Deep Neural Networks with Outdoor Bridge Image Datasets for Concrete Crack Detection and Quantification

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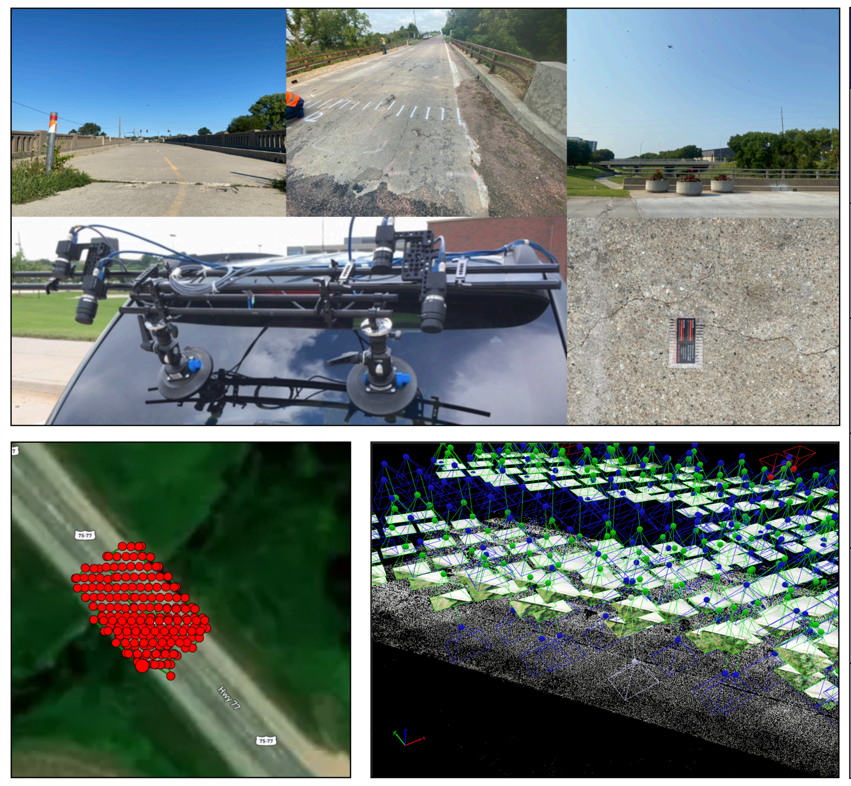
Summary

- Crack observed in concrete bridge elements can accelerate deterioration of bridge health
- Current system exclusively rely on data provided from human inspectors
- Many researches have been studied under restricted environments
- This project demonstrated the inspection framework using deep learning model with images collected from outdoor concrete bridges
- Additionally measured crack width for further assessment

Datasets

- Collected concrete bridge surface images from outdoor bridges located in Nebraska
- Stitched and mapped raw images to generate bridge crack map

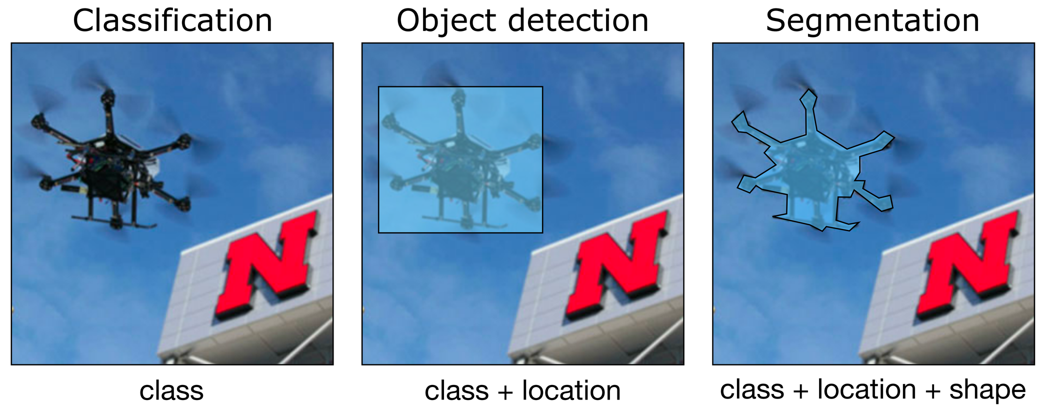
Dataset Collection and Mapping



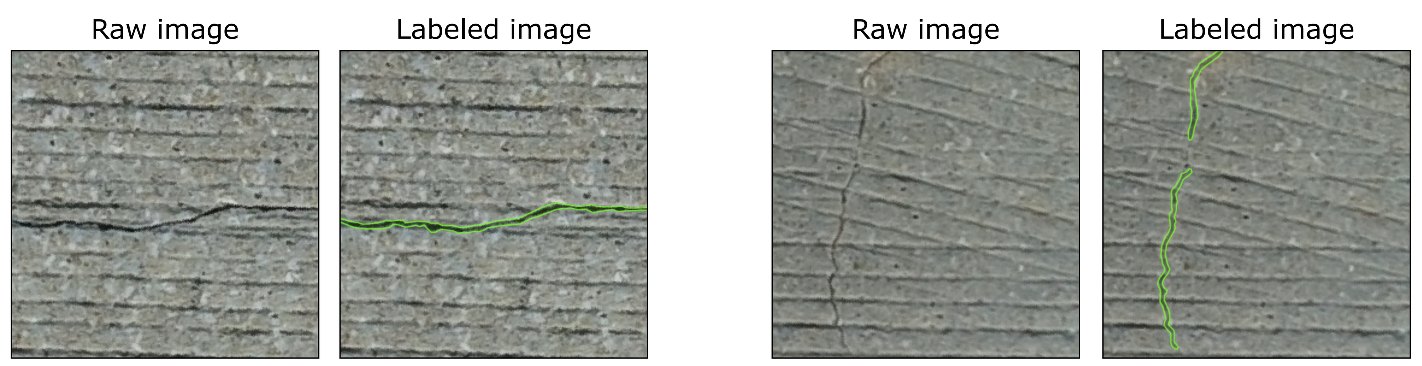
Dataset Configuration

Title (Location)	Keyword	Example	# of images (raw / augmented)
UAV19-1 (Elkhorn, NE)	• concrete overlay • construction marks • patches		13 / 3367
UAV19-2 (Elkhorn, NE)	• concrete overlay • tining marks		9 / 3266
UAV21 (Omaha, NE)	• concrete overlay • pier		219 / 2761
GV18 (Lincoln, NE)	• concrete overlay • expansion joints • tining marks		260 / 3108
PD_DECK (Lincoln, NE)	• pedestrian bridge • deck		100 / 100
PD_PIER (Lincoln, NE)	• concrete overlay • pier		96 / 96

- Vision-based deep learning tasks



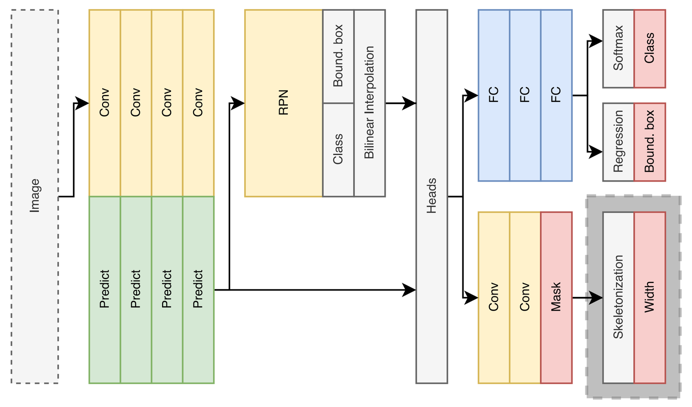
- Labeled cracks for segmentation models

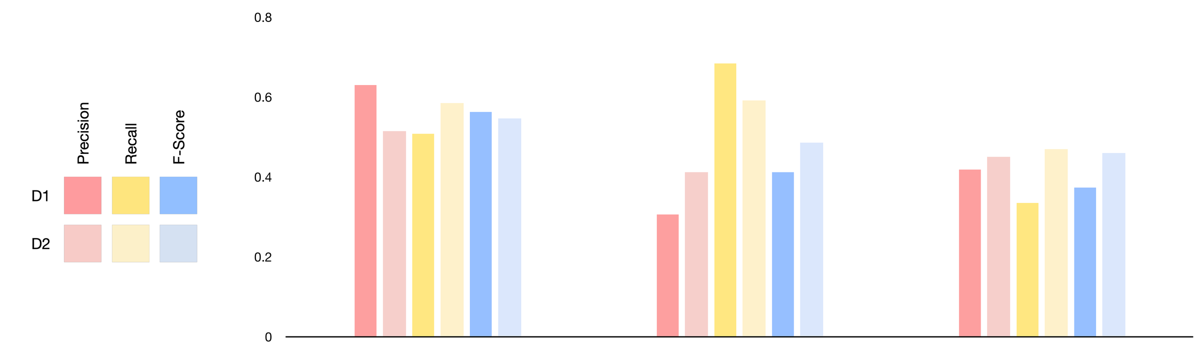


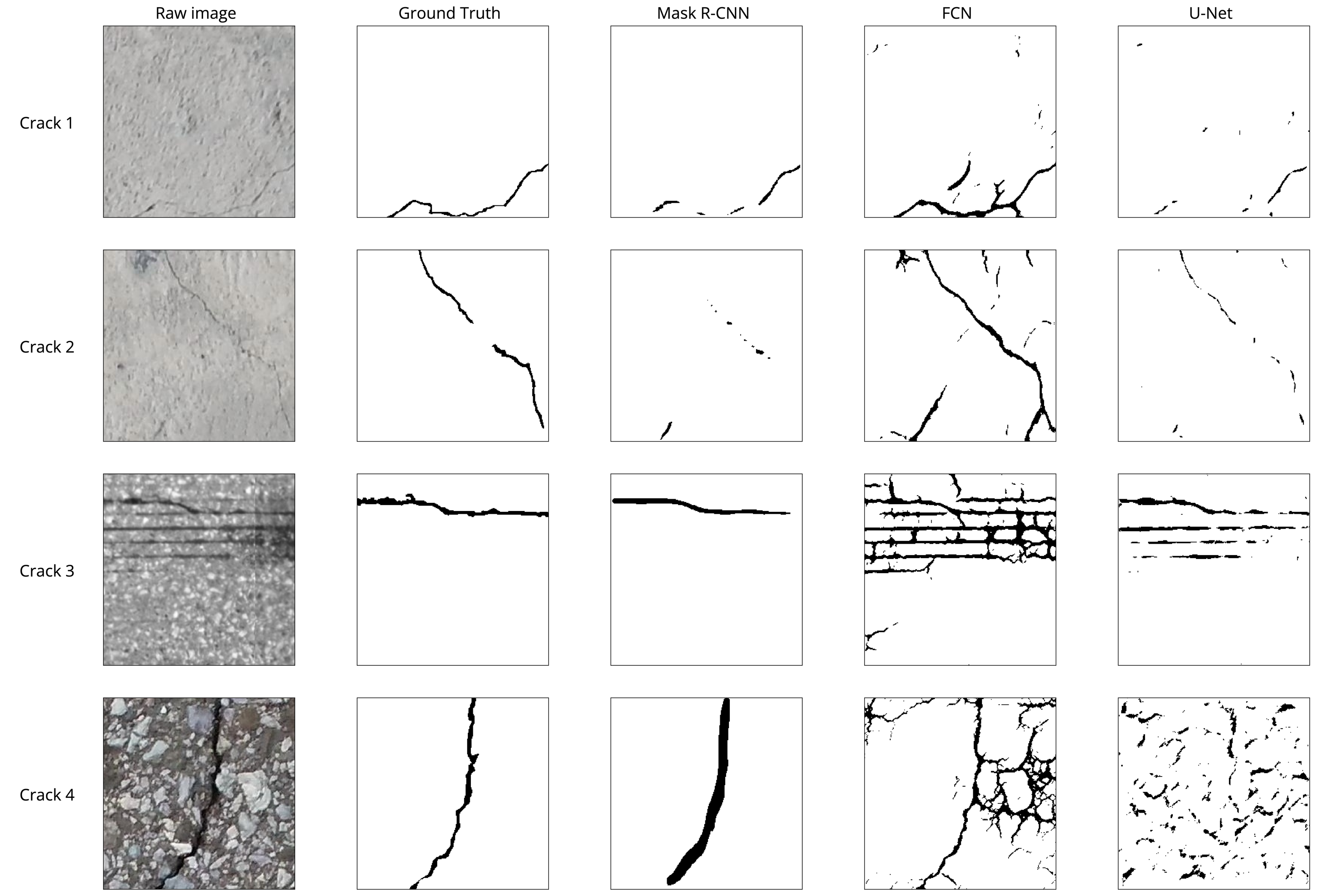
Crack Detection

- **Mask R-CNN**
  - Deep segmentation model with **class**, **bounding box**, and **mask** branches
  - Region-Proposal Network
- **State-of-the-art models comparison**

Architecture of Mask R-CNN

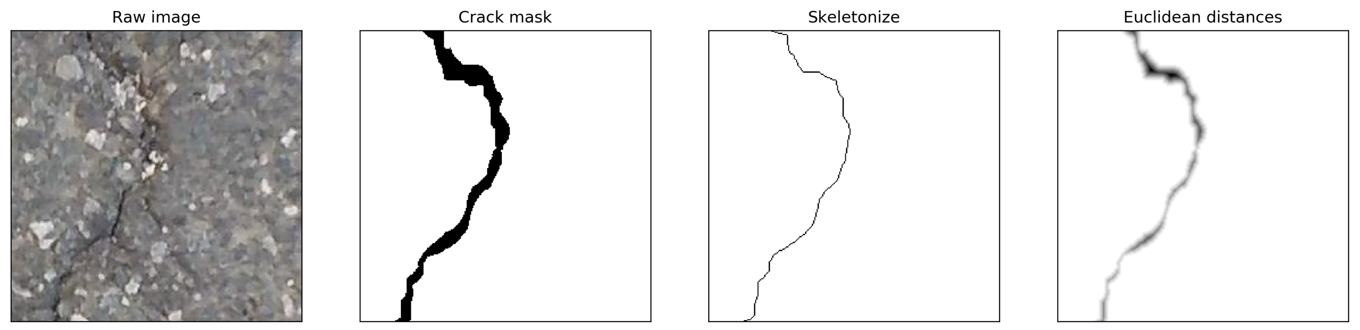




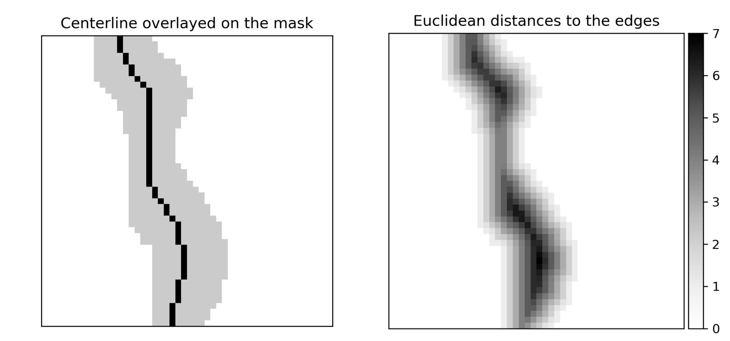


Crack Width Measurement

- Expanded loss to measure L1 norm for crack width distribution
- Extracted Euclidean distances between centerline to boundary pixels



$$L = L_{cls} + L_{box} + L_{mask} + L_{width}$$
$$L_{width} = L_{1:smooth}(y_{true}, y_{pred})$$
$$y = [\mu(\mathrm{dist}(\mathbf{b},\mathbf{c})), \sigma(\mathrm{dist}(\mathbf{b},\mathbf{c}))]$$
$$L_{1:smooth} = \begin{cases} |x| & \text{if } |x| > \alpha \\ \frac{1}{|\alpha|}x^2 & \text{if } |x| \le \alpha \end{cases}$$



- Average errors between the predicted and measured values with the crack meter are less than 30 mils

$$width = 2 \times \max(\mathrm{dist}(\mathbf{b},\mathbf{c}))$$

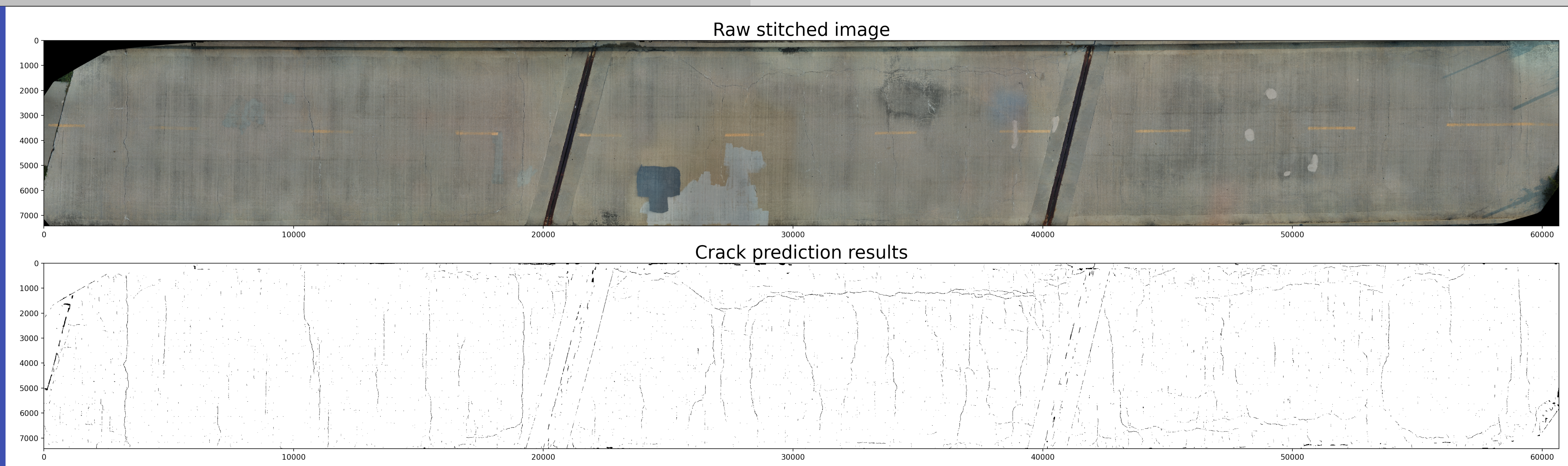
Image #	Measured width	Predicted width	Absolute error
1	0.0600	0.0688	0.0088
2	0.0930	0.0938	0.0008
3	0.1250	0.0750	0.0500
4	0.1375	0.1150	0.0225
5	0.0800	0.1417	0.0617
6	0.0400	0.0600	0.0200
7	0.0500	0.0750	0.0250
8	0.0500	0.0962	0.0462
9	0.1250	0.1172	0.0078
10	0.0625	0.1154	0.0529
Average			0.0296

(unit: inch)

Conclusion

- Mimicked the visual inspection performed with human inspectors by reading images, localizing cracks, and measuring the crack widths
- Concluded the vision-based data analytics can provide useful information for bridge inspections and assist the health monitoring of aging concrete bridges

Prediction on Bridge Map



This study was financially supported by the **NSF-BD Spokes Program** (Award #1762034), **NSF-IIS** (Award #1925052), and **MADS-OPP** (Award #W912HZ21C0060). Their support is gratefully acknowledged.