doi:10.1017/S1431927622007929
Microsc. Microanal. 28 (Suppl 1), 2022

Real-time, On-Microscope Automated Quantification of Features in Microcopy Experiments Using Machine Learning and Edge Computing

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Machine learning (ML) techniques, including deep learning-based object detection models, are rapidly becoming common in data intensive microscopy workflows. The rise of ML over human-based, or even "classic" machine vision techniques (*e.g.*, image thresholding, Hough transforms, etc.) is the result of ML techniques being significantly faster, less computationally intensive (on inference), and highly repeatable between various microscopists and research groups [1]. Furthermore, ML techniques are far easier to scale towards large (>16M pixels) image datasets, including time-series data collected via video-based formats. Scalable ML is achieved with ML-based methods becoming more light weight and computationally inexpensive, while commodity computing hardware, such as graphical processing units (GPUs) and tensor cores, are witnessing exponential growth rates in performance. However, adoption of ML-based methods in various microscopy workflows has been restricted to only a few "super-user" groups due to the limited toolsets for performing distributed ML computing and difficulties with sharing software stacks that can be easily downloaded and run by any microscopist.

The lack of adoption has been apparent in our own ML methods development [1–5], which have focused on enabling automated detection and quantification of irradiated microstructures using Scanning/Transmission Electron Microscopy (S/TEM). Recent work has developed well qualified models for the determination of dislocation loops [3,4] and cavities, but these methods have yet to be widely used in real microscopy workflows. Inspection of current citations of these studies reveal their impact heavily revolves around ML technique development and not scientific discovery in irradiated materials. This is occurring even with web-based runnable software stacks based on the Google Collaboration Python environment (Google CoLab) that are being shared at the time of publication. Within our own work, and those of others with similar interests [6–8], the additional realization of performing real-time ML-based quantification for experiments, such as *in-situ* S/TEM mechanical straining, *in-situ* S/TEM irradiation, and *in-situ* S/TEM corrosion, has not been met.

Here, we demonstrate the development of a framework for enabling real-time, on-microscope automated ML-based quantification [9] that enables rapid scientific discovery in static (*e.g.*, single image) or time resolved microscopy workflows. The generalized framework is shown in Fig. 1a, where a GPU-enabled edge-computing device hosts and operates the ML-based quantification algorithm(s). The software stack is fully web-enabled, meaning no software installation and no code editing is needed to begin use of ML in microscopy workflows. The edge device enables the web-application to run fully remote, or effectively in "air-gapped" network environments that are common to most S/TEM instruments. The deployed framework has been demonstrated to be microscope agnostic, with successful deployments on a Thermo Scientific Tecnai G2 F30, Thermo Scientific Titan ChemiSTEM, and a Zeiss Celldiscoverer 7, among others and software compatibility with Thermo Scientific TIA, Thermo Scientific Velox, Gatan GMS, and Protochips AXON microscope control and imaging suites. We will show the power of such on-microscope deployments for ML through case studies using the You Only Look Once (YOLO) real time object detection algorithm, where the YOLO detector has undergone supervised learning for dislocation loops and/or cavities using experimental and/or simulated datasets [5] resulting in various YOLO-based ML configurations. A discussion on the current state of training YOLO models including implementation of synthetic data and recent advances and pitfalls using ML-based quantification will be discussed in parallel.

For the framework in Fig. 1a, we will demonstrate the platform operating in real-time via *in-situ* TEM ion irradiation and *in-situ* post irradiation annealing TEM experiments. Fig 1b-c shows such demonstration, where a dislocation loop splits under continued ion irradiation and the framework captures and quantifies the split in real-time. The samples were imaged under two-beam condition along ⟨200⟩ using a DENS solution Wildfire heating holder operating at 375°C. Primary data was collected using the Protochips AXON in-situ TEM software and the framework in Fig. 1a extracted the data in real-time, streamed video frames to a 384-core NVIDIA Volta^{TM} GPU-enabled edge device, performed real-time object detection using a modified YOLO model from [2], and then back-streamed and overlaid the detections on the AXON software as seen in the reduced areas of interest frame grabs in Fig 1b-c. The Fe-13wt%Cr-7%Al sample was irradiated with 1 MeV Kr^{3+} with a dose rate of 7×10^{-4} dpa/s and was prepared using standard focused ion-beam lift-out procedures for DENS solution Wildfire heating chips. The experiment was performed at the Michigan Ion Beam Laboratory. Additional real-time dynamic events such as nucleation, growth, defect loss, and coalescence will be demonstrated as part of the presentation [10].

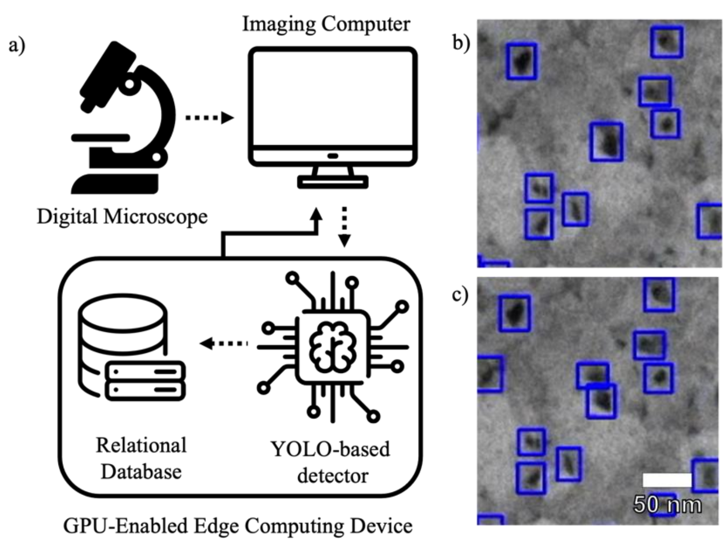

Figure 1. Simplified schematic of the edge-computing architecture that communicates over a closed local area network interface [9] (a) and example showing real time object detection (blue squares) of black dot damage formed under irradiation in an FeCrAl alloy (b) and dynamic defect splitting event and detection (c). Data from (b-c) is from screenshots of the web-based interface that was running in real-time and streaming both captured image frames from Protochips Axon *in-situ* TEM software and corresponding detection data running a modified YOLO model from [2]. Scale bar identical in Figure.

https://doi.org/10.1017/S1431927622007929 Published online by Cambridge University Press

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[10] This material is based upon work supported by the U.S. Department of Energy, Office of Science, Office of Basic Energy Sciences under Award Number DE-SC0021529 and U.S. Department of Energy, Office of Science, Office of Nuclear Energy under Award Number DE-SC0021936. Additional support for K.G.F., D.M. and R.J. was provided by Idaho National Laboratory as part of the Department of Energy (DOE) Office of Nuclear Energy, Nuclear Materials Discovery and Qualification Initiative (NMDQi). The authors would like to thank Dr. Yukinori Yamamoto of Oak Ridge National Laboratory for provision of the bulk sample used to develop microscopy samples for Fig. 1b-c.