# U-Net-based pipeline for high-throughput quantification of crack growth during in situ TEM tensile testing

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## Abstract

Crack propagation in thin films is governed by complex interactions between material properties, loading conditions, and microstructural features. Manual measurement of crack parameters from transmission electron microscopy (TEM) image sequences is time-consuming and prone to inconsistencies [1, 2]. I developed a U-Net-based deep learning pipeline to automatically segment crack regions in TEM videos of thin films with varying interlayer spacings (30nm, 60nm, and 120nm). The model was trained on manually annotated frames and achieved high segmentation accuracy, enabling automated extraction of 13 quantitative parameters per frame including crack tip position, tip radius (bluntness), and crack tip opening displacement (CTOD). This automated approach processed 2,300 frames across three samples, demonstrating the capability to extract diverse fracture mechanics measurements from large image datasets. As a proof-of-concept, analysis of crack tip blunting revealed distinct morphological differences between samples, with 60nm films showing sharper crack tips during the observed growth stages compared to the more blunted tips in 30nm and 120nm films.

## Methodology

I implemented a U-Net convolutional neural network [3] with a ResNet-34 encoder (pretrained on ImageNet) for semantic segmentation of crack regions in grayscale TEM images. Approximately 50 frames per sample were manually annotated using Napari to create binary masks identifying crack pixels. The model was trained using a combined Dice and Binary Cross-Entropy loss function, with data augmentation and an 80/10/10 train/validation/test split. After training, the model performed inference on all 2,300 frames across the three samples. From the segmented binary masks, I extracted quantitative measurements using image processing techniques: the crack tip was identified as the leftmost point of the crack region, tip radius was calculated by fitting a circle to the tip contour using least-squares optimization. The pipeline successfully demonstrates the capability to automatically extract diverse fracture mechanics parameters including crack trajectory, opening profiles, tip morphology, and temporal evolution,measurements that would be prohibitively time-consuming to obtain manually across thousands of frames.

## Results and discussion

The U-Net model achieved robust segmentation performance across all three sample types, successfully tracking cracks through diverse morphologies and imaging conditions. Figure 1 demonstrates the pipeline's capability to detect and segment cracks at different growth stages,

with automated tip detection (marked by red stars) remaining accurate even as crack morphology evolved. The model processed all 2,300 frames without manual intervention, extracting 13 quantitative parameters per frame.

Analysis of the automated measurements revealed interesting material behavior patterns. The 60nm interlayer spacing sample exhibited significantly greater tip blunting (mean radius: 18.3±5.4 nm) compared to both the 30nm sample (4.4±0.8 nm) and the 120nm sample (8.0±3.4 nm), as shown in Figure 2. This observation suggests a potential transition in fracture mechanisms at intermediate length scales, though controlled experiments with equivalent loading conditions would be needed to confirm this hypothesis. The large standard deviation in the 60nm sample indicates dynamic tip behavior during crack propagation.

This work demonstrates that deep learning can enable high-throughput quantitative analysis of fracture mechanics in TEM videos, opening possibilities for systematic studies of crack behavior across parameter spaces that would be impractical with manual analysis
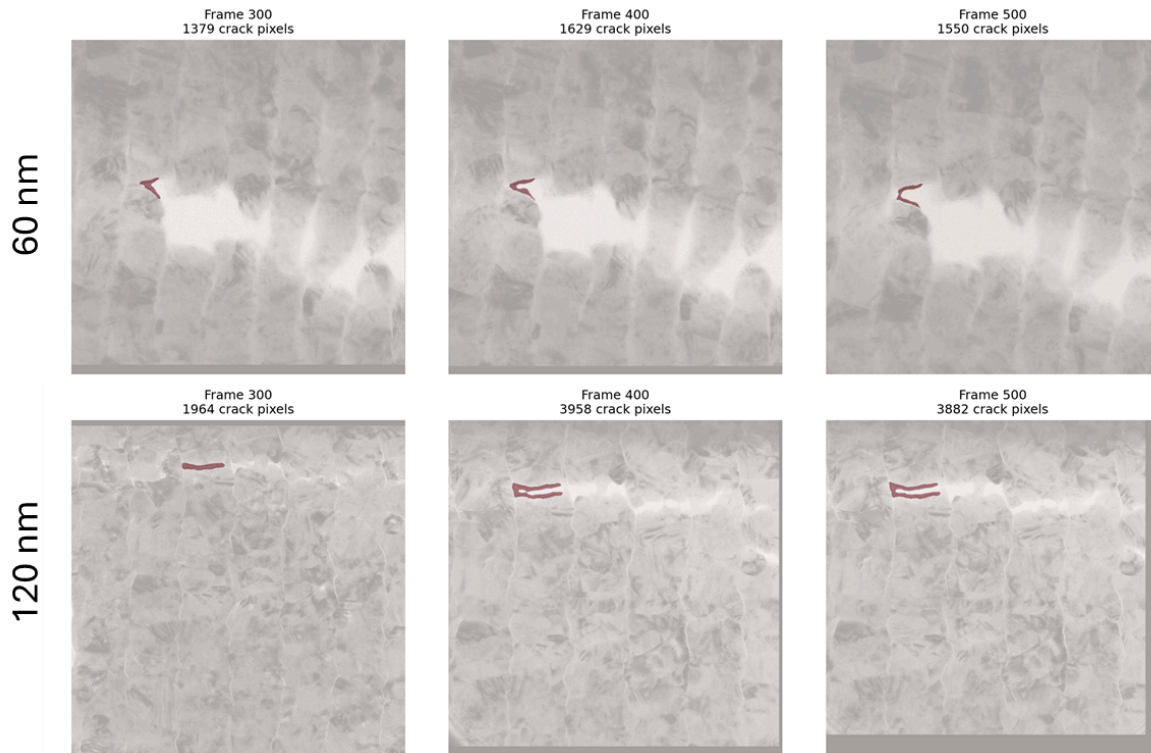


**Fig. 1: Automated crack detection in TEM videos of thin films.** Representative frames from (top row) 60nm and (bottom row) 120nm interlayer spacing samples showing U-Net segmentation results. Red overlays indicate automated crack segmentation; red stars mark detected crack tip positions. The pipeline successfully tracks crack evolution across diverse morphologies and growth stages without manual intervention.
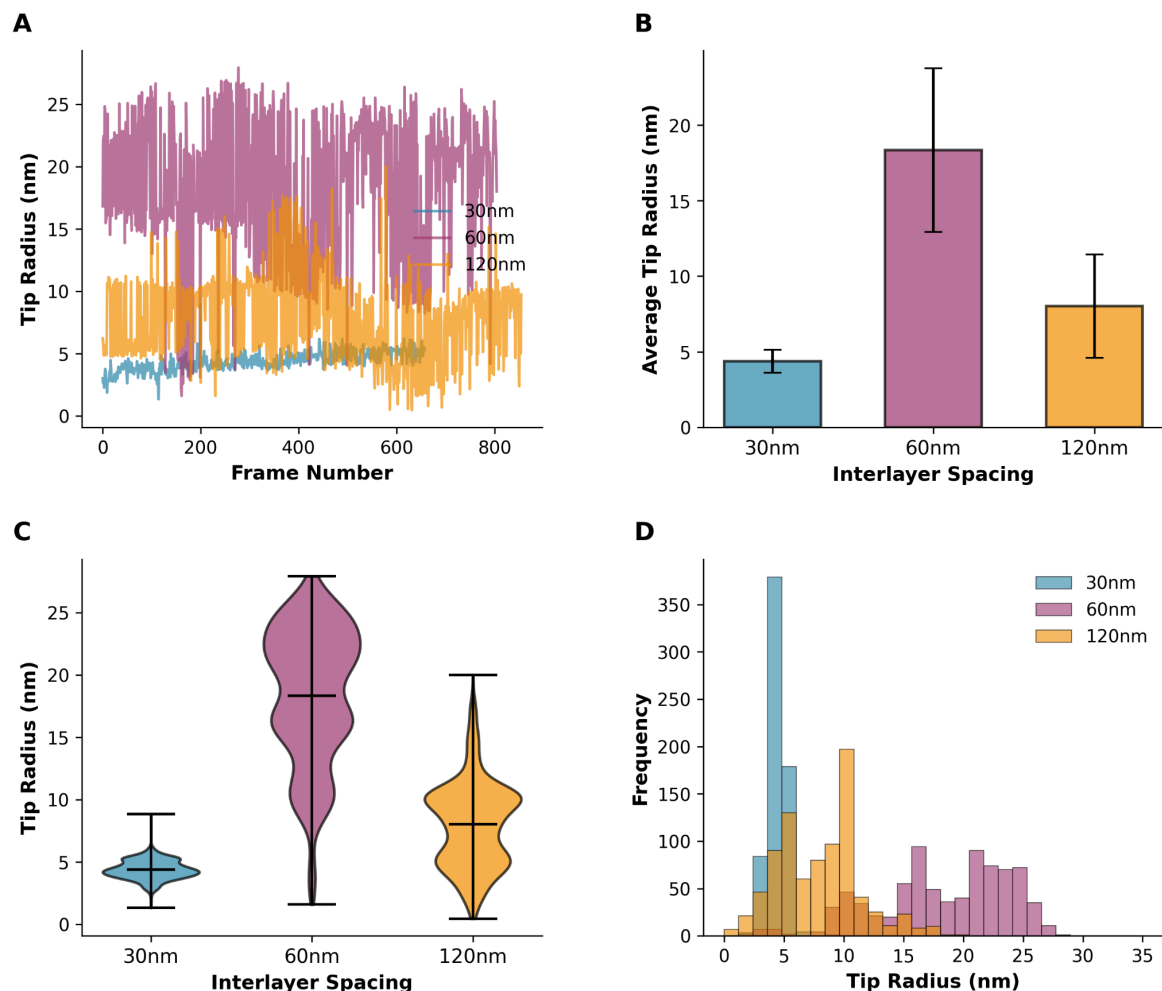
**Figure 2: Automated extraction of crack tip blunting measurements.** (A) Temporal evolution of tip radius for representative frames from each sample showing morphological changes during crack growth. (B) Average tip radius with standard deviation error bars. (C) Distribution of tip radius measurements displayed as violin plots. (D) Overlaid histograms comparing tip radius frequency distributions. Videos were captured at different stages of crack growth and for different durations; comparisons demonstrate the pipeline's capability to extract quantitative fracture mechanics parameters rather than definitive material property differences.

**References**
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