTM D 4788	Delamination and corrosion, crack	Reliability of results depends on Environment; and Cannot provide information about the depth of defects.
Electrical resistivity	ASTM D 3633	Corrosion and chloride penetration	Surface has to be prewetted; the data interpretation is challenging. Automated measurement systems for roads are not available on the market.
Half-cell potential	ASTM C 876	Corrosion	Not suitable for overlays or coated rebar; and moisture content will cause negative shift in potential voltage measurement.

Lavadiya, D. N., & Dorafshan, S. (2022). Deep learning models for analysis of non-destructive evaluation data to evaluate reinforced concrete bridge decks: A survey. Engineering Reports, e12608.

Delamination Detection with IE

- Depends on the variation in the stress wave (P-wave) propagation in solid medium for
  - Delaminated regions reflect the mechanical stress wave differently than sound regions
  - Using only this feature may result in inconsistent classification of signals
  - Unsupervised learning

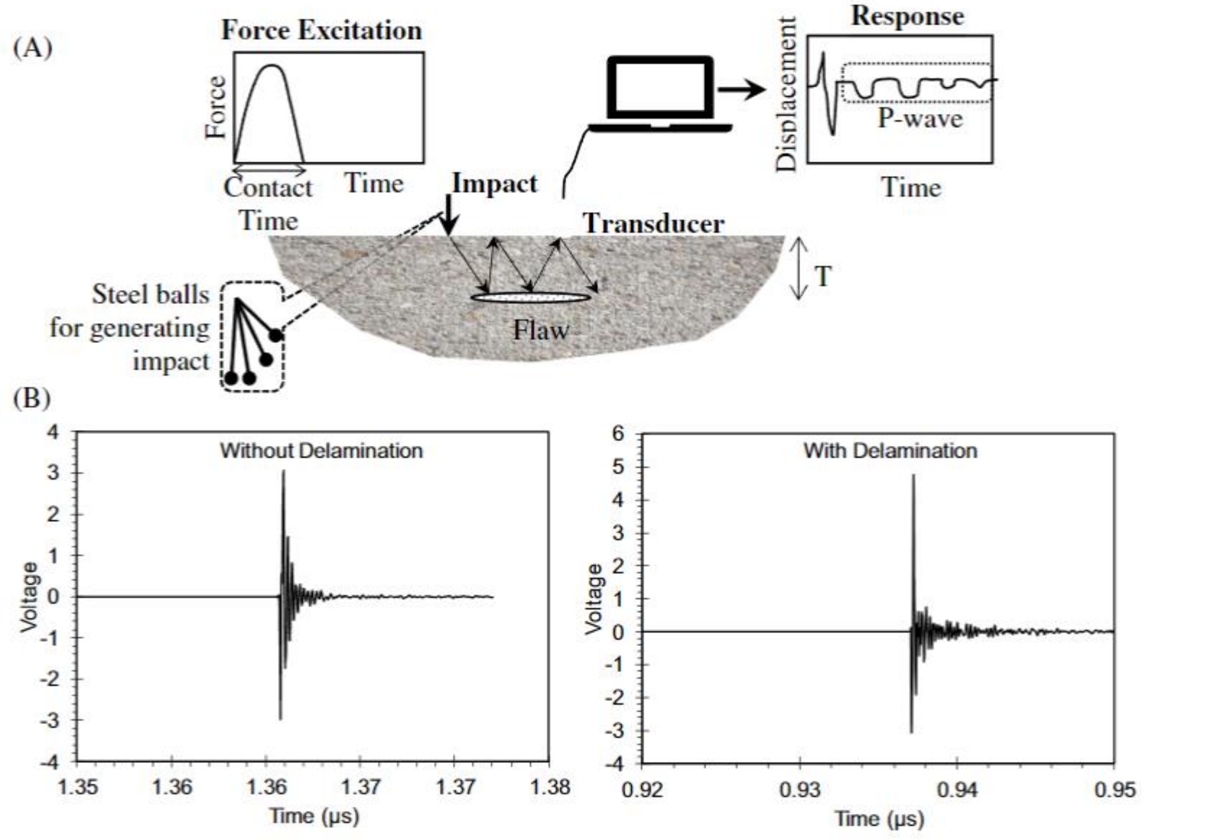
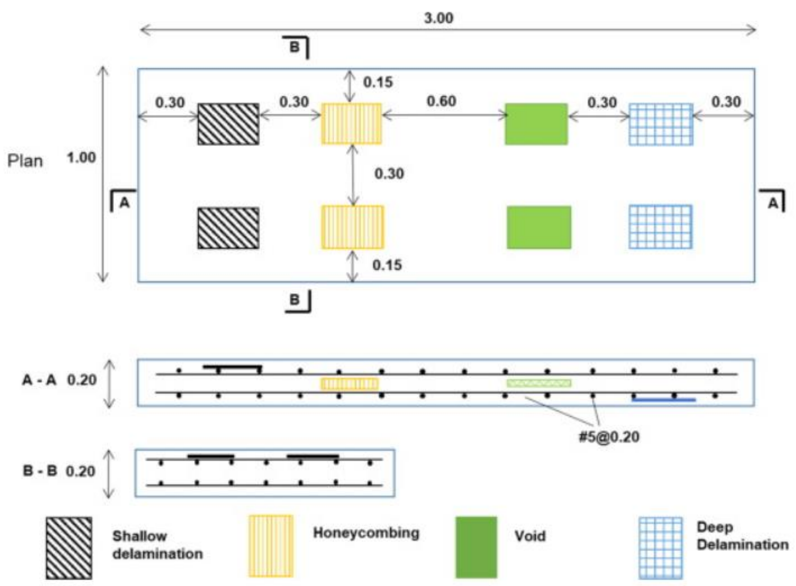
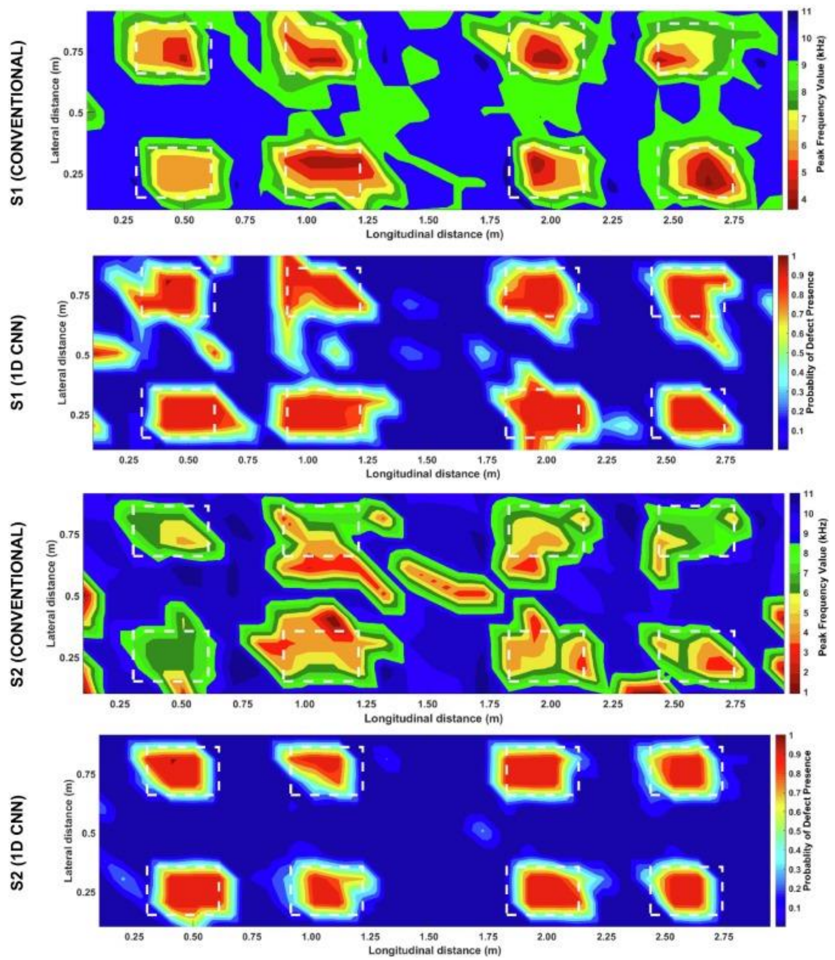


FIGURE 3 (A) Schematic of impact echo set up (adapted from Redrawn[33]) and (B) signal of non-defective and defective bridge deck (generated based on data from SDNET database[30])

Delamination Detection with IE

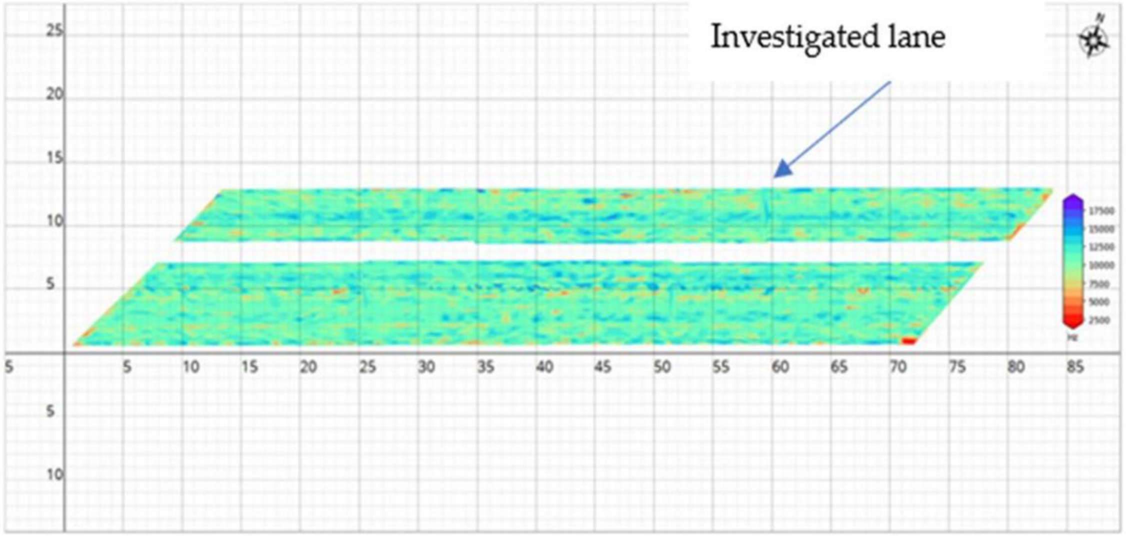
- Improved accuracy over peak frequency method
- More consistency in defect maps
- Less reliant on user input

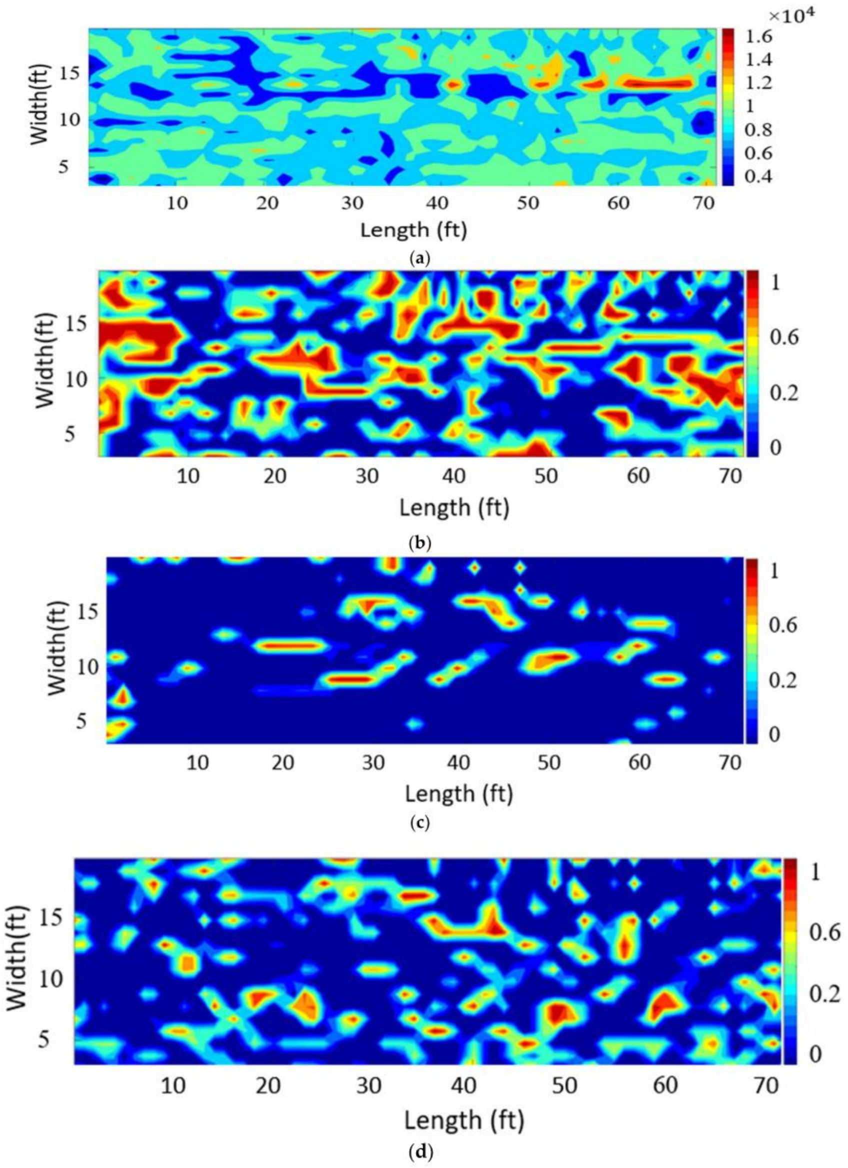




Delamination Detection with IE

- Challenges arise when applied on data of real bridges
- Inconsistency between peak frequency, ML, DL





Delamination detection with IRT

- Objects above 0k emit thermal radiation
  - Each material has its signature thermal radiation
  - Delaminated region is filled with air instead of concrete
  - The effectiveness of IRT is has been in question when applied on real bridges

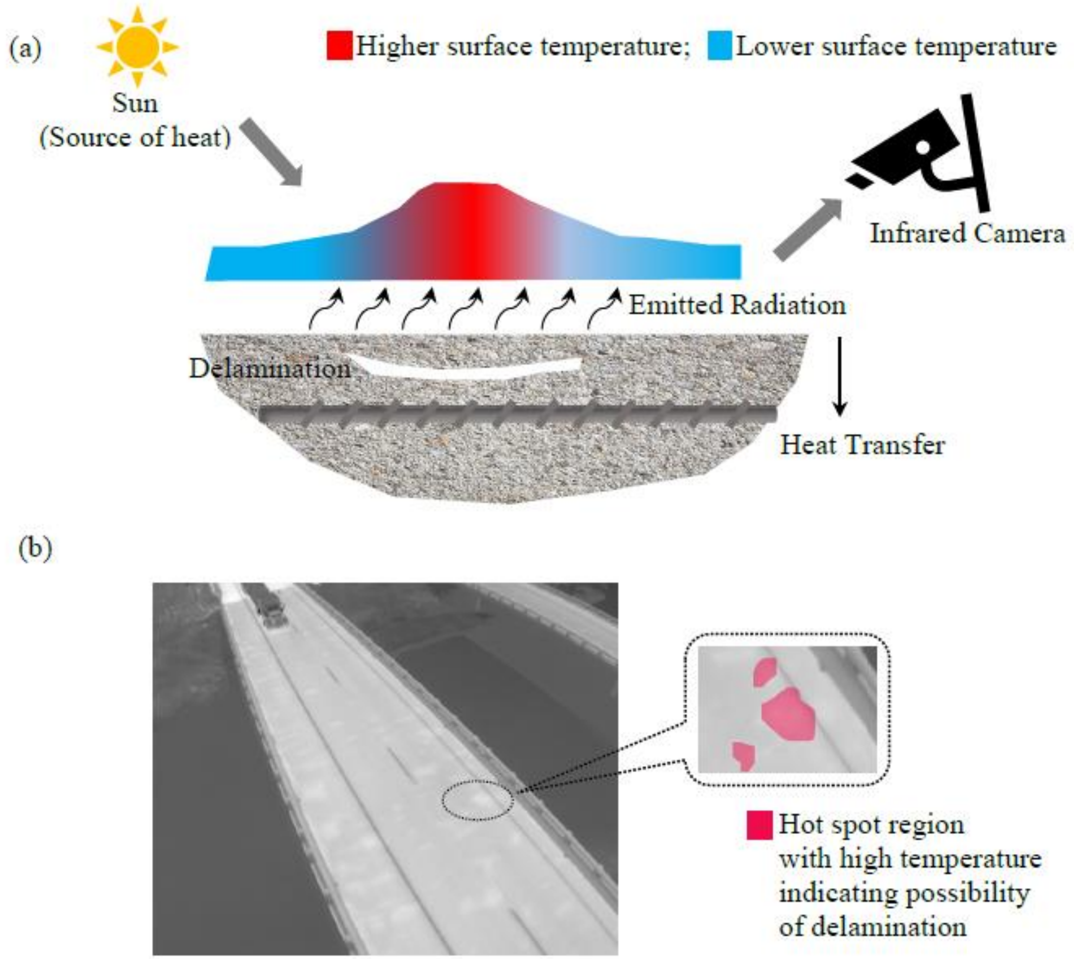
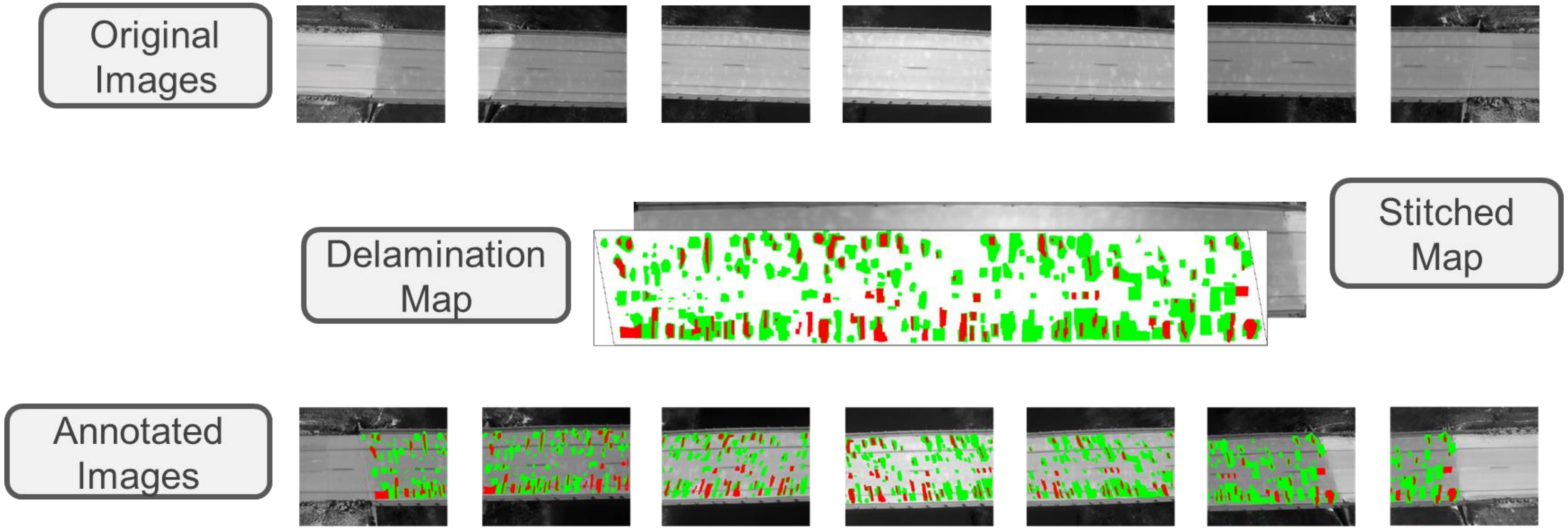


Figure 2. (a) Illustration of working principle of Infrared Thermography, (b) infrared thermography image from SDNET 2021 database [29].

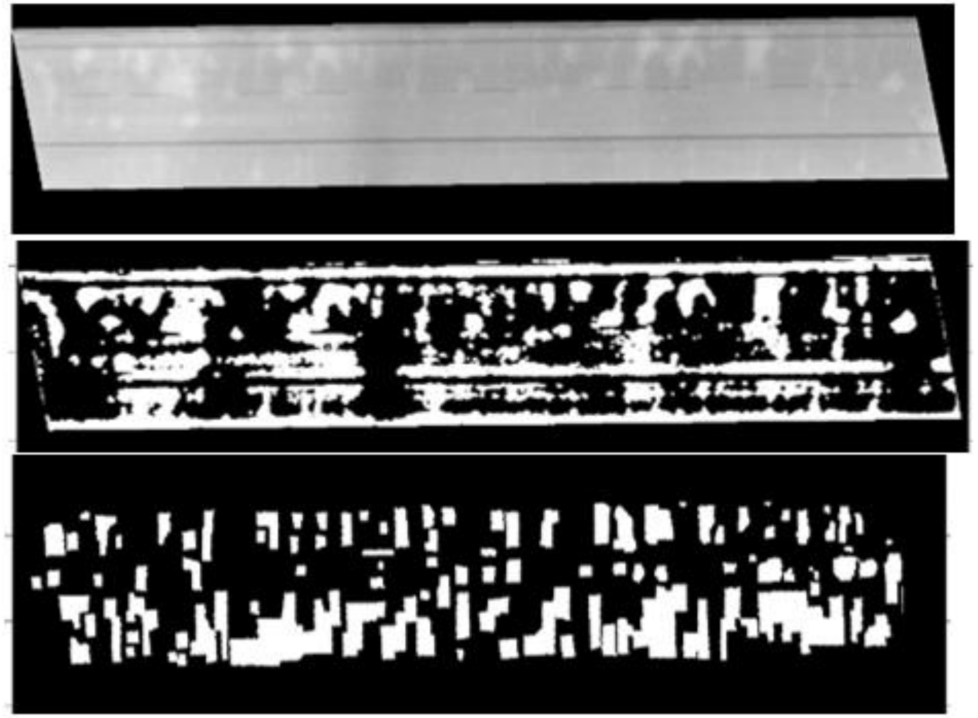
Delamination detection with IRT

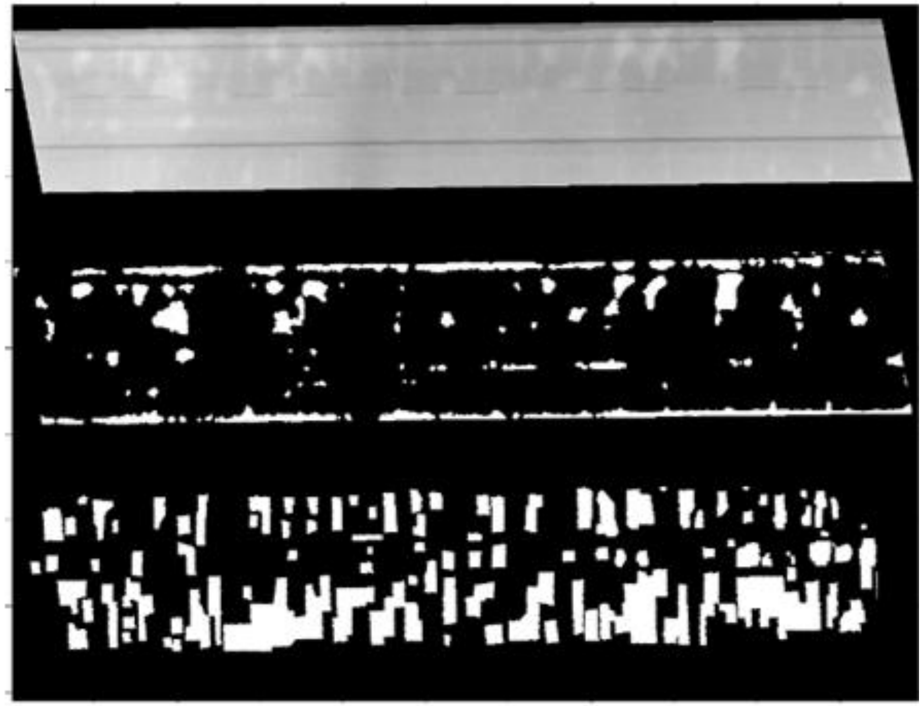
- Data collection
- Image stitching to find the map of the bridge deck
- Grand truth



Challenges with IRT

- At best only 70% of pixels were associated with delimitated regions (ML)
- DL methods did marginally better (lack of available data)





Takeaways

- Pay close attention to the need
  - Occam's Razor, put simply, states: “the simplest solution is almost always the best.”
- AI for concrete condition is a proven technology
  - TRL varies
    - IRT TRL?
- AI models can reach acceptable accuracies
  - Under the right circumstances
- Choice of proper AI model for each type of data affect the results
  - Be cautious, don’t trust the first results especially if they are too accurate.
- Unsupervised learning can be more generic however, without realistic annotated datasets (training):
  - Could not match their performance in real scenarios

Acknowledgement

Dayakar Lavadiya, Assistant Professor University of Mary

Eberechi Ichi, PhD Student, University of North Dakota

Faezeh Jafari, PhD Student, University of North Dakota

Boshra Besharatian, PhD Student University of North Dakota

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