Project Title: Continuous Computer Vision Inspection of Crane Wire Ropes for Overhead Cranes

Bradley Cline, Undergraduate Student

Department of Mechanical Engineering, Cullen College of Engineering

Problem Statement

A common source of crane catastrophic failures is broken and damaged wire ropes. This can cause a suspended load to suddenly crash to the ground. Typical factor cranes have capacities approaching 50 tons. Overhead cranes can be mounted more than 20 feet from the ground. Cranes are required to be inspected by OSHA at the before and during each use and to require annual inspections [1]. The inspection before use is limited to what is easily seen. Automated inspection techniques can supplement these inspections by providing continuous inspection and differing views for inspection. A computer vision system based on Convolutional Neural Networks (CNN) can be trained to distinguish images of the rope while in use.

Brief Literature Review

- Various patents and papers show the potential to inspect a wire rope using magnetic flux leakage which is a slow and costly method of inspection not suitable for live use [2].
- No papers exist for the rapid visual inspection of wire rope while in use.

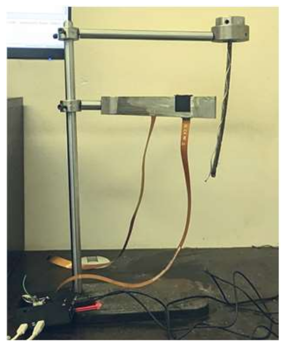
Experimental Setup and Collection of Data

- A stand containing 2 cameras was built to hole a piece of wire rope for photographing. The wire rope is hand spun inside of the stand to allow multiple angles of photographs

- 1,000+ photos of healthy and another 1,000+ photos of damaged wire were taken with either a missing strand of wire or a strand freely hanging.

Missing Strand

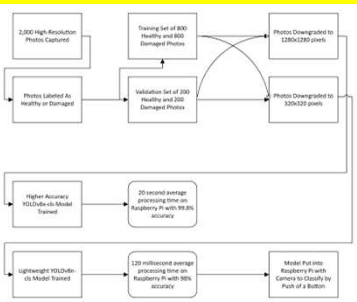
Loose Strand



Test Stand for Data Gathering

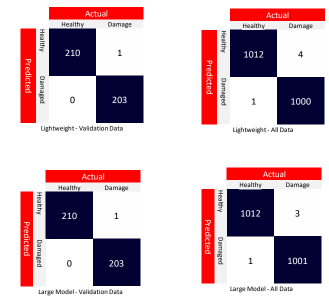
Methods

- A convolutional neural network was employed to differentiate between the two test cases.
- You Only Look Once version 8 (YOLOv8), a type of CNN, was used with a classification model
- YOLO runs a single detection and classification algorithm in one pass. Other models sometimes identify locations of items in image and later classify.
- With one pass architecture, images are classified faster for real-time detection.
- Some items placed in background to determine effect on image processing. Others were dimly lit to test low-light detection.
- Photos hand labeled at first, then used a model trained on limited data to classify as data was recorded. Retrained when full dataset collected.



Results, Analysis and Discussion

- Image processing with lightweight model rapid processed, but with limitations in detection of less obvious defects such as missing strands.
- Both models show very high accuracy of detection. Validation results are exactly the same. Misclassified image is poorly lit image used to test image robustness. Other poorly lit images classified properly
- Over 2,000 images in testing and validation set, lightweight model using on 2.7 million parameters misclassified 5. Model runs in 10-30 milliseconds per image on i7-12700 CPU. Runs in 120 milliseconds on Raspberry Pi.
- Future tests can involve installing on factory equipment with 3-D printed enclosure and connection to factory IT or PLC systems.
- Lightweight model rapidly processed on various cheap System on a Chip (SoC) systems. Model size of 2.83 MB still remarkably accurate.
- SoC architecture allows deployment for $125 per module with ability to process up to 8 images per second.
- Robust model capable of 1 second processing on more powerful desktop CPUs with a 322 MB model.



Confusion Matrices of Validation Data and all Available Data including Trai

Model	Size Label	Accuracy (% ImageNet)	Speed CPU (ms)	Speed A100 GPU (ms)	Parameters (millions)	Accuracy (% Rope)
YOLOv8n-cls	Nano	69	12.9	0.31	2.7	99.8
YOLOv8s-cls	Small	73.8	23.4	0.35	6.4	
YOLOv8m-cls	Medium	76.8	85.4	0.62	17	
YOLOv8l-cls	Large	76.8	163	0.87	37.5	
YOLOv8x-cls	Extra Large	79	232	1.01	57.4	99.8

Different Pre-trained Models Available from Ultralytics [3]

Poorly light image Misclassified in Validation Data

Conclusion

Model highly successful at detection a damaged wire condition, and therefore suitable as part of inspections based on OSHA requirements especially the requirement for inspection during use. Enhanced views from heights and angles allow better early detection of dangerous conditions. A fixed camera can scan the rope as it moves past the camera from the drum at the top of the crane. Multiple cameras can scan different areas of the rope.

Typical Overhead Crane [4]

Acknowledgements

The financial support from Midstream Integrity Services (MIS) and Borusan Pipe USA and technical support from Smart Materials & Structures Lab (SMSL) and Artificial Intelligence Lab for Monitoring & Inspection (AILMI) at UH.

References (brief)

1. "Identification, Inspection, and Marking of Cranes When Manufacturer-Supplied Identifications Are Unavailable." Occupational Safety and Health Administration, www.osha.gov/lawsregs/standardinterpretations/2004-02-23. Accessed 28 Apr. 2024.
2. Liu, Shiwei; Sun, Yanhua; Jiang, Xiaoyuan,; Kang, Yihua. "A Review of Wire Rope Detection Methods, Sensors and Signal Processing Techniques" Springer Link, https://link.springer.com/article/10.1007/s10921-020-00732-y. Accessed 28 Apr. 2024.
3. "Image Classification." Ultralytics. https://docs.ultralytics.com/tasks/classify/. Accessed 28 Apr. 2024
4. Sclaferriere. https://en.wikipedia.org/wiki/Overhead_crane#/media/File:Essais_de_charge.jpg