# Microscopy Hackathon 2025: EM-Caddie

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Traditional microscopy image analysis relies on fragmented toolchains: researchers must learn specialized software, write custom scripts, and understand ML frameworks to apply state-of-the-art methods reliably. This approach creates a steep learning curve for new users, and analyses must be recreated from scratch for each use-case. EM-Caddie addresses these challenges through a modular, no-coding-required platform. It applies natural language processing through sentence transformers[1] for tool selection, mapping the intent of a user's text input to a curated suite of image manipulations and ML-powered operations. The platform shifts workflows from "knowing the right software" to "stating the objective." This unified *upload→process→analyze→export* workflow allows researchers to stay focused on scientific interpretation, rather than software integration. Every operation can be undone or redone, enabling confident exploration, and data export is streamlined and intuitive. Experienced users can enhance the program by adding new models and features, extending the capabilities of the platform.

## AI-Powered Analysis Tools

*AtomAI*[2] provides a pre-trained segmentation model for atomic-scale microscopy tasks, producing binary masks or atom-probability outputs from complex images. Within EM-Caddie, raw images are converted into structured segmentations suitable for quantitative analysis.

*Grain-UNet*[3] is a grain boundary segmentation tool designed for bright-field TEM images. This tool outputs pixelwise masks that can be post-processed into clean binary boundary maps, supporting rapid microstructure characterization. In combination with preprocessing and export features, it reduces the effort required to move from raw images to consistent, repeatable grain-boundary results.

*Super-Resolution*[4] is a pre-trained neural network in PyTorch used to upscale images while preserving or reconstructing high-frequency detail. It is typically applied early in the workflow, and reduces pixelation and improves interpretability of fine structures, particularly when acquisition constraints limit native resolution.

## Classical Analysis and Utilities

*Fast Fourier Transform (FFT)* converts images from real space to frequency domain, using NumPy, revealing periodicities and crystallographic signatures. This enables rapid assessment of lattice spacing, texture, and dominant spatial frequencies critical for materials characterization.

*Line Profile Extraction* samples pixel intensities along user-defined lines or shapes to quantify contrast changes across features. Users can rapidly draw and place multiple lines, with in-app plotting and CSV export of intensity profiles.

Other classical transformations include interactive cropping, Gaussian blur, edge detection, and color inversion. These conventional image processing steps–built using OpenCV[5]–support visualization and stabilize downstream analysis. Scale bar addition is simplified with pixel-to-image size calculations and streamlined options for size, color, and location.

## Future Development

Near-term improvements include enhancing intent-to-tool routing through LLM API integration and developing a custom GPT chatbot, fine-tuned on modern microscopy techniques. Expanding the pretrained model library to include denoising, defect characterization, and additional grain analysis methods would allow users to select approaches better matched to their imaging modality and scientific question. Stabilizing and standardizing tool interfaces, particularly for measurement and line-based analyses, would improve reliability as the platform scales. Quality-of-life enhancements such as automatic scale bar detection, memory-aware handling of large images, and clearer feedback for ambiguous or resource-intensive operations align with short-term roadmap goals. These incremental additions focus on strengthening EM-Caddie as a practical, extensible analysis environment while preserving its core objective: lowering the barrier between microscopy data and meaningful, researcher-driven insight.

## References

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*Additionally using code obtained from* https://github.com/xinhuolin/TEMUpSamplerNet and https://github.com/MatthewJPatrick/grain_unet