AI-Enabled Cathode Crack Analysis

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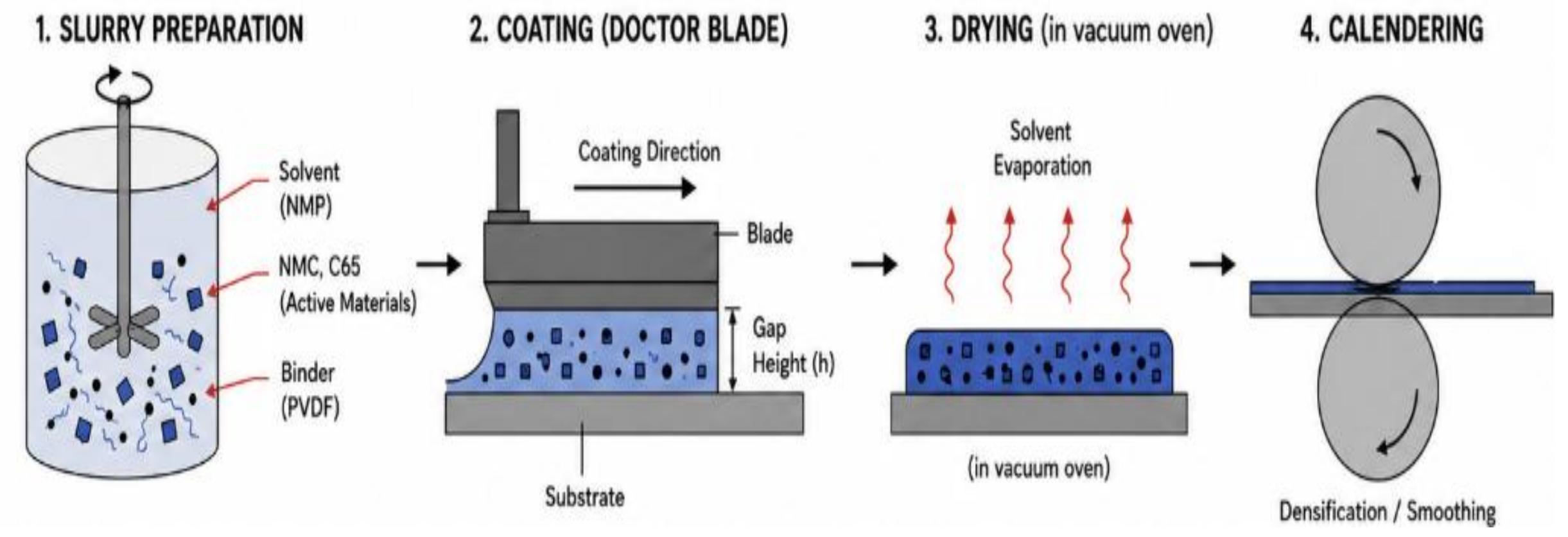
Goal: Develop an AI-enabled framework for automated cathode crack detection and quantification from SEM images

- **Scanning Electron Microscopy (SEM): imaging technique that scans the surface with focused stream of electrons**

BACKGROUND

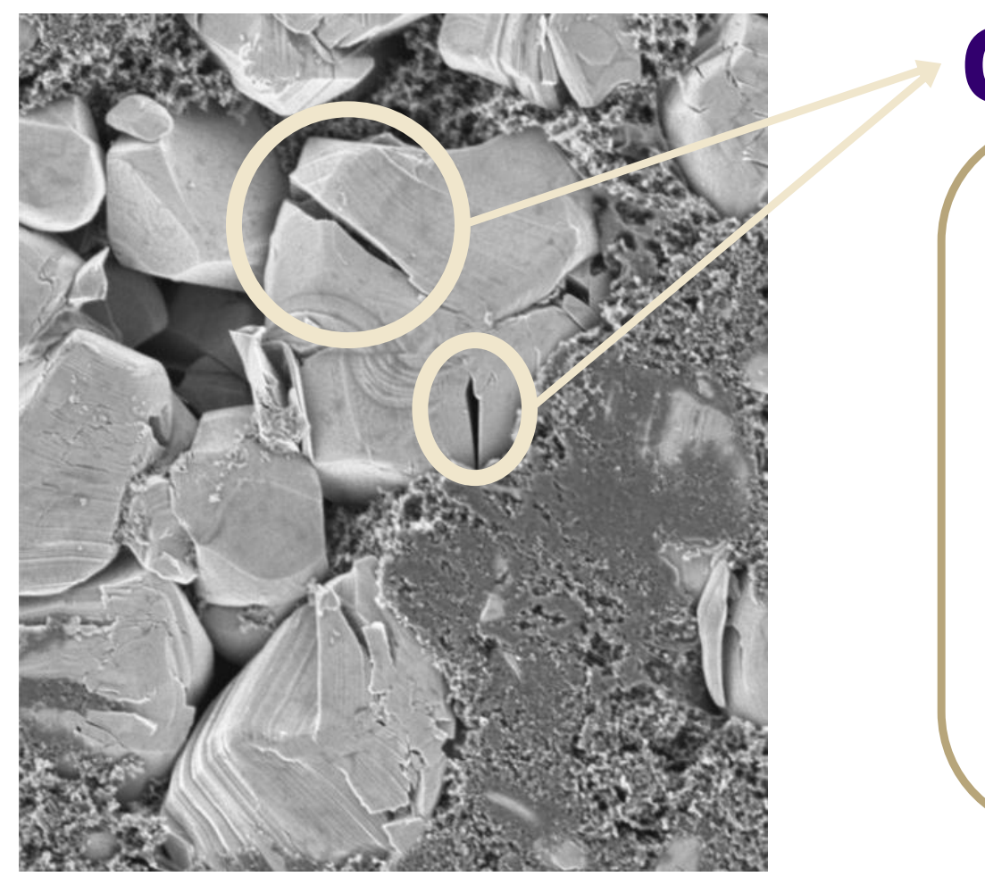


During cathode manufacturing, **cracks** can form due to several factors, including calendaring pressure, inside the vacuum oven, etc. Crack formation can **negatively impact battery performance** by exposing fresh cathode surfaces to the electrolyte, accelerating unwanted side reactions and capacity fade.

Terms

Lithium **N**ickel **M**anganese **C**obalt Oxide (NMC): cathode active material
N-**M**ethyl-2-**P**yrrolidone (NMP): solvent used to disperse active materials uniformly
C65: Conductive carbon that improves internal electrical conductivity
Poly**v**inyli**d**ene **F**luoride (PVDF): binder that holds electrode together

WHY Crack Quantification?



(Single-Crystal NMC) SEM by Shineui Hwang[1,5]

Crack!

Definition: A crack is a **connected fracture** or **separation** within **a single cathode particle**

- Includes: line or branched feature that represent **internal** (Cross-Sectional SEM only) or **surface break** in particle structure
- Excludes: boundaries, glides

- **Comparison** across samples (e.g. calendaring pressure, NMC compositions)
- **Identification of root causes** of degradation by correlating crack with performance loss

SAM3: WHY THIS MODEL

SAM3 is a prompt-based segmentation model that generates masks directly from user prompts. It is useful for small, irregular crack regions where bounding boxes are too coarse. The promotability also allows it to be applied to new data with no adaptation.

What it does
Generates segmentation masks from prompts

Useful in
Creates initial particle and crack masks for SEM images

Why selected
Strong baseline performance with LoRA adaptation for cathode-specific defects.

Workflow:
SAM3 particle segmentation → Human correction → LoRA model refinement

LoRA: QUICK EXPLAINER

Low-Rank Adaptation (LoRA) trains a small set of adapter weights inside SAM3 instead of updating the full model.

- Keeps SAM3's general segmentation knowledge
- Learns cathode-specific crack features from a small labeled dataset
- Enables faster training, comparing, and swaping across image sources
- Reduces labeling effort by converting corrected SAM3 masks into reusable training data

Takeaway:
LoRA bridges AI-assisted labeling and a domain-specific crack segmentation model

LABELED DATA WORKFLOW

Use initial trained models to generate improved candidates and expedite labeling

AI-assisted labeling loop

1. SEM tiles
Batch images are prepared without microscope infobars.

2. SAM3 proposals
Prompted masks initialize crack/particle labels.

3. Label Studio
Editable brush masks are refined by human annotator.

4. Mask export
RLE annotations are decoded to binary PNG masks.

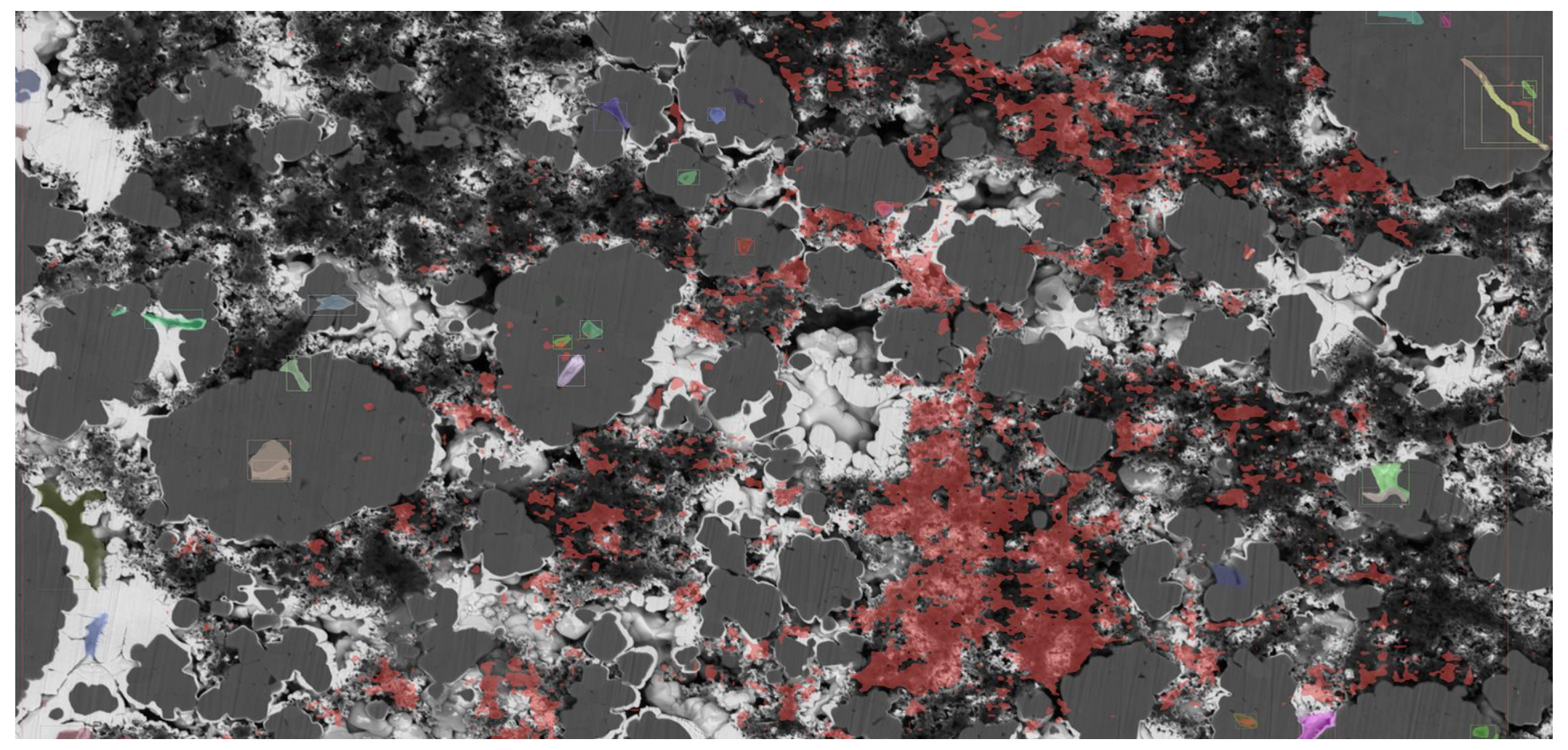
5. Train/Test Data Split
Train/holdout split specs prevent leakage.

6. LoRA training
Adapter-only SAM3 weights learn crack prompt output.

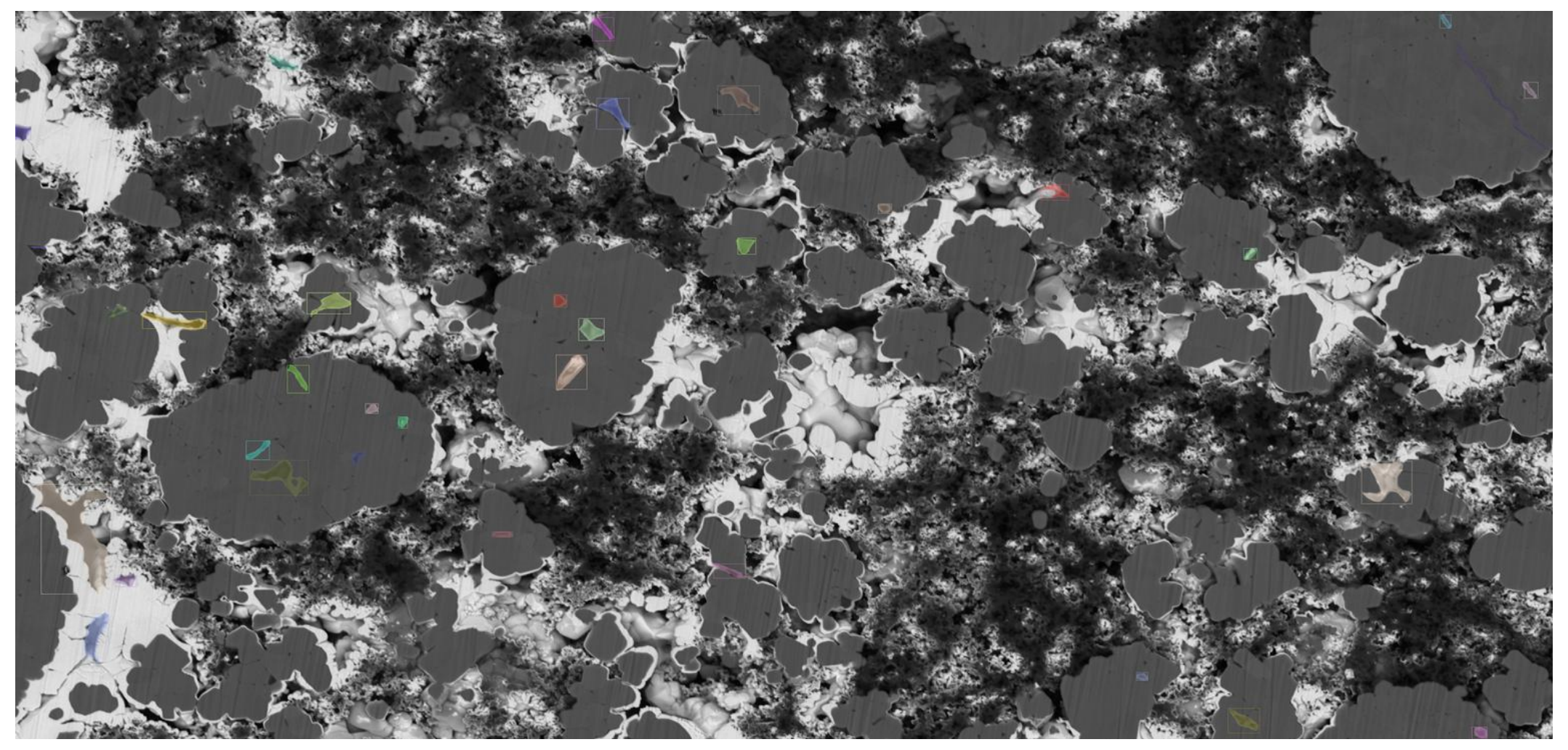
7. Evaluation and upload
Run full-image and particle-cutout inference; use new adapter for production Label Studio imports.

FINAL MODEL PIPELINE

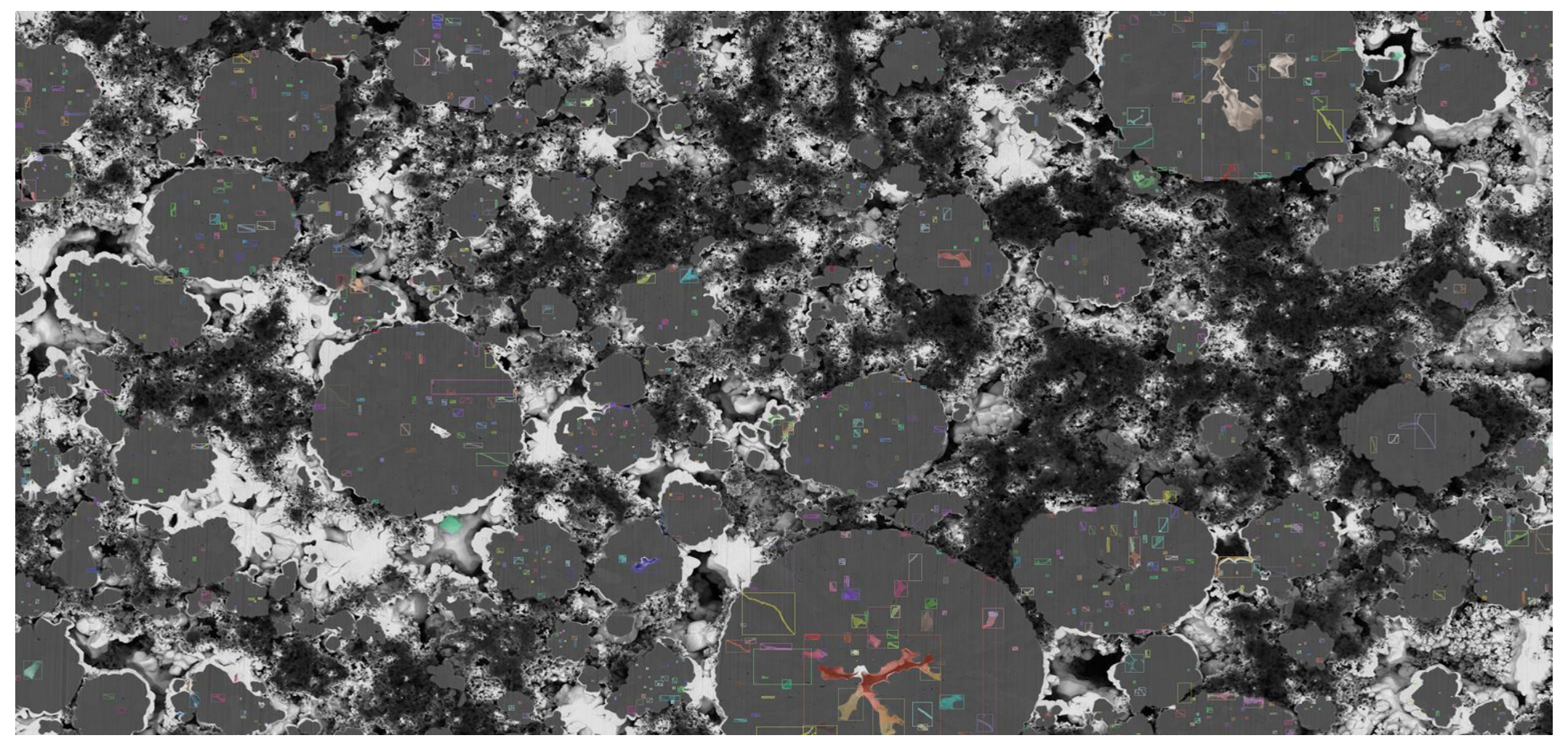
Production inference uses a two-stage prompt strategy. Base SAM3 first identifies cathode particles; each particle is cropped or masked, then the LoRA crack adapter predicts defects inside the bounded region.



(Polycrystalline NMC) SEM image from Thermo Fisher Scientific[4]
Base SAM3 full-image crack prompt: high false-positive area



LoRA full-image prompt: reduced over-segmentation



Final Model 4 on holdout task 16: NMC_Cathode__HFW_100um_M90_C10_Run3_098

Run settings: particle prompt='particle', particle threshold=0.005, crack prompt='crack', crack threshold=0.35, max particle fraction=0.30, min crop=384.

CRACK QUANTIFICATION

The workflow detects bounded-crack regions, maps them to segmented particles, and quantifies crack area, length, and severity for each particle.

Results:

- 1098 particles analyzed, 491 cracked particles,
  Mean Crack Fraction = 20.13%
- 29,154 crack pixels, 7,001 crack-length pixels,
  841 total crack detected, and 1.34% image crack coverage
  (Image pixels: 1802 x 1206)

RESULTS / FINDINGS

Final model runs on held-out images
Task 16 was not included in training data

Run	IoU	Dice	Prec.	Recall
Base Full Image	0.026	0.050	0.028	0.266
Prior particle LoRA, task 12	0.403	0.575	0.441	0.825
Final Model 4, task 16	**0.519**	**0.683**	**0.723**	**0.647**

New final run improves IoU, Dice, and precision on a separate held-out TFS cross-section image.

0.683	0.723	0.519
Dice on task 16	precision	IoU

Error counts from final run

246,063	94,201	134,081	340,264	380,144
TP	FP	FN	Pred area	GT area

Interpretation: the final adapter is less recall-heavy than the earlier task-12 run, but produces cleaner masks with higher precision and a higher Dice score.
Model 4 adapter: trained on four TFS cross-sectional SEM images; evaluated here on held-out task 16.

CONCLUSION

- LoRA improved SAM3 crack detection while keeping training lightweight.
- Final Model 4 reached Dice 0.683, IoU 0.519, and precision 0.723 on held-out task 16.
- Particle cutouts remain important because cracks are small relative to the full SEM tile.
- Data available was extremely limited; additional data would have improved preliminary results; approach validated

FUTURE PLANS

1. Train on pre-processed images & feature maps revealing localized planar gliding and nearby cracks
2. Label 50+ additional SEM images and compare full fine-tuning v. LoRA
3. Test model performance on cross-sectional SEM images

→ Quantify the effect of **calendaring pressure** on crack formation

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REFERENCE

Nanoscience Instruments. (n.d.). Scanning electron microscopy (SEM).
Lee et al., “Cracking vs. surface reactivity in high-nickel cathodes for lithium-ion batteries”, 2023
Bi et al., “Reversible planar gliding and microcracking in a single-crystalline Ni-rich cathode”, 2020