Crack identification and characterization in deformed Nb_3Sn Rutherford cable stacks using machine learning

General MDP Meeting

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Outline

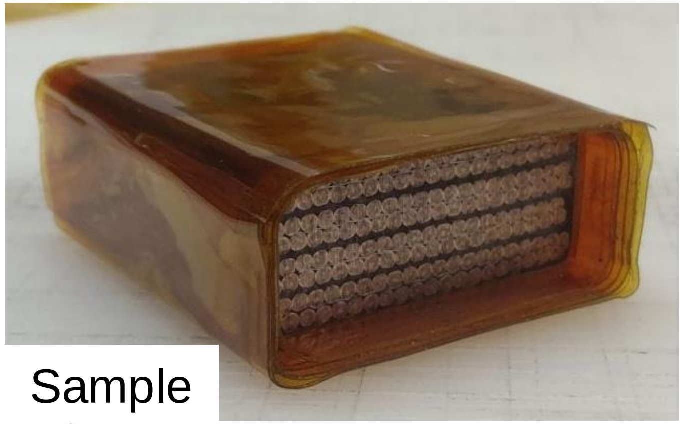
Background and Objectives

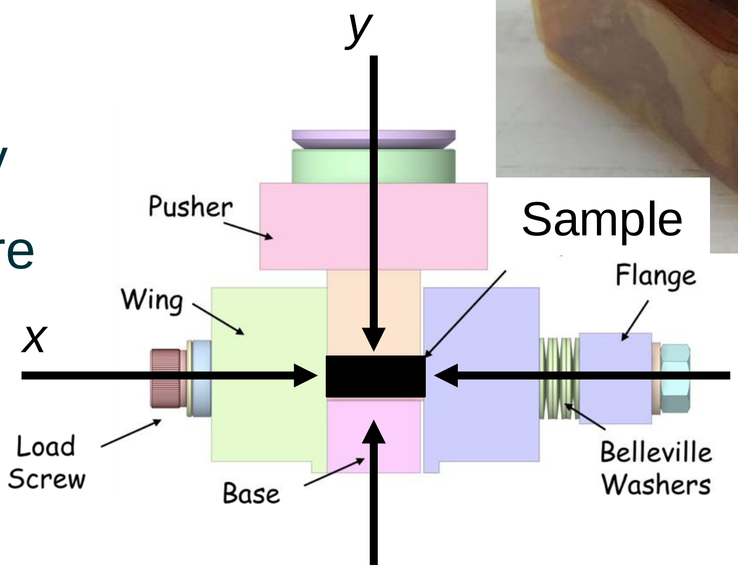
Sample Preparation and Loading

G. Vallone *et al.*, “Measurement and Computation of Nb_3Sn Rutherford Cables Strength Under Multi-Axial Loading Conditions,” *IEEE TAS*,. 2024, doi: 10.1109/TASC.2023.3340126.

- 4-stack of AUP Rutherford cables (40-strand, RRP, 0.85 mm diameter)
- Standard AUP heat treatment
- Impregnated with CTD-101K after heat treatment

- Samples were wrapped in Kapton tape
- Fuji papers were used to confirm load uniformity
- Uniaxial and bi-axial loading at room temperature
- Pre-loading along *x* or *z* for biaxial samples



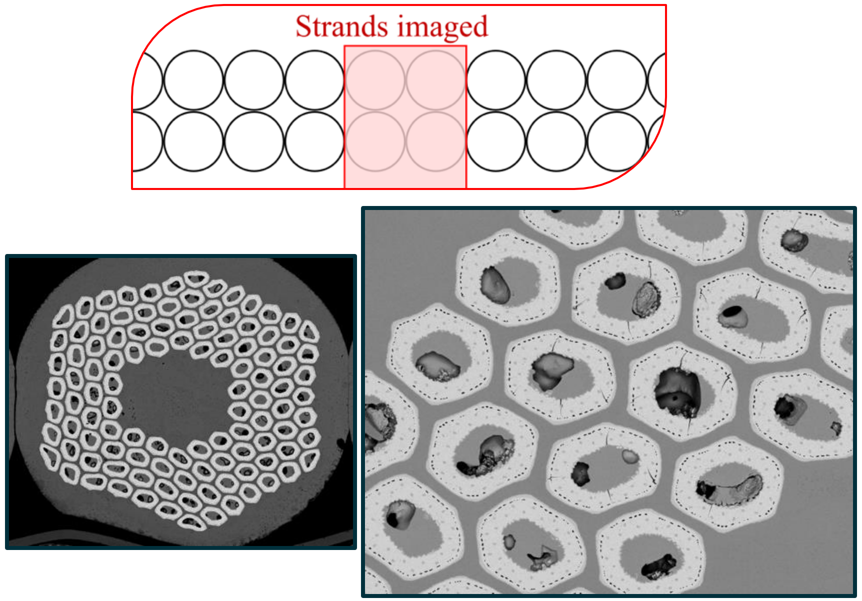


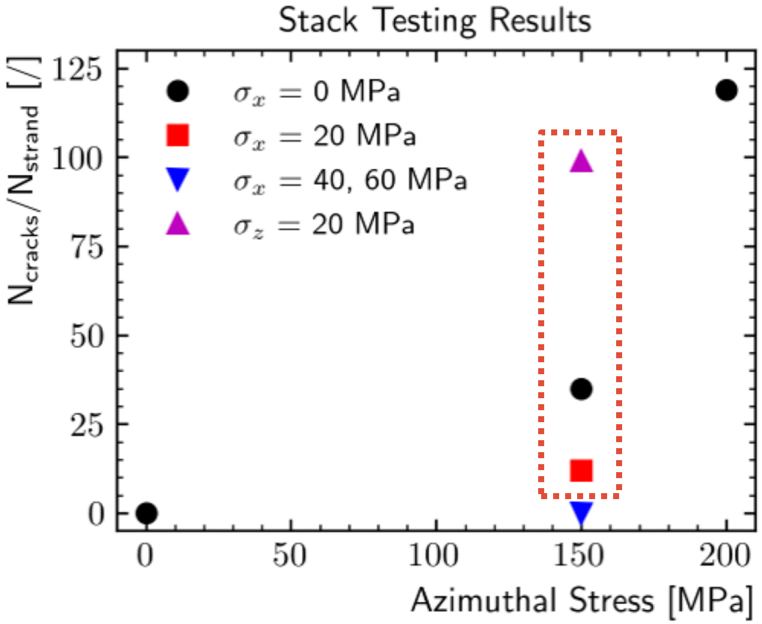
Schematic of the loading setup

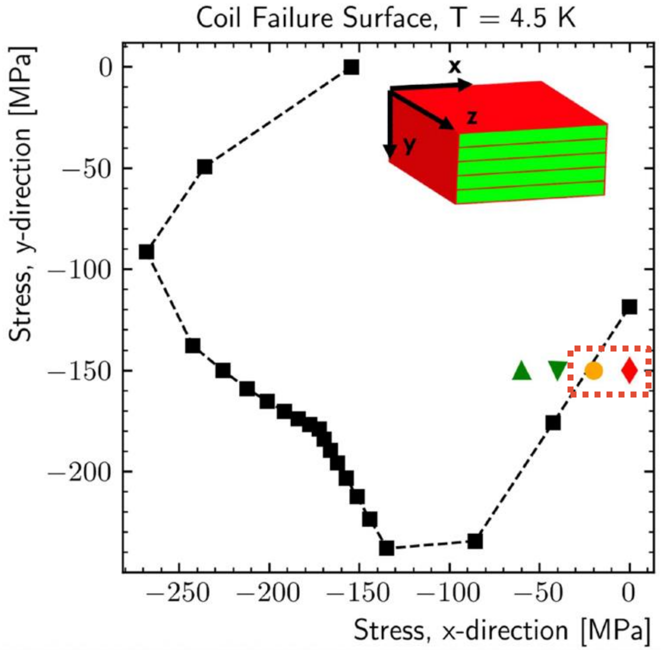
Sample Imaging and Crack Counting

G. Vallone *et al.*, "Measurement and Computation of Nb_3Sn Rutherford Cables Strength Under Multi-Axial Loading Conditions," *IEEE TAS*,. 2024, doi: 10.1109/TASC.2023.3340126.

- In 2023, we had to manually count and locate the cracks in the stacks (Marika d'Addazio), so we limited our observation to a few wires in the center of each stack
- SEM images took a lot of time to acquire (high resolution), SEM access was limited and can be expensive, and samples had to be sputtered before imaging







SEM images from 2023

Failure surface for different stress-states

Objectives: (1) use image analysis to segment the cracks and (2) move away from the SEM

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Experimental Method

1. Background and objectives
2. Experimental method
3. ML for image analysis
4. Crack segmentation and statistics
5. Conclusions

Sample Preparation

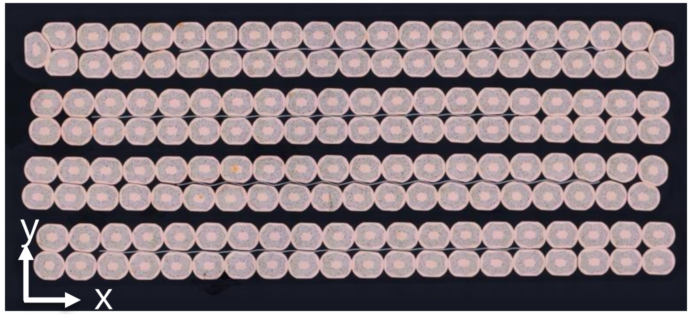
1. Cold mount 4-stack in epoxy
2. Grind ~4 mm from the edge
3. Polish sample up to 1 µm particle size
4. Overnight vibratory polishing with OP-S solution (0.04 µm)
5. Sample cleaning
   1. Clean surface with dish soap under running water
   2. Ultrasonic bath and drying in Struers Lavamin
   3. Sample drying with hair dryer

Vibratory polishing

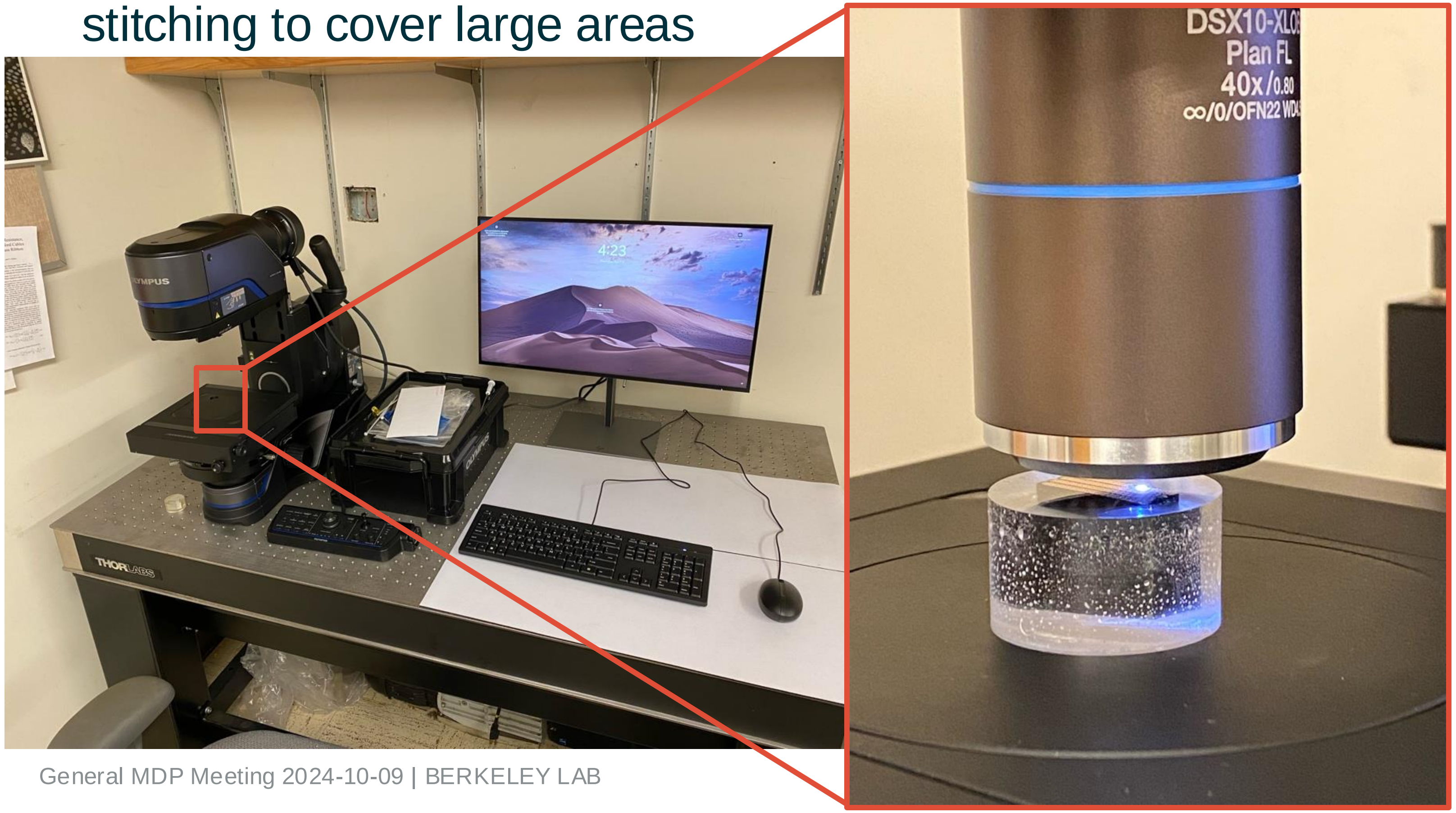
Struers Lavamin

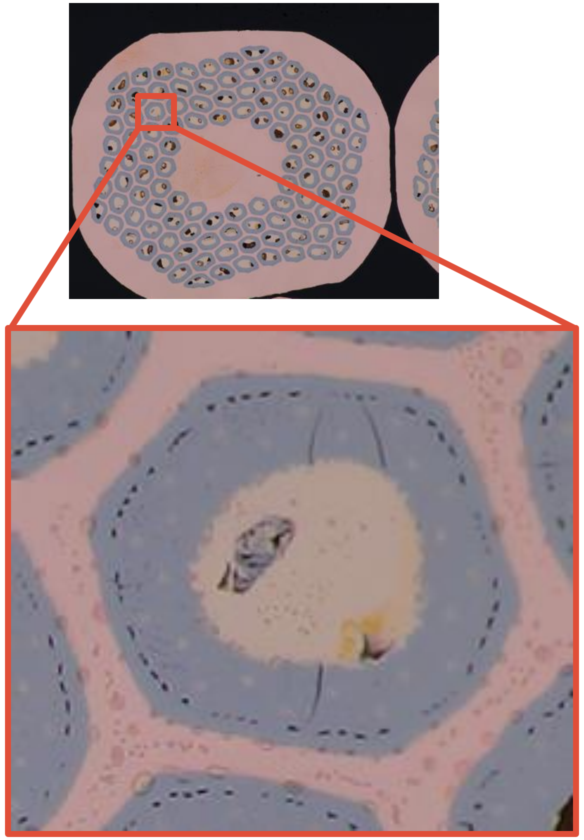
Sample drying

Sample Imaging



- Sample imaging with digital microscope Olympus DSX-1000
- Imaging at high magnification with image stacking to ensure focusing over the entire wire and stitching to cover large areas





Sample Cleaning and Imaging Artefacts

- Cleaning artefacts were never completely removed despite trying different techniques and discussing with other labs

- We decided to move forward with these images and included them in the training dataset in the hope of having a more robust model

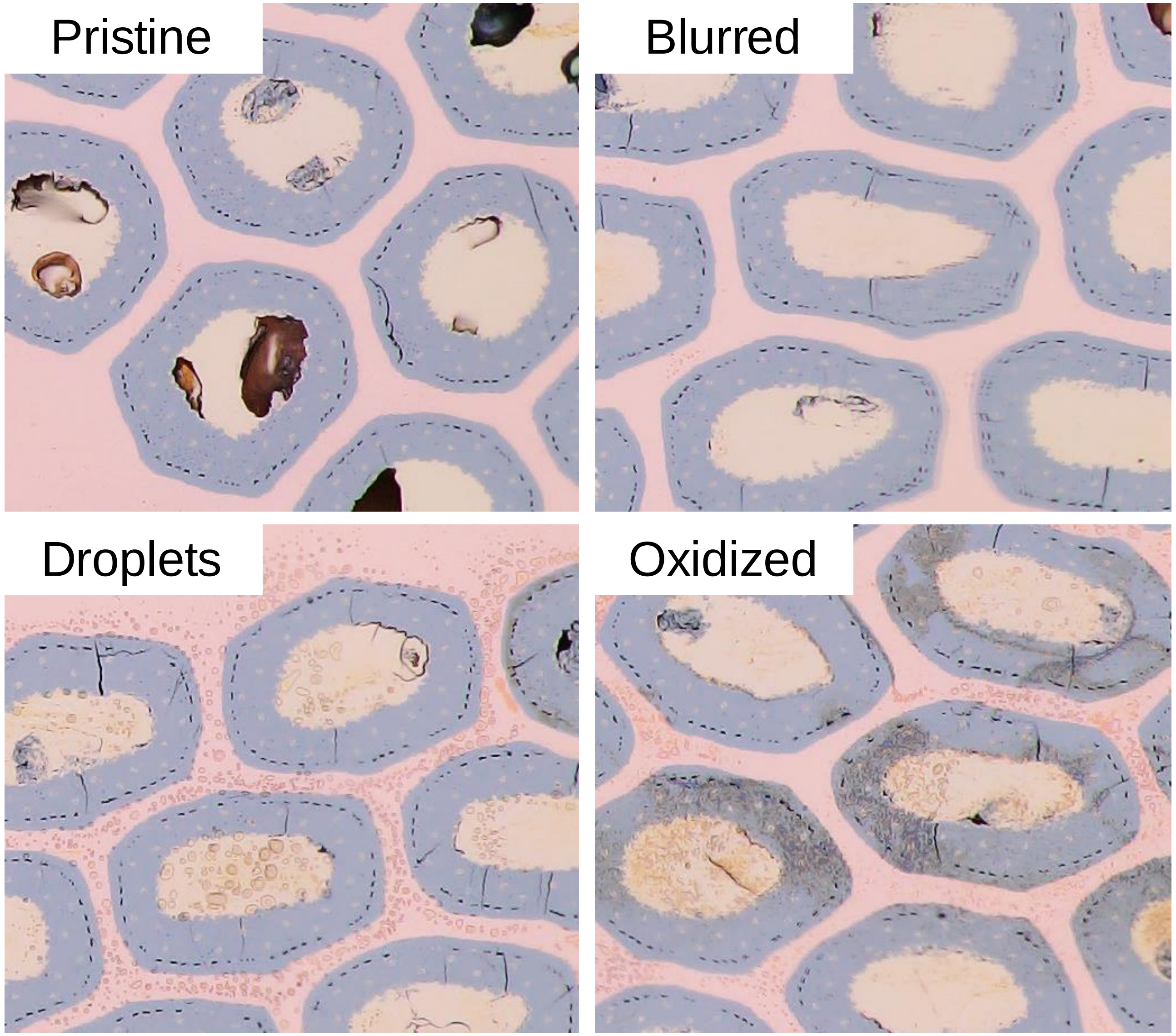


Image Analysis in Python

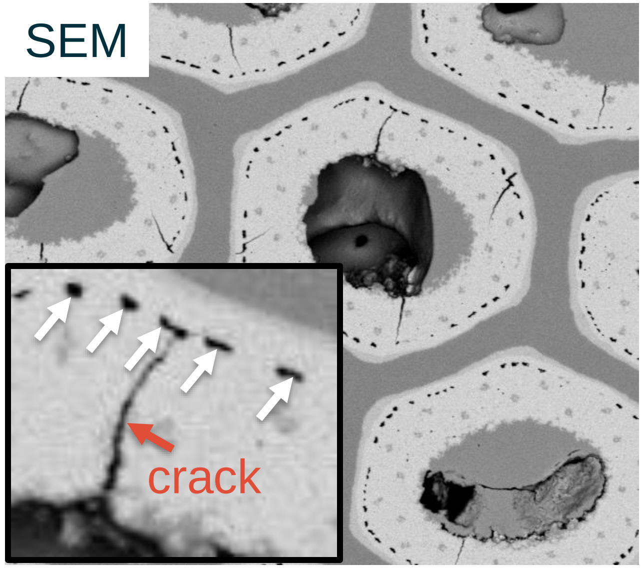
- All image analysis and crack statistics was done using Python
- **Detectron2:** computer vision framework from Meta AI with the Mask R-CNN model
- **PyTorch:** machine learning library with GPU-accelerated tensor computing
- **Scikit-image:** image analysis library
- **Seaborn:** plotting and visualization library
- **Numpy:** array and matrix manipulation library
- …

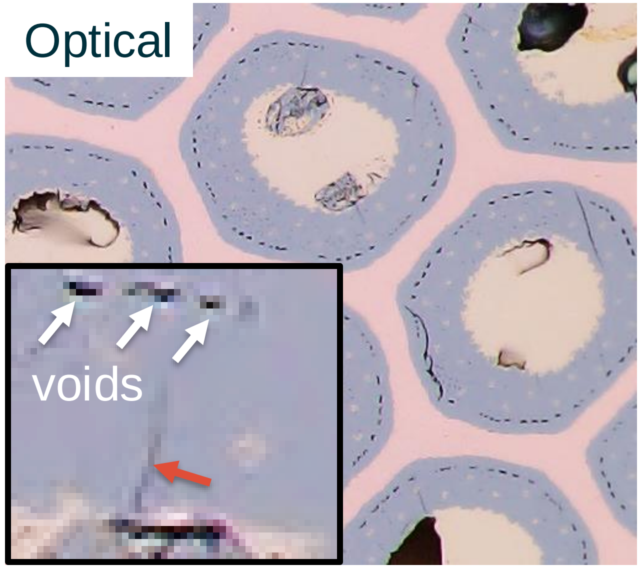
ML

Machine Learning for Image Analysis

Why Machine Learning?

- Cracks and voids have similar colors (dark) and contrast with the Nb_3Sn surroundings
  - Traditional thresholding fails to differentiate the two
- Looking at morphological features is more appropriate
  - Convolutional Neural Networks are suitable for this





Announcement made yesterday!

The Nobel Prize in Physics 2024

Ill. Niklas Elmehed © Nobel Prize Outreach

John J. Hopfield

Prize share: 1/2

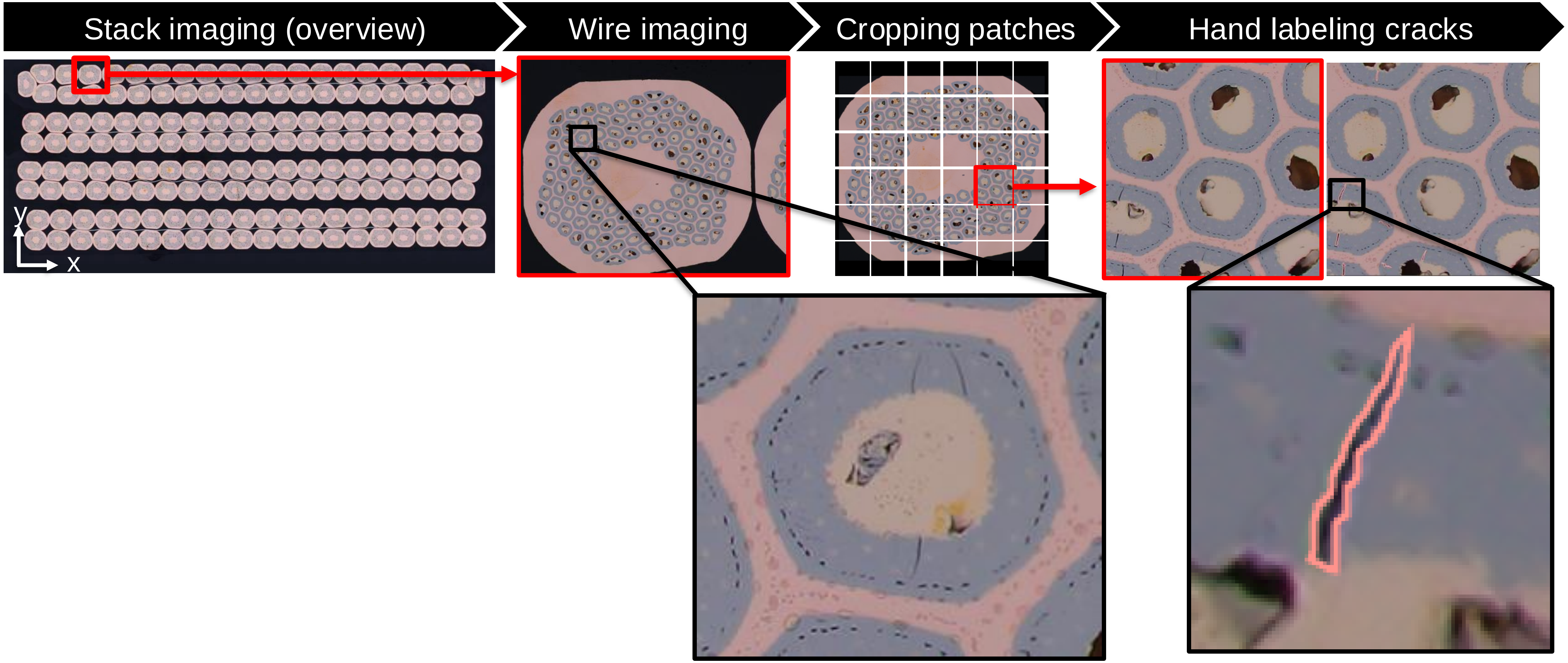
Ill. Niklas Elmehed © Nobel Prize Outreach

Geoffrey E. Hinton

Prize share: 1/2

The Nobel Prize in Physics 2024 was awarded to John J. Hopfield and Geoffrey E. Hinton "for foundational discoveries and inventions that enable machine learning with artificial neural networks"

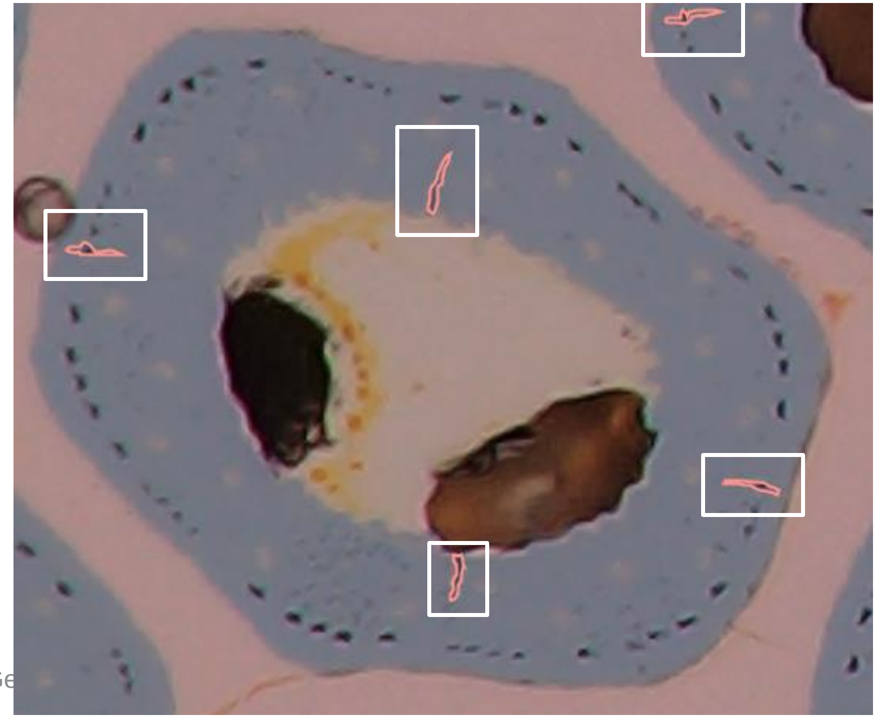
Machine Learning Workflow

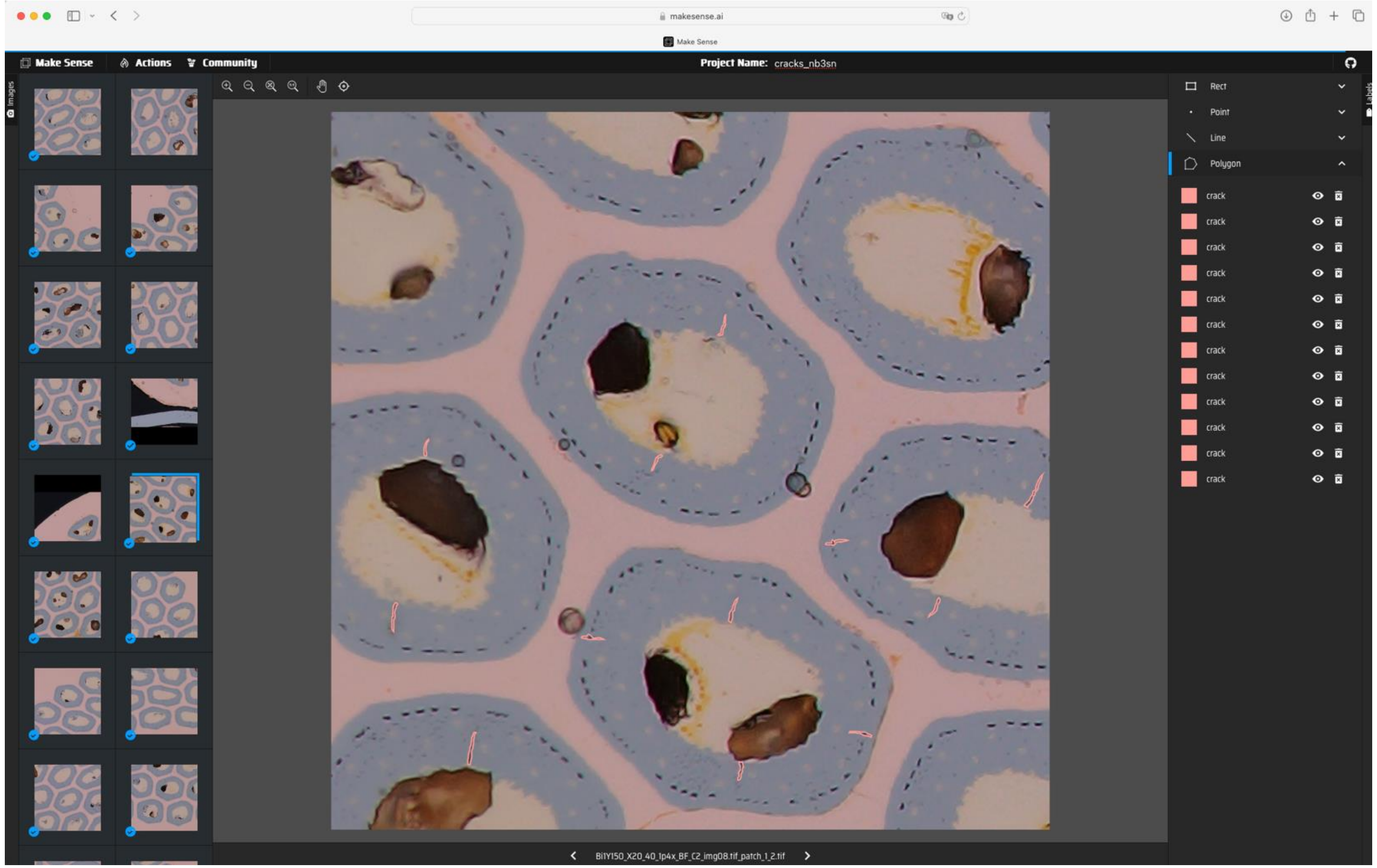


Machine Learning Workflow

Stack imaging (overview) → Wire imaging → Cropping patches → Hand labeling cracks

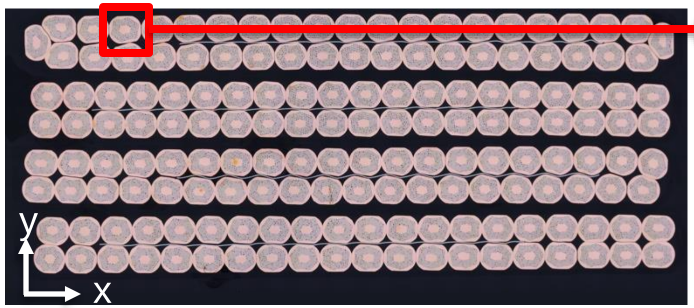
- Manual annotation using MakeSense.ai (clicking to draw the boundary around all cracks)
- Nandana will present a more efficient annotation approach

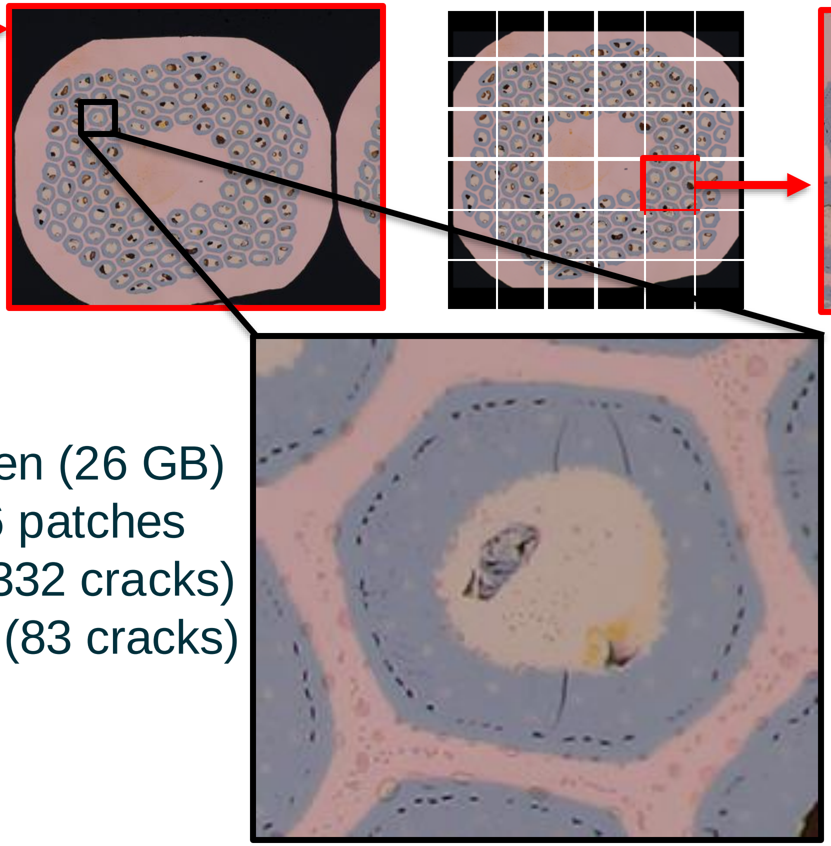


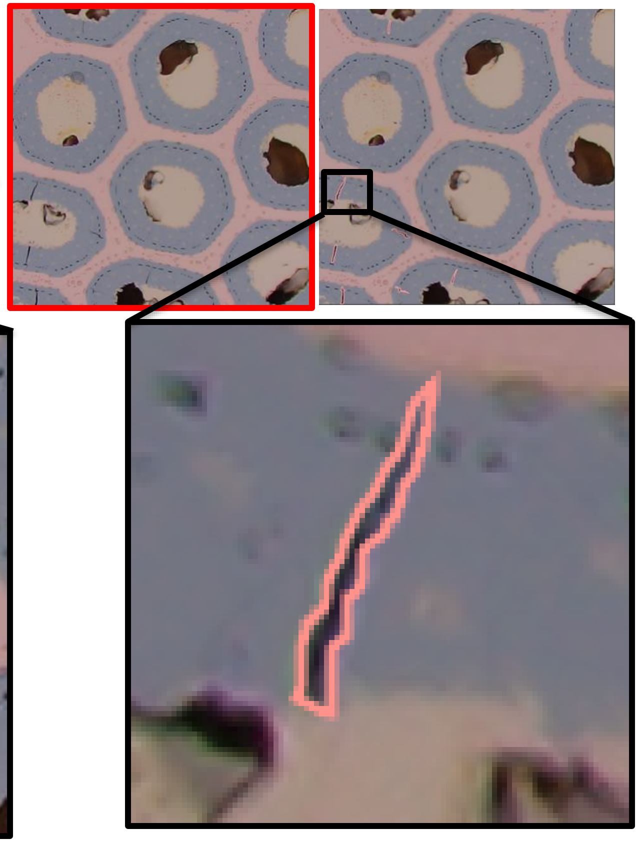


Machine Learning Workflow

Stack imaging (overview) → Wire imaging → Cropping patches → Hand labeling cracks → Model training







Conducted on Einsteinium GPU cluster at LBNL

Dataset key facts

- Images of 480 wires were taken (26 GB)
- Wires were cropped in 18,046 patches
- Training dataset: 43 images (332 cracks)
- Validation dataset: 11 images (83 cracks)

What models should we use for instance segmentation of the cracks in this dataset?

Mask R-CNN and Detectron 2 – Leveraging Computer Vision Open-Source Models

- For this study, we decided to explore the use of open-source models from leaders in computer vision and applying them to scientific problems*
- New novel ML models from the computer vision community are released almost on a daily basis
- We should take advantage of those models

- Mask R-CNN, Detectron2, and Segment Anything Model were all built by Meta AI Research's division

Detectron2

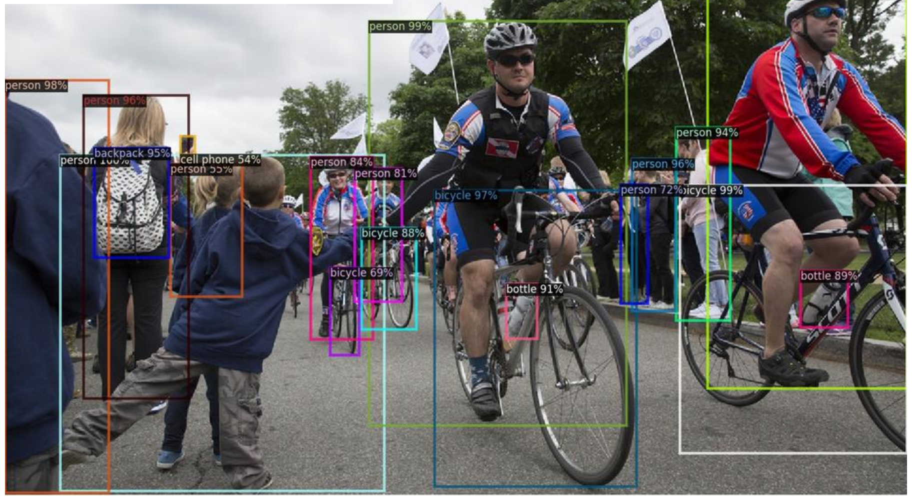
Waymo self-driving car in San Francisco are using 3D object detection with their different detectors (cameras and mid- and short-range lidars)

*Digital Sreeni's YouTube channel: https://www.youtube.com/@DigitalSreeni

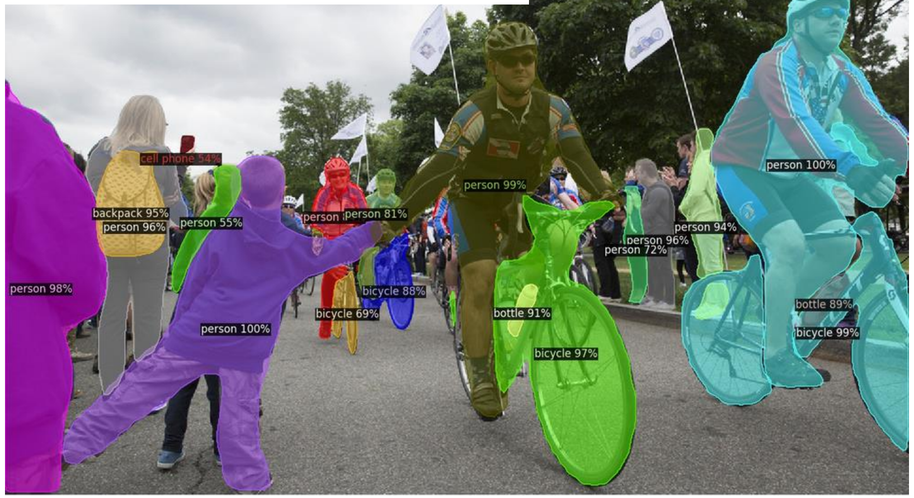
Detectron2

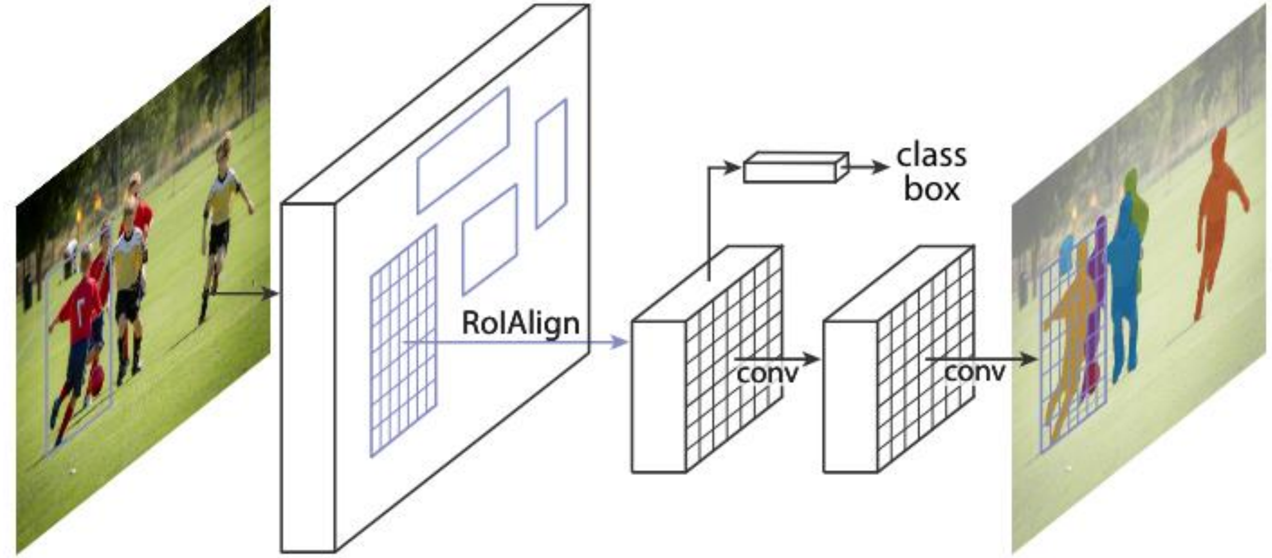
Mask R-CNN – Model Overview

Object detection



Instance segmentation





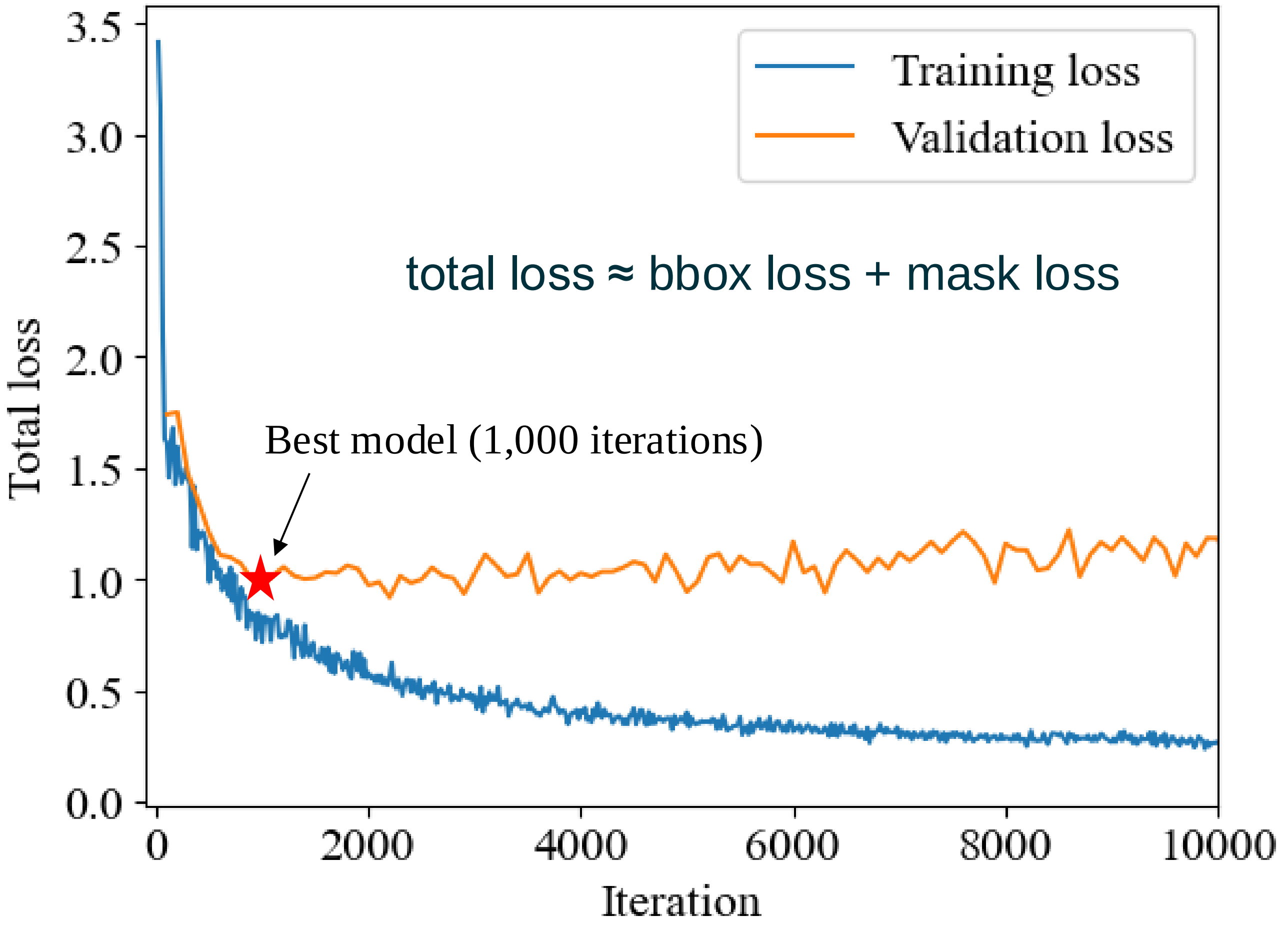
Step 1
Object detection over the entire image

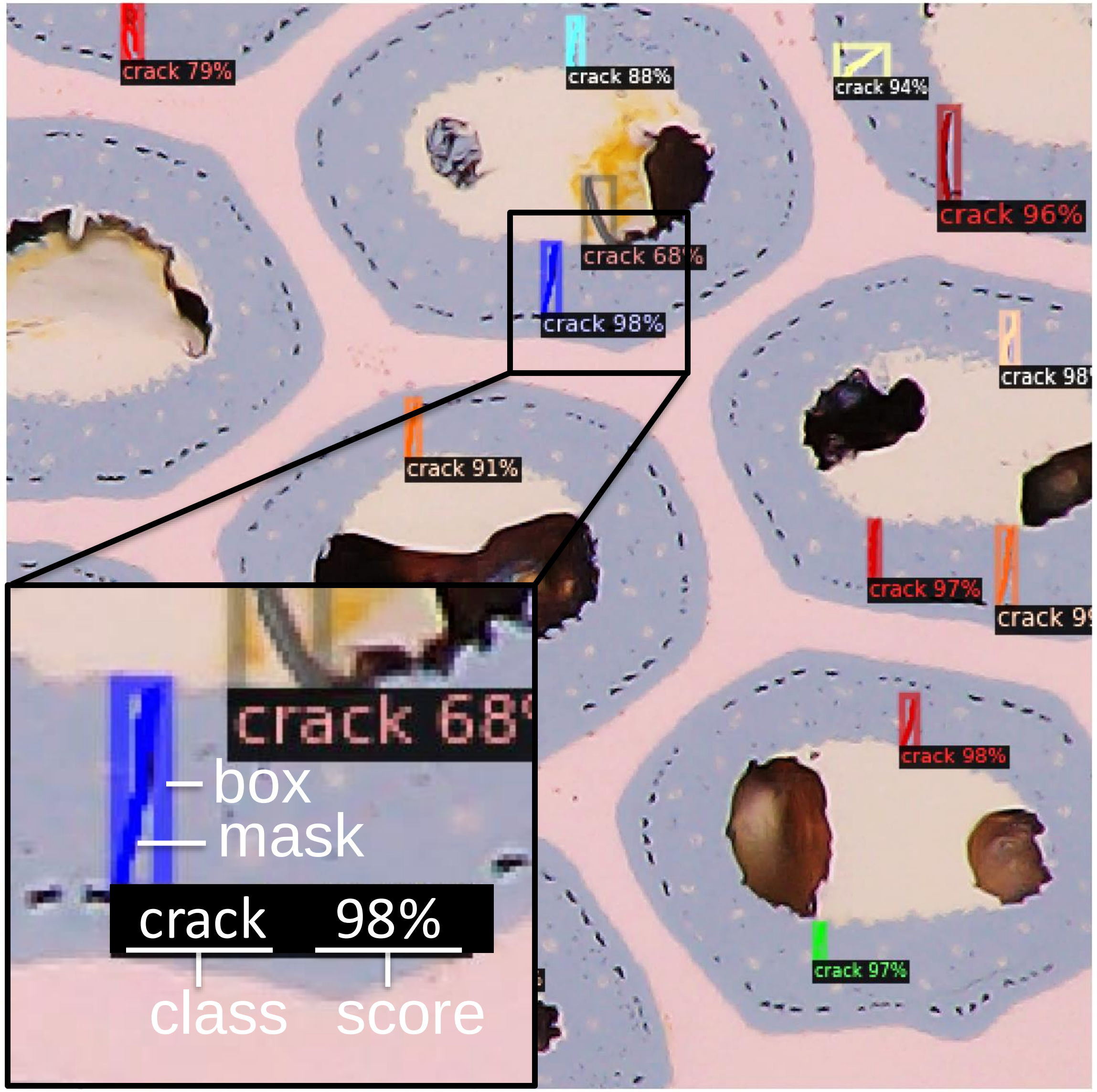
Step 2
Semantic segmentation in the regions of interest (bounding boxes)

Detectron2 has pre-trained Mask R-CNN models with slightly different architectures and parameters. These pre-trained models and their weights were used to initialize the models that we trained (or fine-tuned) for our application.

Mask R-CNN – Model Training

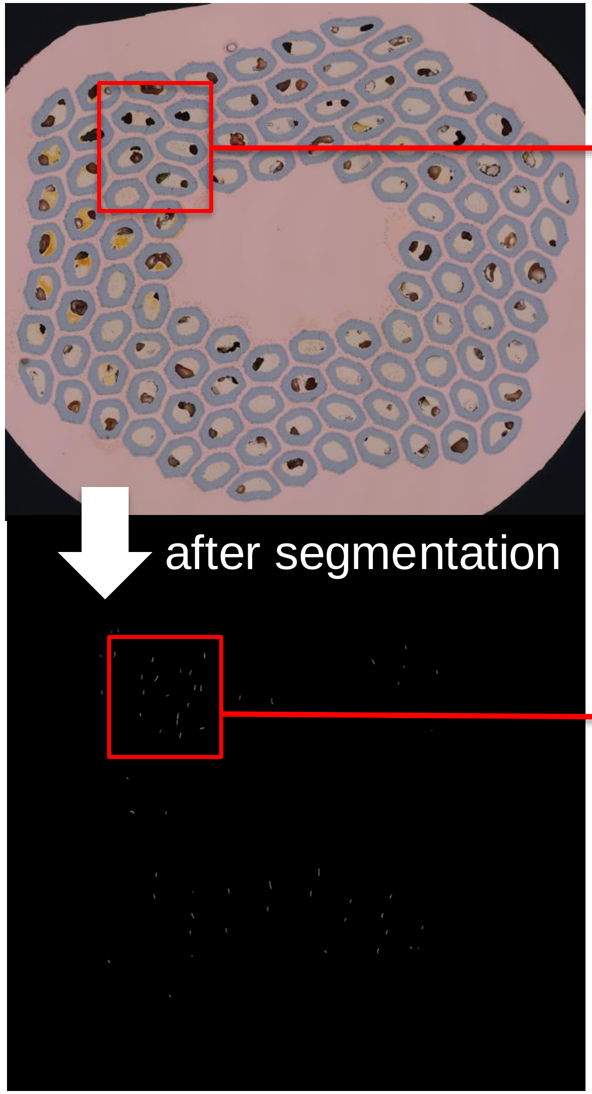
The model was trained on the Einsteinium/Lawrencium cluster on 1 GPU node (2 min 37 s) and weights from the 1,000th iteration were used for instance segmentation of the entire dataset (< 2.5 h).

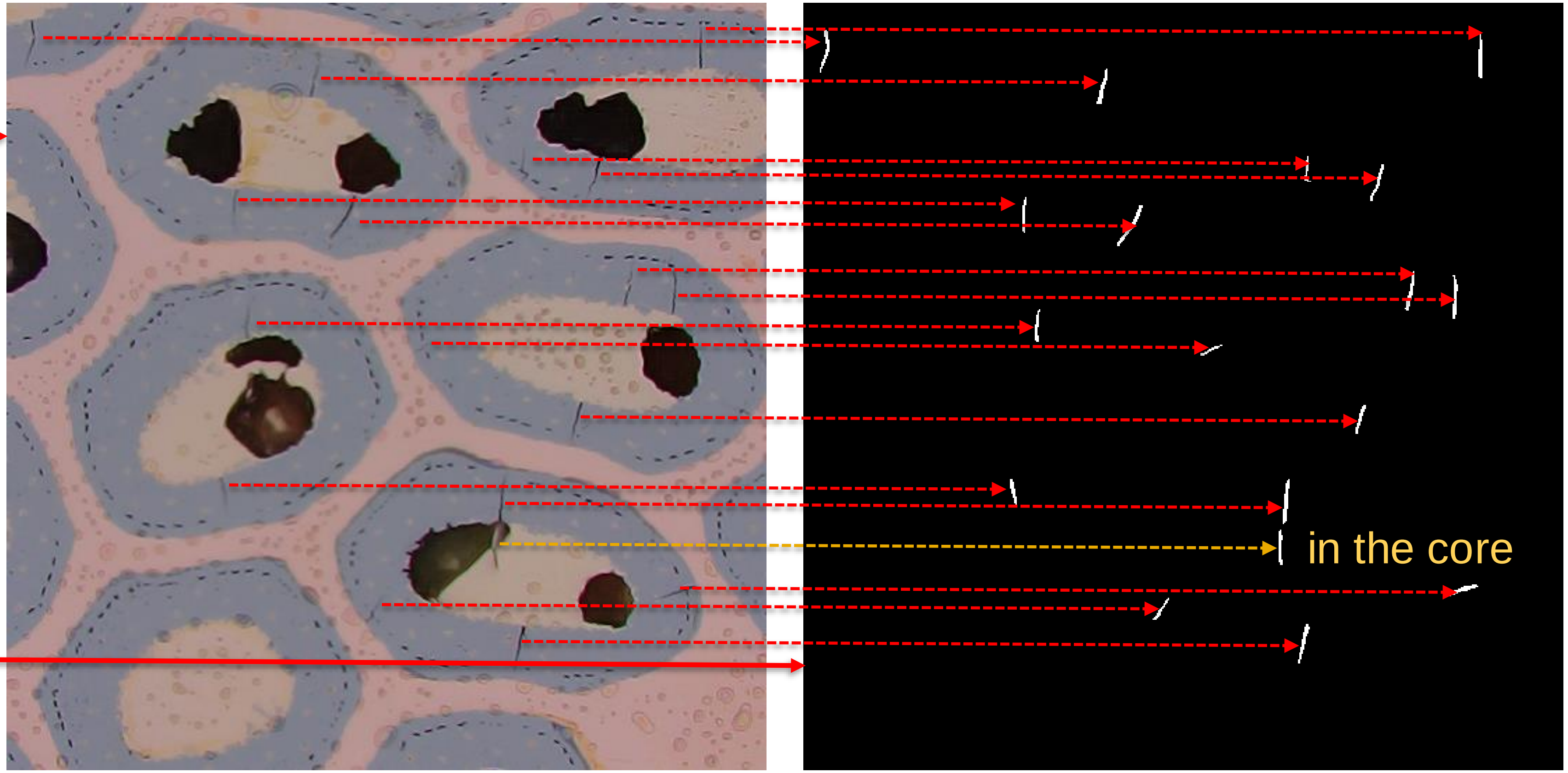




Crack Segmentation and Statistics

Crack Segmentation





Optical microscopy brightfield image

Binary mask of cracks

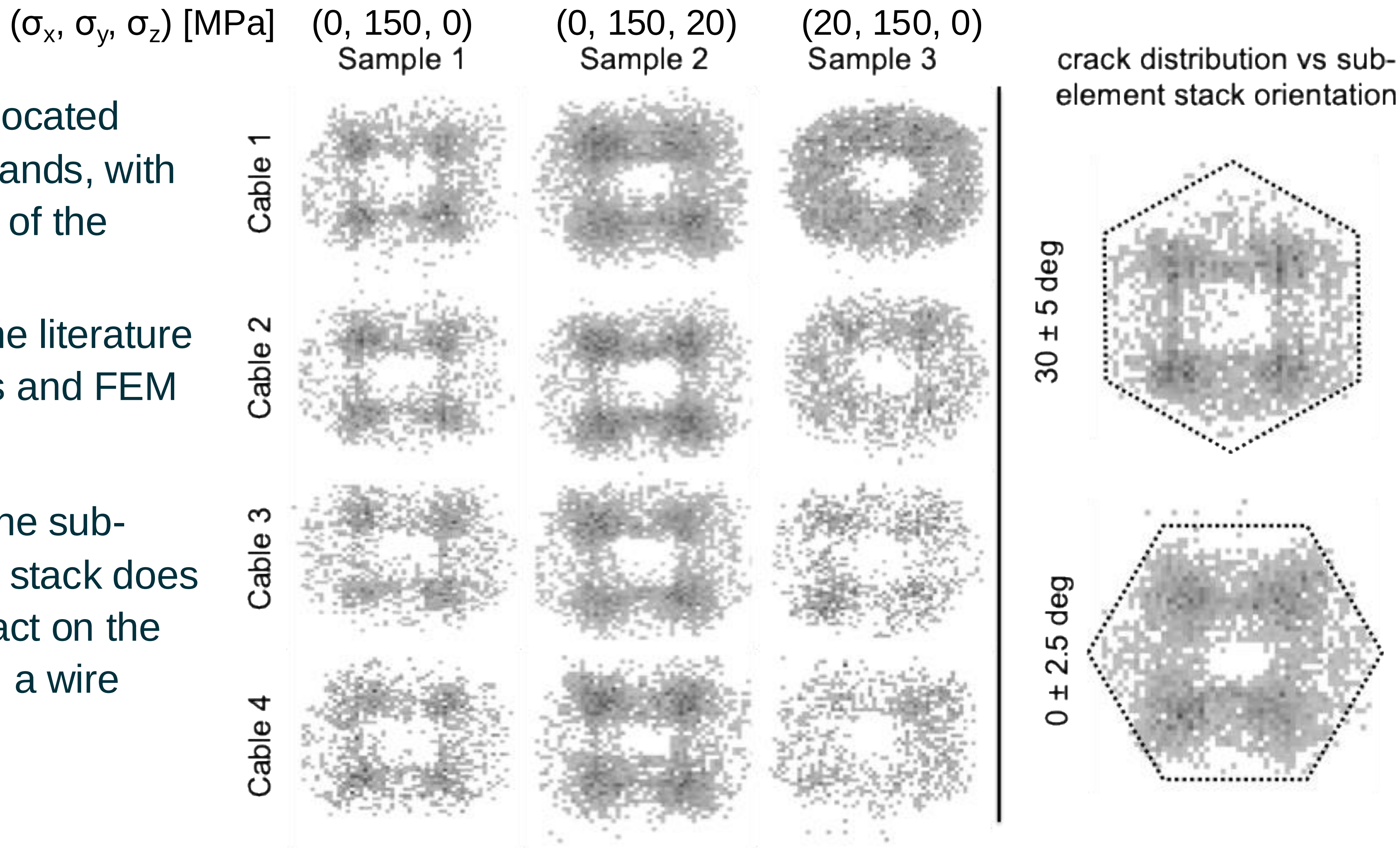
From the binary masks, we computed (1) the number of cracks in each wire, (2) the length of each crack, (3) the orientation of each crack, and more.

Crack Statistics – Distribution in a Wire

2D histograms of the crack centroid

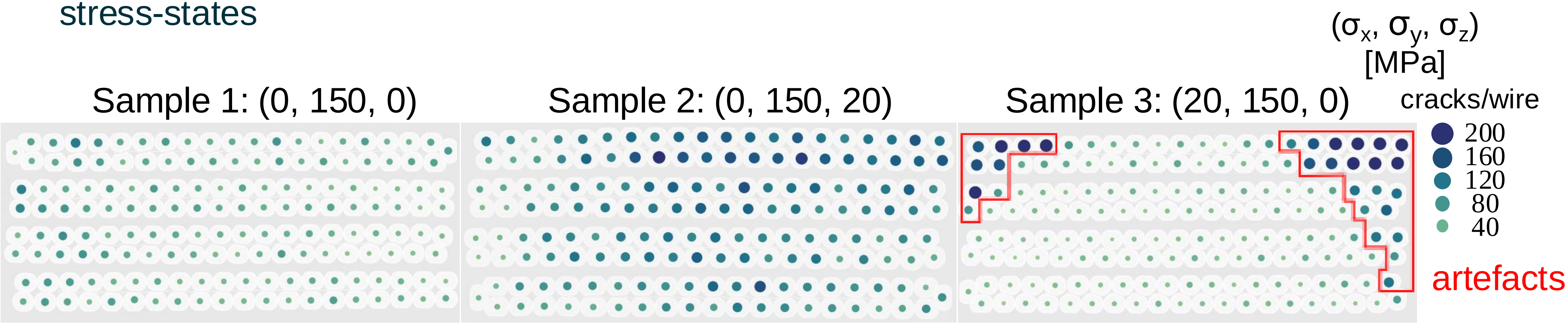
- Cracks are mainly located along ~45° shear bands, with respect to direction of the largest load
  – As observed in the literature from experiments and FEM

- The orientation of the sub-element hexagonal stack does not have a big impact on the crack distribution in a wire



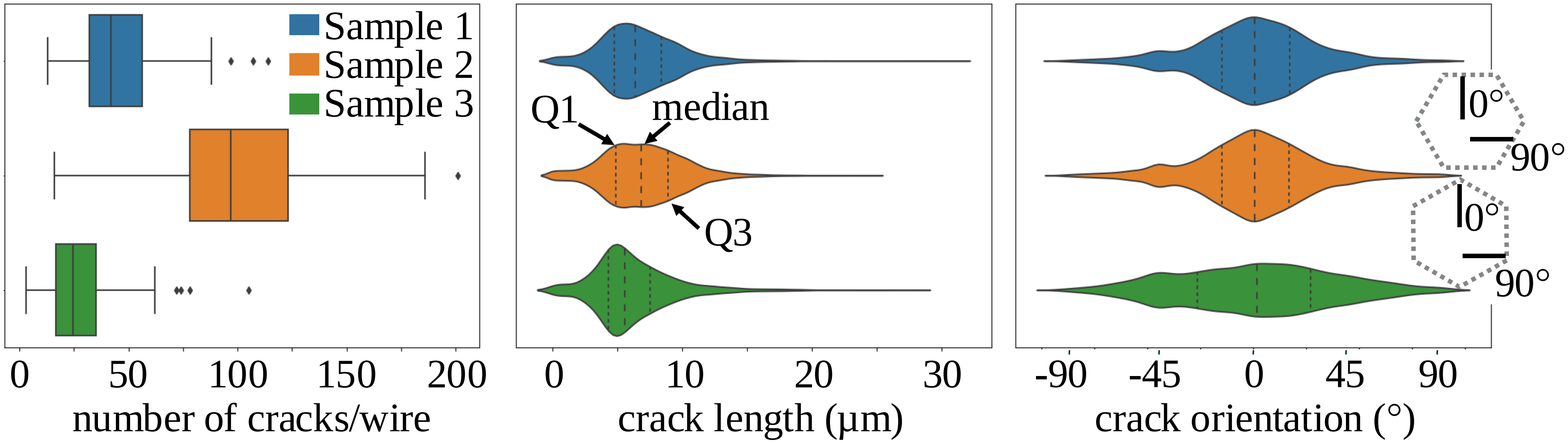
Crack Statistics – Distribution in Stacks

- There are more cracks in the sample pre-loaded along the *z*-axis (as observed last year)
- Some loading and polishing artefacts were found at two corners of the sample pre-loaded along the *x*-axis
- No ~45° shear bands were observed at the stack level, therefore observations around the center of the stack are representative of the bulk properties or the bulk response to different stress-states



Crack Statistics – Crack Count and Morphology

- There are more cracks in the sample pre-loaded along the *z*-axis and less cracks in the one pre-loaded along the *x*-axis.
- The sample pre-loaded along the *x*-axis has (1) slightly shorter cracks and a narrower length distribution and (2) the crack orientation is more spread and not all mostly vertical



Conclusions

1. Background and objectives | 2. Experimental method | 3. ML for image analysis | 4. Crack segmentation and statistics | 5. Conclusions

Conclusions

- We trained the Mask R-CNN model for instance segmentation of cracks in Nb_3Sn and used it on three 4-stacks. This trained model could be used to accelerate the inspection of coil cross-sections cut along the same plane.
- Automated crack instance segmentation and got statistics on the number of cracks, their distribution in wires and in stacks, and on morphological descriptors (crack length and orientation).
- Previous studies always required a human to manually count and locate the cracks (very time consuming) and information about their shape was always qualitative.
- Next step: study more stress-states to better understand the effect of pre-loading on crack length and orientation

Thank you

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Transversal Cracks

- Voids are now lines, so they look similar to cracks.
- More annotated data is required to re-train the model.