

# Deep Learning-Based Segmentation of AFM Data for Epitaxial Graphene Analysis and SiC Terrace Identification

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## INTRODUCTION

Atomic Force Microscopy (AFM) provides nanoscale information about surface structure and material properties. In epitaxial graphene grown on silicon carbide (SiC), surface regions differ based on:

- underlying SiC terraces (S2, S3)
- number of graphene layers (e.g., single-layer, bilayer)

Manual analysis of AFM images is: time-consuming, subjective, difficult to scale.

Goal: automate segmentation of AFM images into physically meaningful regions.

## DATASET

Each AFM image contains information:

- Topography → surface height → identifies terraces
- Friction → mechanical response → indicates graphene layers
- Ground Truth Preparation: Converts colors to cluster IDs and then convert to boundary map.

Challenge:

- Overlapping signals between regions
- Limited annotated real data
- Difficult distinction (e.g., bilayer graphene on S2 vs S3)

## DATASET PROPERTIES

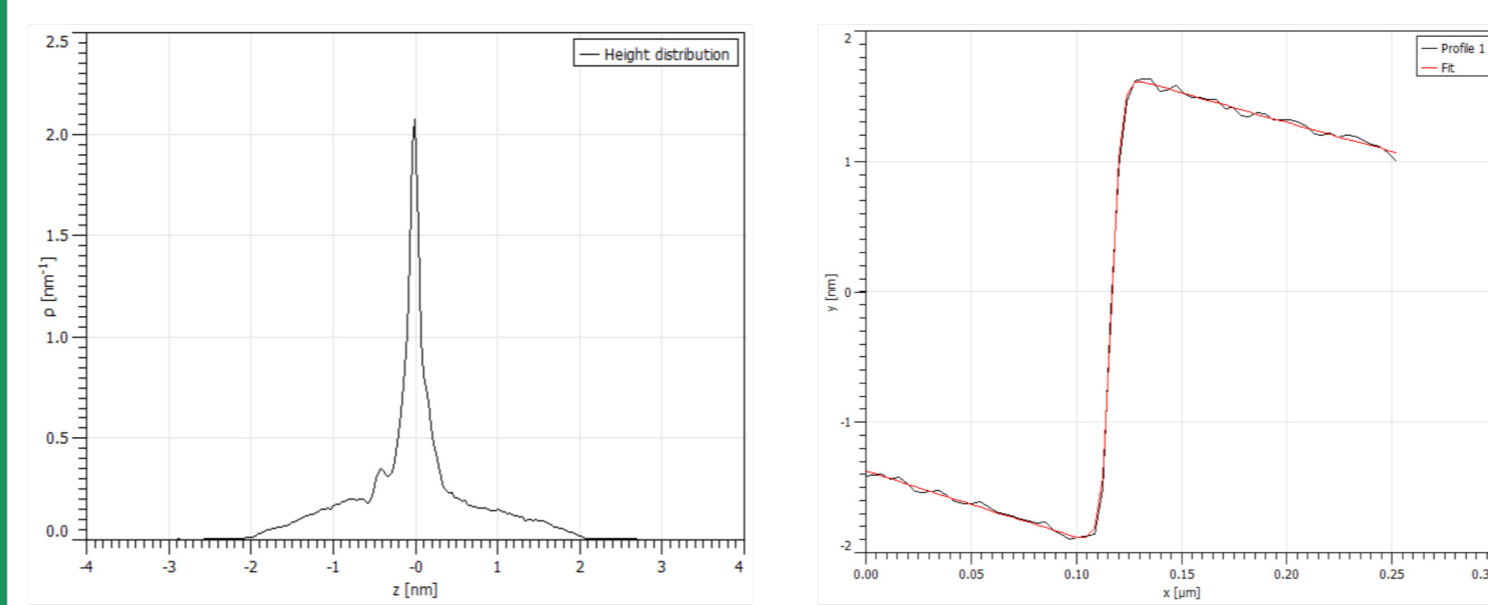


Figure: Height distribution

Figure: Fitting function to detect height differences between terraces.

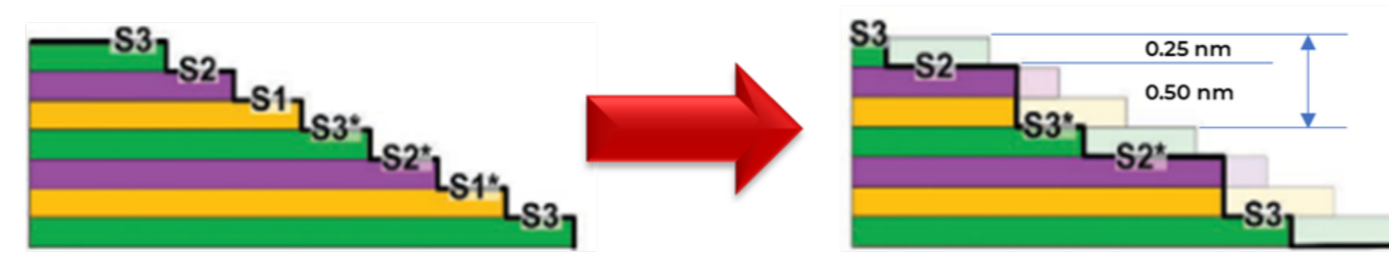


Figure: Termination of SiC surface before epitaxial graphene growth (left) and after epitaxial graphene growth (right).

## WORKFLOW

We propose a pipeline combining synthetic data generation + machine learning. Pipeline:

- Generate synthetic AFM data (Blender)
- Train segmentation model
- Apply model to real AFM images
- Compare and evaluate performance

## SYNTHETIC DATA

To overcome lack of labeled data:

Surfaces are simulated using Blender

Controlled variations: terrace structures (step-like geometry), graphene layer distributions, noise and imaging artifacts.

Advantages:

- fully labeled data
- scalable dataset generation
- controlled experiments

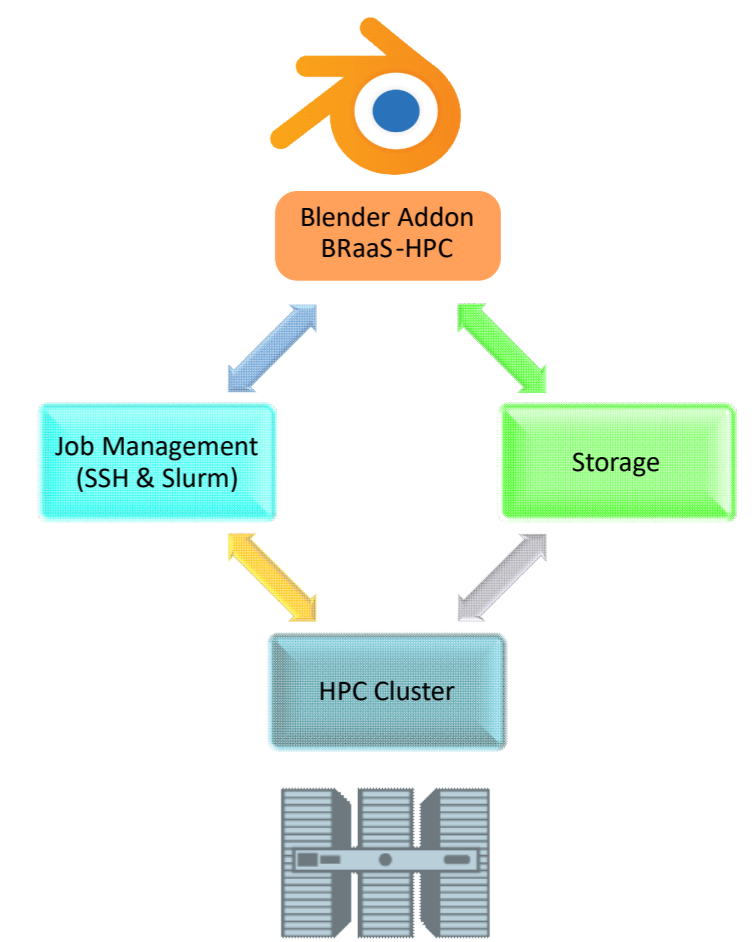


Figure: Distributed rendering using Blender addon and HPC

## OVERVIEW OF THE PIPELINE

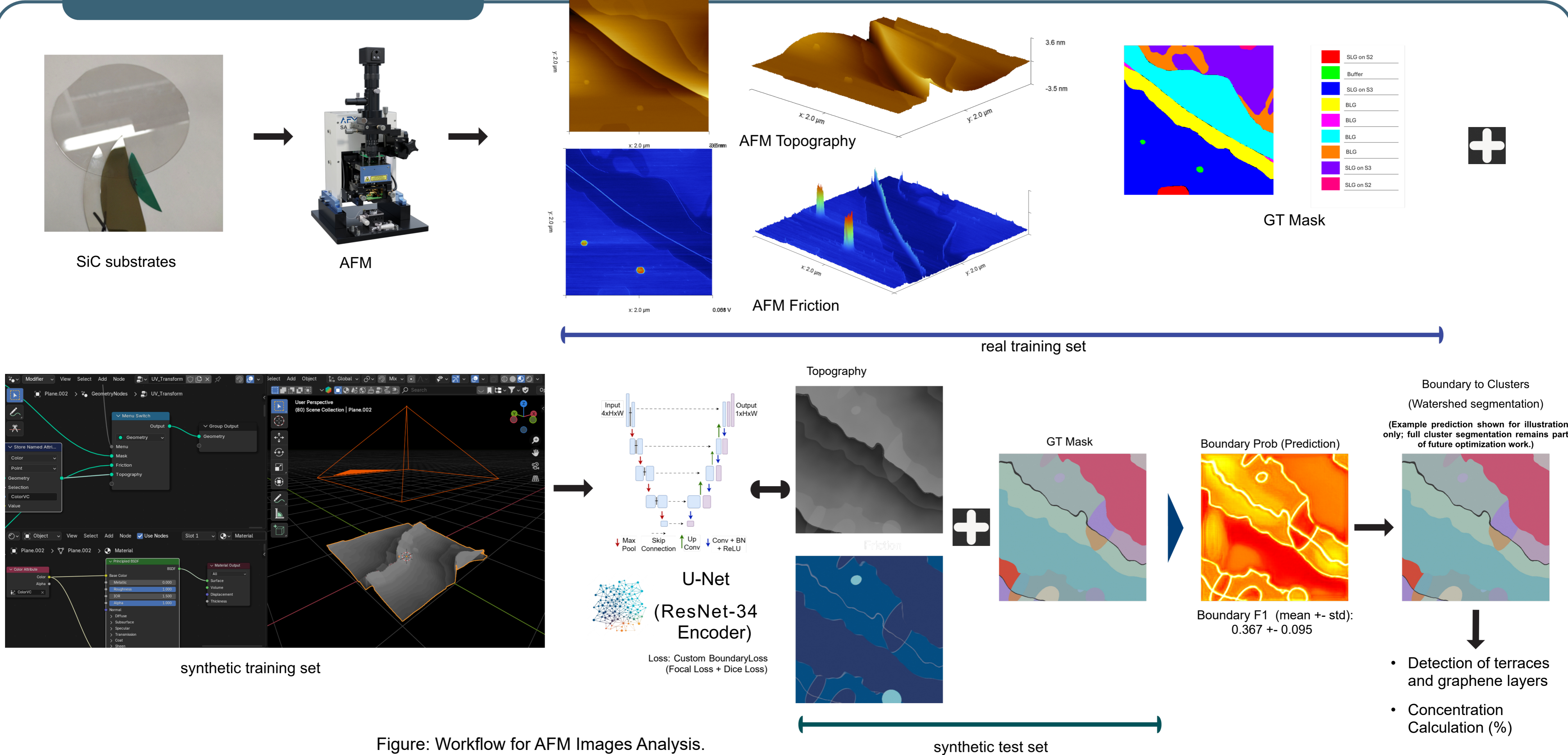


Figure: Workflow for AFM Images Analysis.

## CONCLUSION

- Boundary-aware learning framework for variable cluster counts. Uses those boundaries to reconstruct full clusters using watershed segmentation.
- Full region segmentation still requires further optimization (increased model capacity, expanded dataset, multimodal learning, improved architectures. Instance-level cluster separation will be explored).
- Impact: This work establishes a foundation for AI-driven nanomaterial analysis, enabling high-throughput screening.

## REFERENCES

- Blender Software: <https://www.blender.org/>, <https://docs.blender.org/manual/en/latest/index.html>
- Kocur, V., Hegrová, V., Patočka, M., Neuman, J., & Herout, A. (2023). Correction of AFM data artifacts using a convolutional neural network trained with synthetically generated data. *Ultramicroscopy*, 246. <https://doi.org/10.1016/j.ultramic.2022.113666>

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