Towards Fully Automated Unmanned Aerial Vehicle (UAV)-Enabled Bridge Inspection

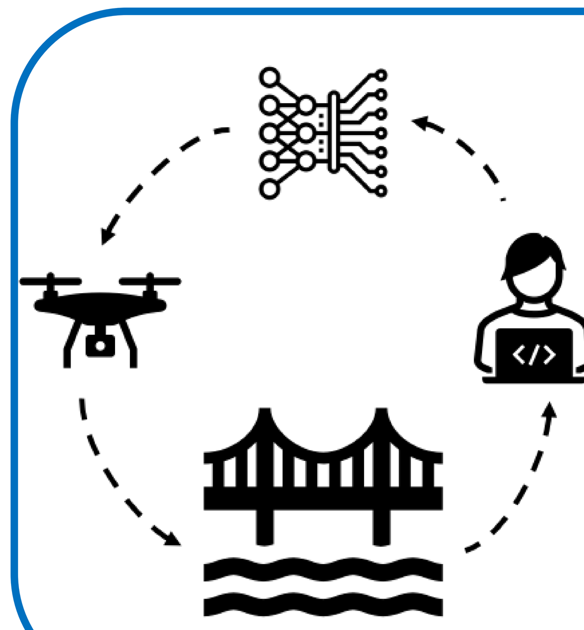
Zahra Ameli, Eric N. Landis, Civil and Environmental Engineering Department, University of Maine

Bridge Inspection Procedure, Where we are now?

- **Data Collection:** Manually or UAV-Based data (image, video ,…) collection
- **Data Processing:** Systematic transformation of acquired raw data into structured, analyzed, and meaningful information. Tasks such as data integration, cleaning, defect detection, feature extraction, visualization, and trend analysis.
- **Decision Making:** Information derived from the processed data support informed decision-making for bridge maintenance, repair, and overall structural management.

➢**Whole bridge inspection process ranging from data collection and analysis to decision-making, still require substantial human intervention which is costly, time consuming, inefficient and subjective.**

Contribution



- Automating data processing: using deep learning algorithms to clean, classify images and detect defects
- Development of open-source semantic segmentation annotated corrosion dataset available at: (https://digitalcommons.library.umaine.edu)
- Quantifying defects: Pixel-wise corrosion classification and condition rating according to AASHTO and BIRM
- Providing valuable information for bridge inspectors for maintenance or replacement decision making

Data Collection and Annotation

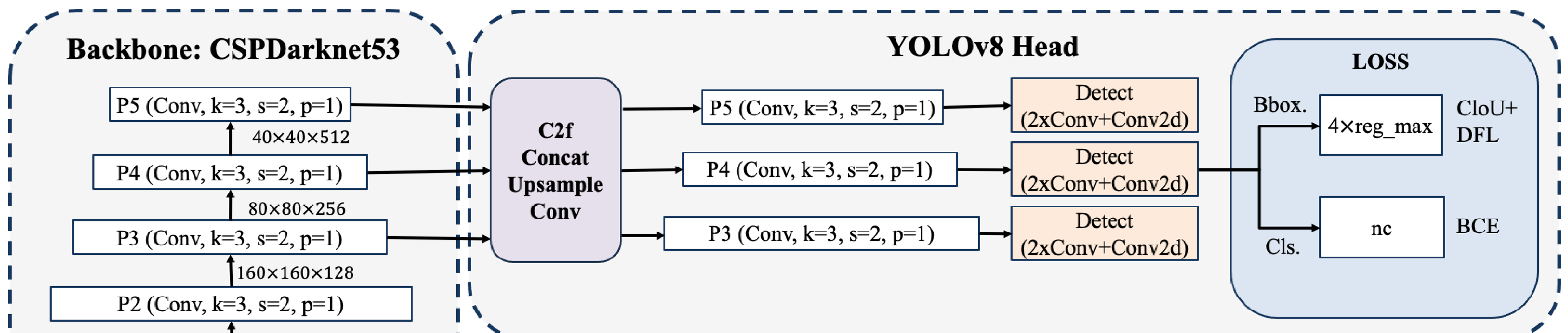
- More than 1200 high quality images containing various types of defects are gathered from bridges using a drone and a Nikon camera

- Labelme and Roboflow annotation tools are used to perform bounding box and pixel-wise annotations

Deep Learning-Based Defect detection Algorithm

Annotated images

Input



- The classification branch uses Binary Cross-Entropy (BCE) Loss.
- The regression branch employs both Distribution Focal Loss (DFL) and CIoU Loss.
- The 3 Losses are weighted by a specific weight ratio.

Output

Detected Defects

- **Classify images into different classes of defects:**
  - Efflorescence
  - Asphalt cracking
  - Corrosion
  - Longitudinal cracking
  - Map cracking
  - Spalling
  - Exposed Rebar

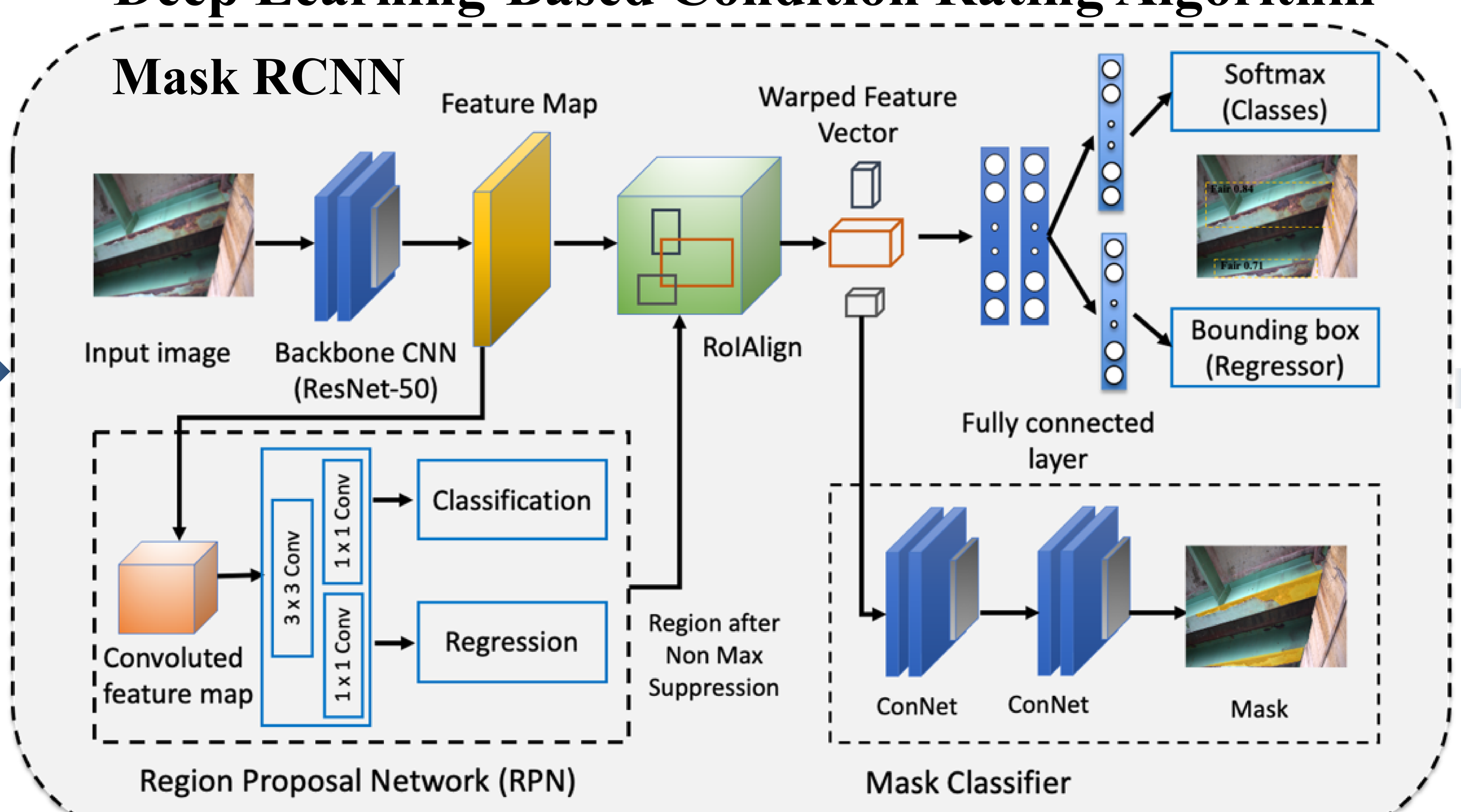
Corrosion condition rating Annotation

- **Background, no annotation (Good):** No visible corrosion, Peeling Paint, Minimal corrosion
- **Class 1 (Fair):** Freckled Rust/Sporadic Corrosion, Exposed Steel, Surface Corrosion
- **Class 2 (Poor):** Deeper corrosion, Disintegrated Portions of Steel, Pack Rust
- **Class 3 (Severe):** Steel with complete section loss (holes or cavities, Multiple perforations)

Annotated Images

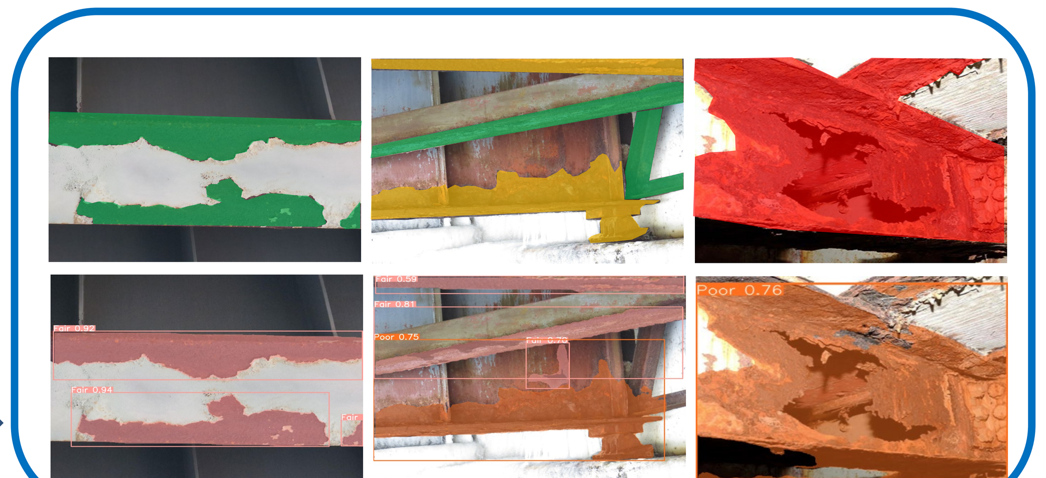
Input

Deep Learning-Based Condition Rating Algorithm



Output

Visualizing Outputs



Results Analysis

Trained Model	Dataset	F1 Score	Precision	Recall	Accuracy	mAP50
YOLOv8	Validation	0.451	0.602	0.360	-	0.484
	Test	0.730	0.853	0.647	-	0.726
Mask R-CNN	Validation	0.519	-	0.660	0.483	0.483
	Test	0.745	-	0.922	0.674	0.674

$$\text{Precision} = \frac{TP}{TP+FP} \quad \text{Recall} = \frac{TP}{TP+FN} \quad \text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}} \quad \text{mAP} = \frac{1}{N}\sum_{i=1}^{N} AP_i$$

Conclusion

- A dataset of 1200 images are collected and a defect detection algorithm was trained to classify the images into 7 categories of defects.
- A semantic segmentation algorithm is trained using corrosion images to perform corrosion condition rating task according to the AASHTO and BIRM regulations.
- The dataset is available online and offers valuable support in advancing the segmentation models by providing high-quality images and corresponding annotations
- Experimental results and comparison on real datasets verify the trained Mask RCNN and YOLOv8 models performs decently for corrosion segmentation and condition rating (mAP50 of 0.67 and 0.73 respectively).

- **Acknowledgements:** This work is funded by a grant from the Transportation Infrastructure Durability Center, with additional support from the Maine Department of Transportation and VHB Consulting Engineers.