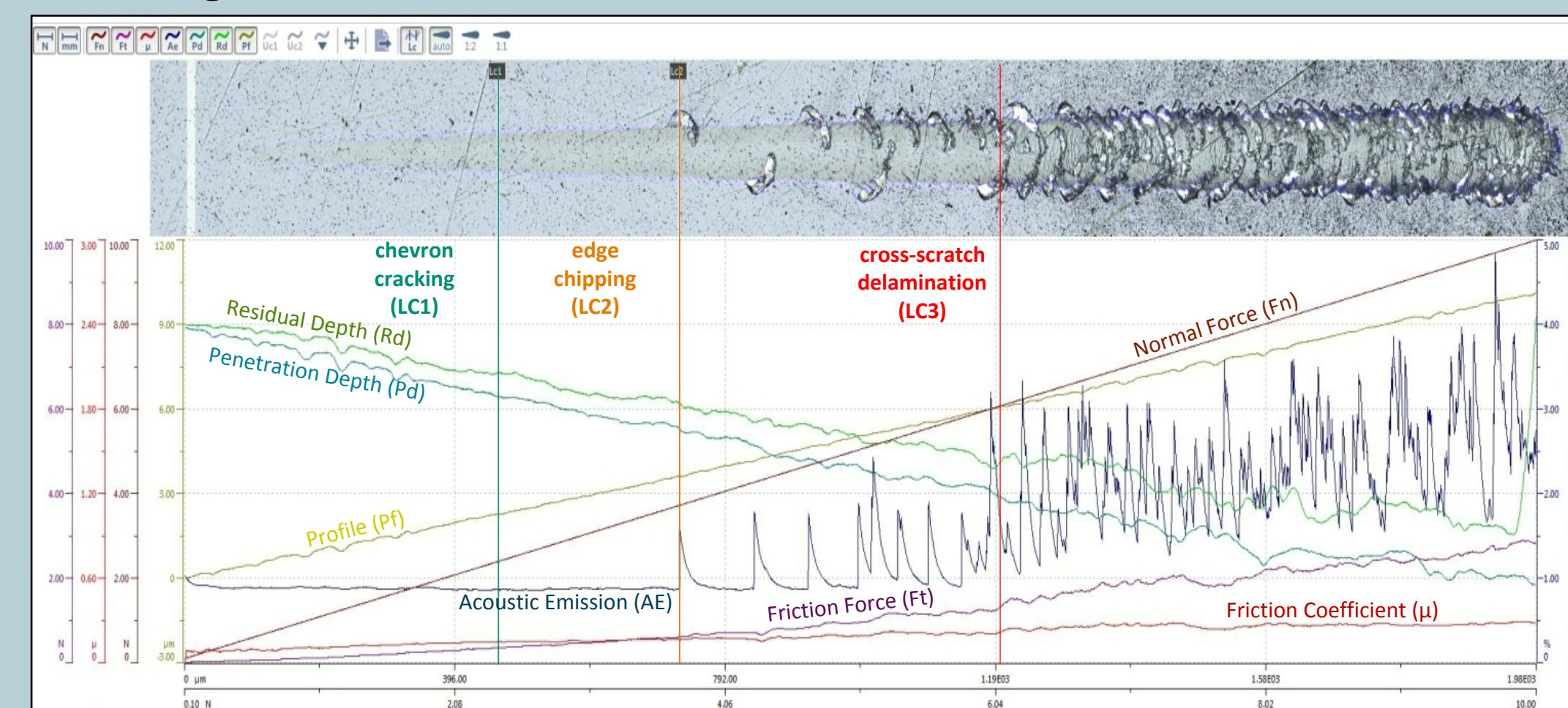


Improved Throughput and Analysis of Scratch Test Results via Automation and Machine Learning

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Introduction

A machine learning algorithm utilizing Convolutional Neural Networks (CNN) has been developed to identify critical load (LC) delamination features for scratch testing of DLC coatings and other material systems adhering to ASTM Standard C1624-05 [1].

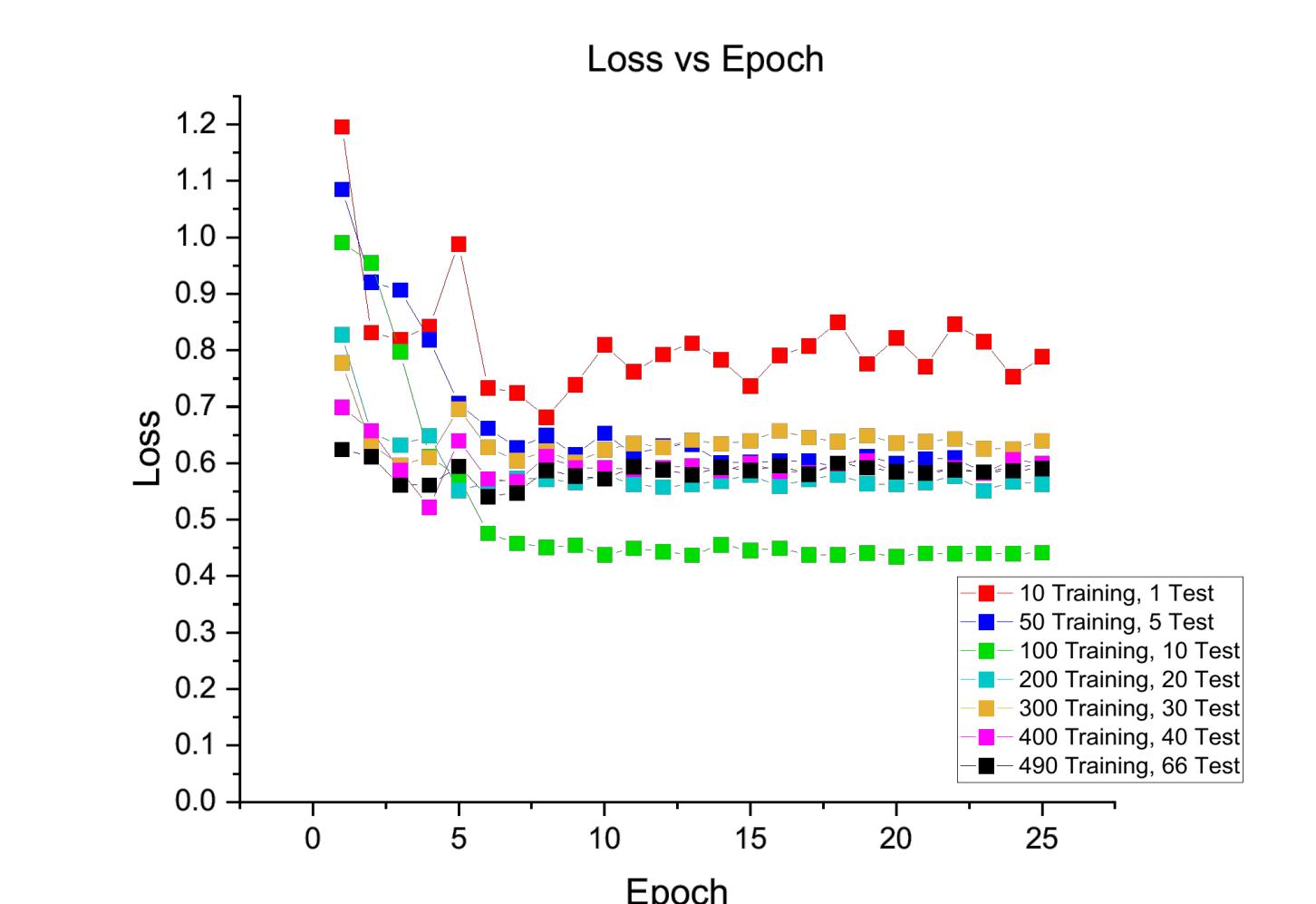
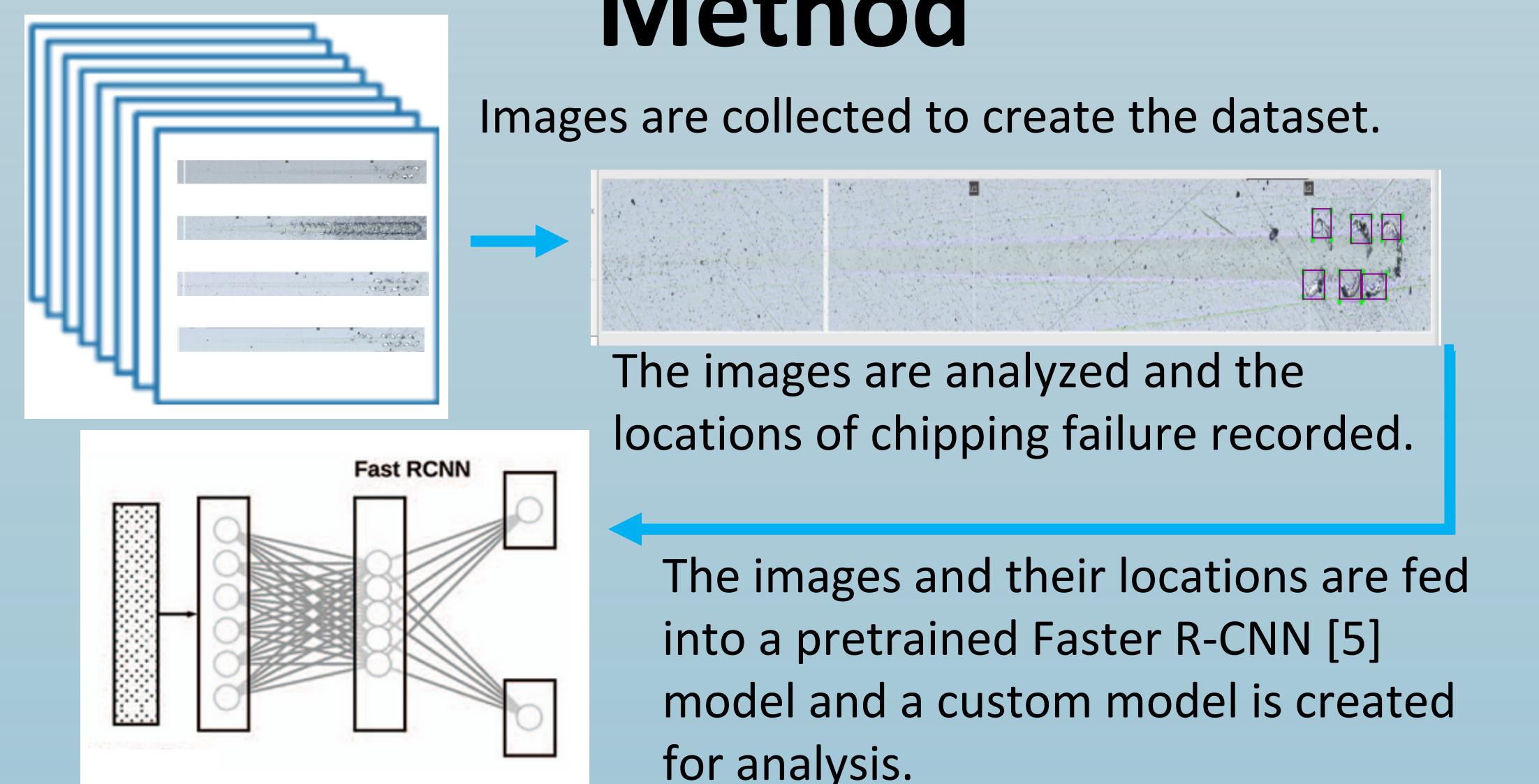


- LC1 – Chevron cracking, indicating cohesive failure in the coating
- LC2 – Edge chipping failure extending from the arc tensile cracks, indicating adhesive failure between the coating and the substrate
- LC3 – Cross-Scratch Delamination, indicating total failure of the coating

CNNs in Materials Science

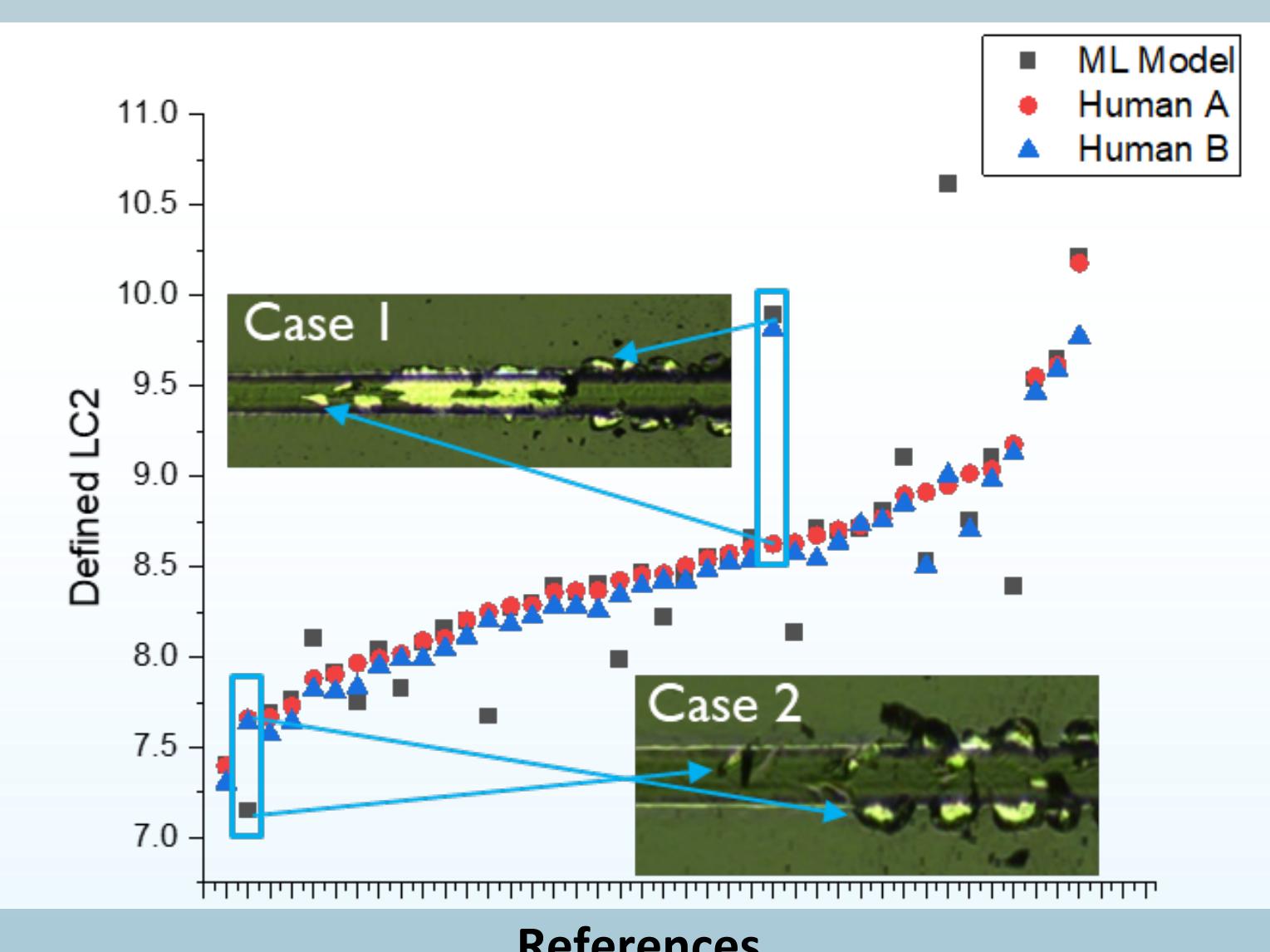
- CNNs have been used to classify Rockwell indentation tests into their expected adhesion classes HF1-HF6 [2].
- CNNs have been used to automate and characterize crosscut tests for organic coatings [3].
- CNNs have been used to detect critical loads in macro- and micro-scratches on a-C:H(:W) coatings [4].

Method



The program's results were compared scratch-by-scratch with an existing dataset to analyze the accuracy of the LC2 locations. There are 2 cases where the locations differ by > 1N:

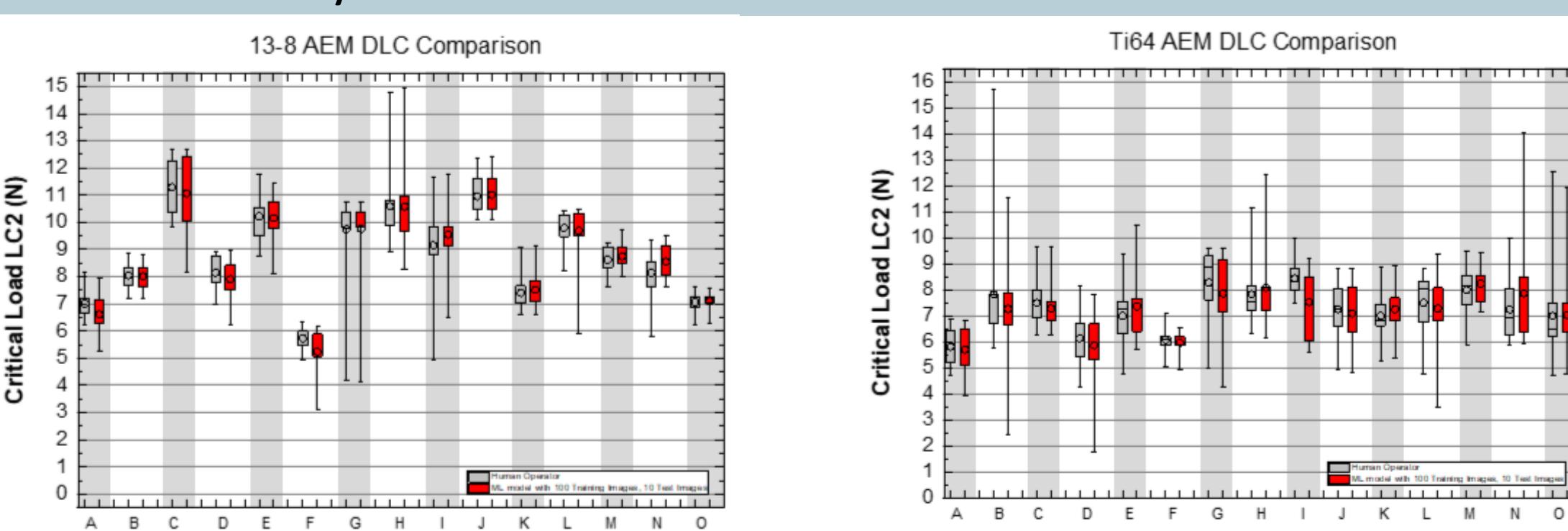
1. The model identified a higher LC2 – delamination of the coating exists on the film prior to the first chipping failure
2. The model identified a lower LC2 - the model picked out an instance of chipping failure within the scratch track that exists before the edge chipping failure



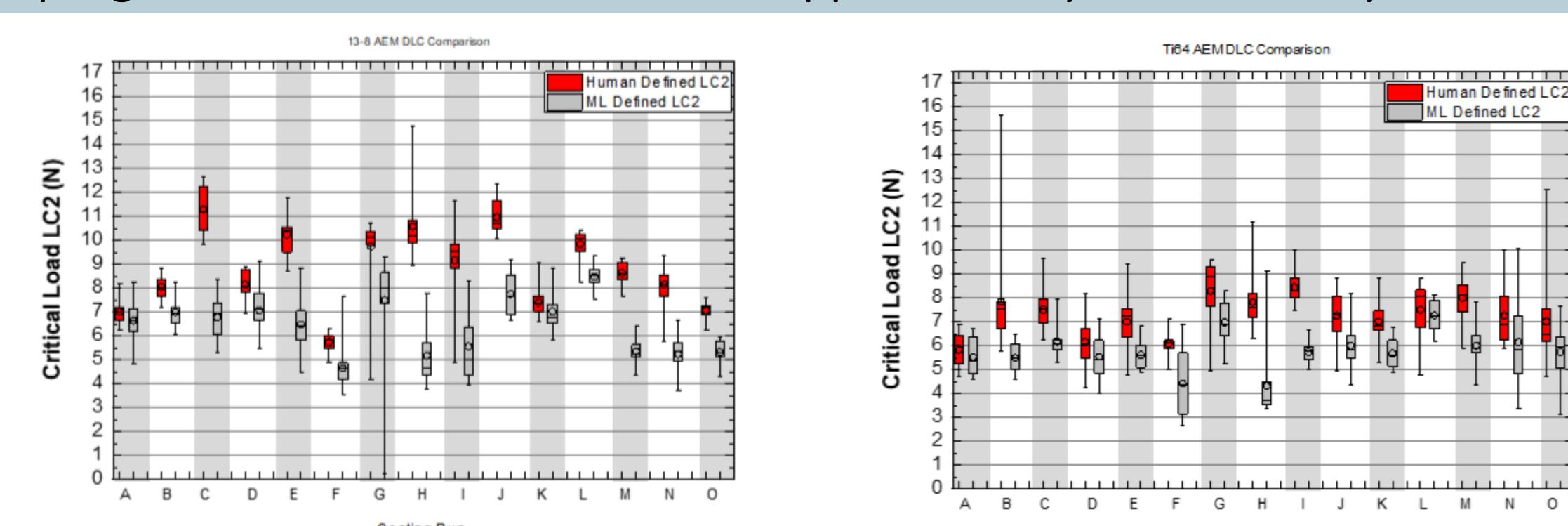
[1] ASTM Standard C1624-05, 2010. Standard Test Method for Adhesion Strength and Mechanical Failure Modes of Ceramic Coatings by Quantitative Single Point Scratch Testing. PA, 2010, DOI: 10.1520/C1624-05R10. West Conshohocken, PA: ASTM International, 2010.
[2] Lenz, Bastian, et al. "Automated Evaluation of Rockwell Adhesion Tests for PVD Coatings Using Convolutional Neural Networks." Surface and Coatings Technology, vol. 385, 2020, p. 125365, doi:https://doi.org/10.1016/j.surcoat.2020.125365.
[3] Song, Yu, et al. Deep Learning-Based Automated Image Segmentation for Concrete Petrographic Analysis. 2020.
[4] Lenz, Bastian, et al. "Application of CNN Networks for an Automatic Determination of Critical Loads in Scratch Tests on A-C:H:W Coatings." Surface and Coatings Technology, vol. 393, 2020, p. 125764, doi:https://doi.org/10.1016/j.surcoat.2020.125764.
[5] Shaoqin Ren. "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks." ArXiv Preprint ArXiv:1506.01497, 2015.

Results (cont.)

The results of the ML program utilizing the model created with 100 training and 10 validation images were compared with previous LC2 values defined by a human operator over nearly 500 scratches on DLC and MoS₂ coatings. The ML program is able to define LC2 with 96% accuracy.



A new ML model was trained on the Acoustic Emission (AE) signal of the same scratch tests that were analyzed with the image based model. The model was tested on the same DLC scratches on two substrates. This ML program is able to define LC2 with approximately 90% accuracy.



Conclusions

This program removes the variability in identification of optical scratch features once discerned by human operators across different sites, as well as increasing throughput and automation to allow operators to pursue other tasks.

Using a standard set of training and testing images or AE signals to create the ML model, the program can be distributed to multiple locations in conjunction with the manufactured software. This will allow the critical load to be identified consistently amongst different laboratories using the automation interface without requiring uniform training of human operators.