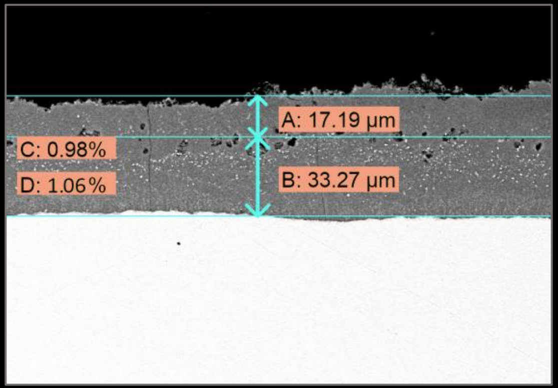
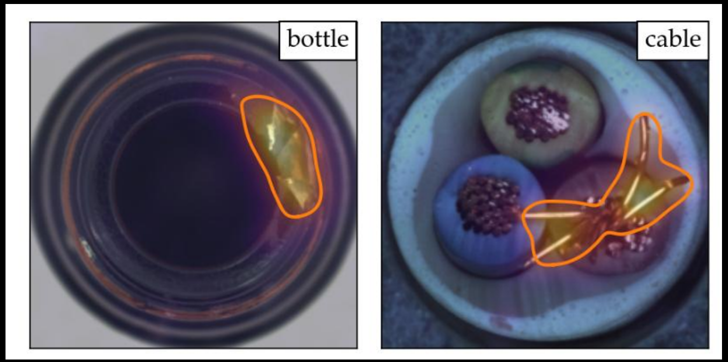
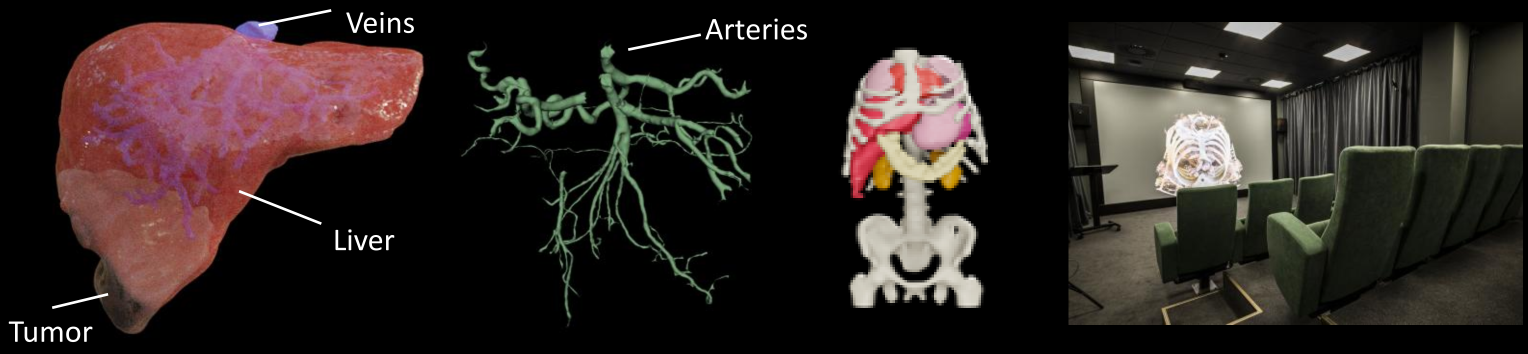


SEM Image Analysis



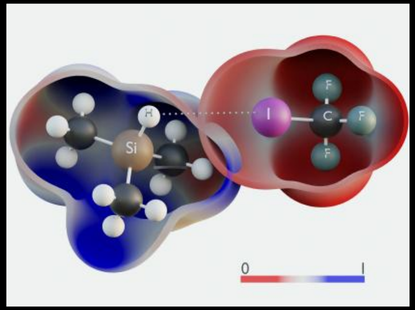
Anamoly detection. Reference Image: https://doi.org/10.48550/arXiv.2106.08265



Medical Imaging


Generating data from a virtual environment and object detection


Volumetric rendering of evolving cell nuclei


Scientific vizualizations of Hydrogen Bonding

DEEP LEARNING APPROACHES FOR SCANNING ELECTRON MICROSCOPE IMAGE ANALYSIS OF SLURRY COATINGS

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INFRA Lab

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IT4INNOVATIONS NATIONAL SUPERCOMPUTING CENTER

Motivation and Context

Deep Learning Approaches for Scanning Electron Microscope Image Analysis of Slurry Coatings

NOVEL APPROACH TO CORROSION PROTECTION IN HIGH-TEMPERATURE ENVIRONMENTS

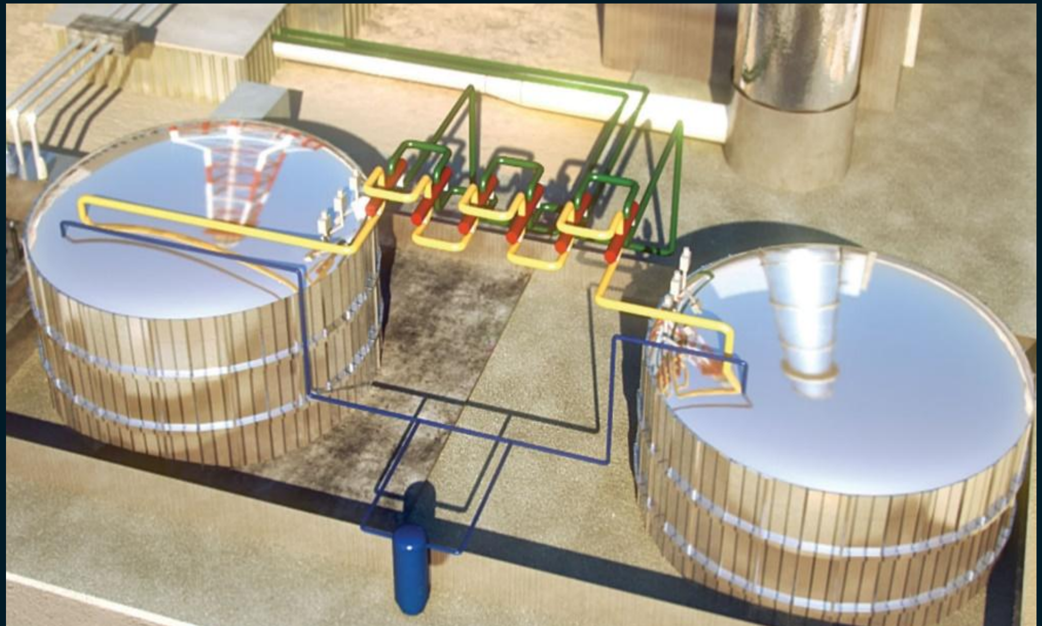

(http://www.bine.info/en/publications/publikation/solarthermische-kraftwerke-2/parabolrinnen-kollektortechnik)

Figure: Possible application in CSP plants.

WHAT ARE SLURRIES?

- Aluminide diffusion coatings, formed by depositing aluminum slurry on steel followed by heat treatment, create protective Fe_2Al_5 and FeAl layers.

Technological areas

- Combustion of alternative fuels, such as hydrogen and ammonia.
- Steam turbines in renewable energies.
- Molten salts in Concenrated Solar Power and High Temperature Thermal storage.

Advantages

- Low cost.
- Environmentally friendly.
- Non-hazardous (REACH).
- Slurry deposition by spraying or brushing.
- Drying and heat treatment in air.

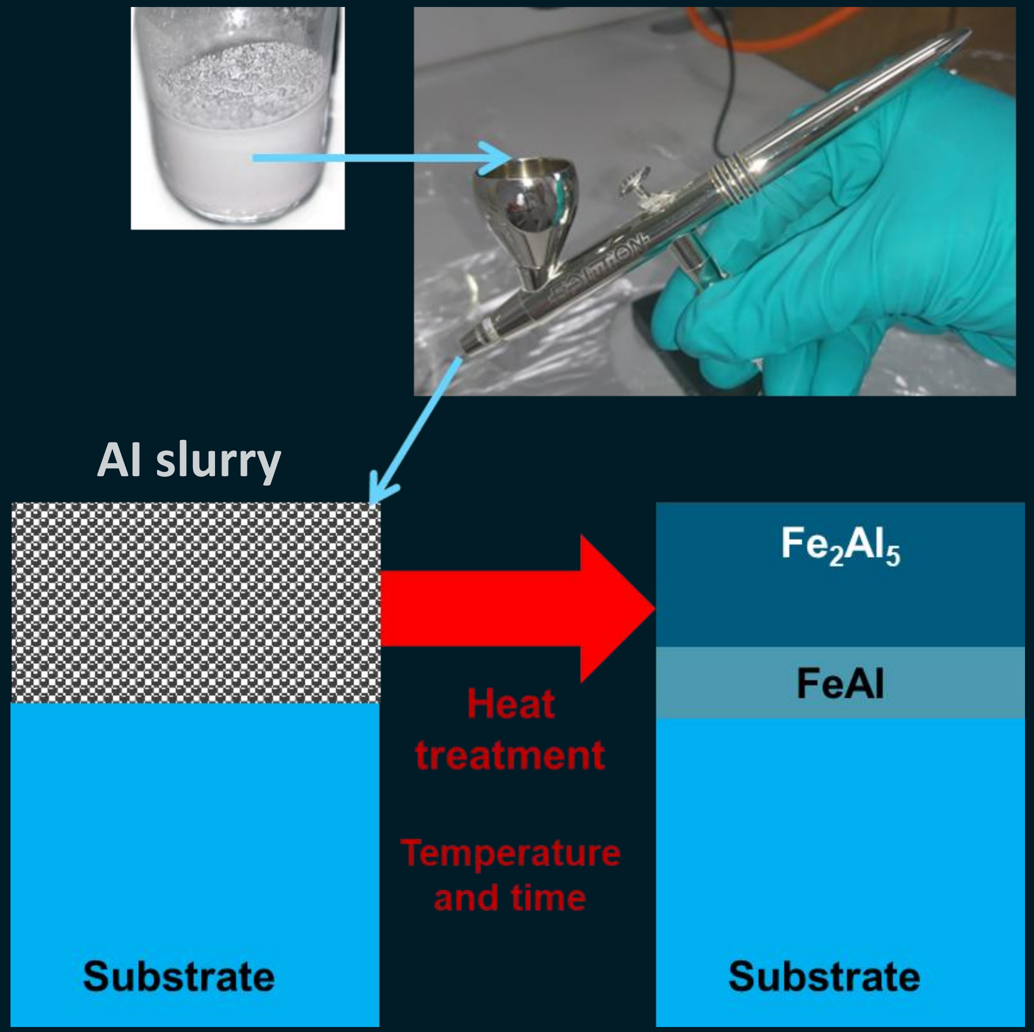
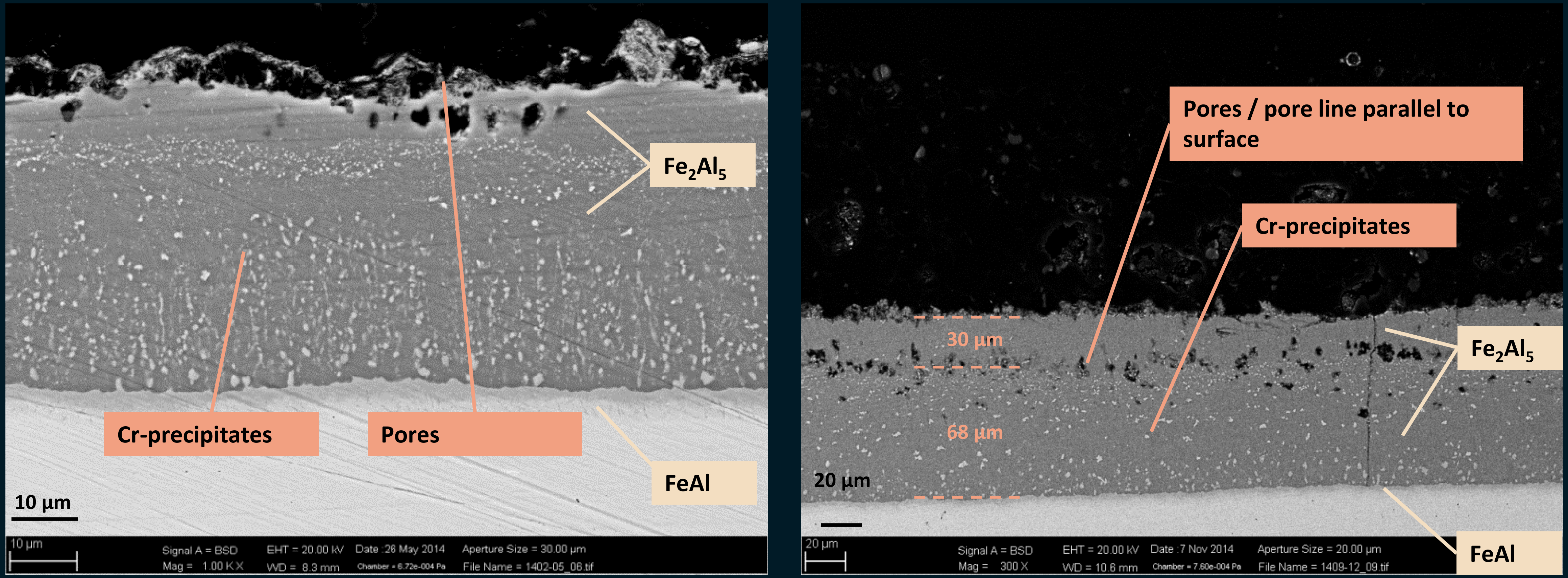


Figure: Slurry-based aluminide diffusion coating.

ALUMINIDE DIFFUSION COATING



Heat treatment: 5h at 650°C in air, Al particle size 32 µm

Heat treatment: 20h at 650°C in air, Al particle size 32 µm

Figure: Features of interest.

Coating layers

- Fe_2Al_5 layer: **Thickness**
- FeAl layer: **yes/no, thickness**

Pores

- Pores in the Fe_2Al_5 layer: **Concentration in %**
- Pore line parallel to surface: **yes/no, distance to surface**

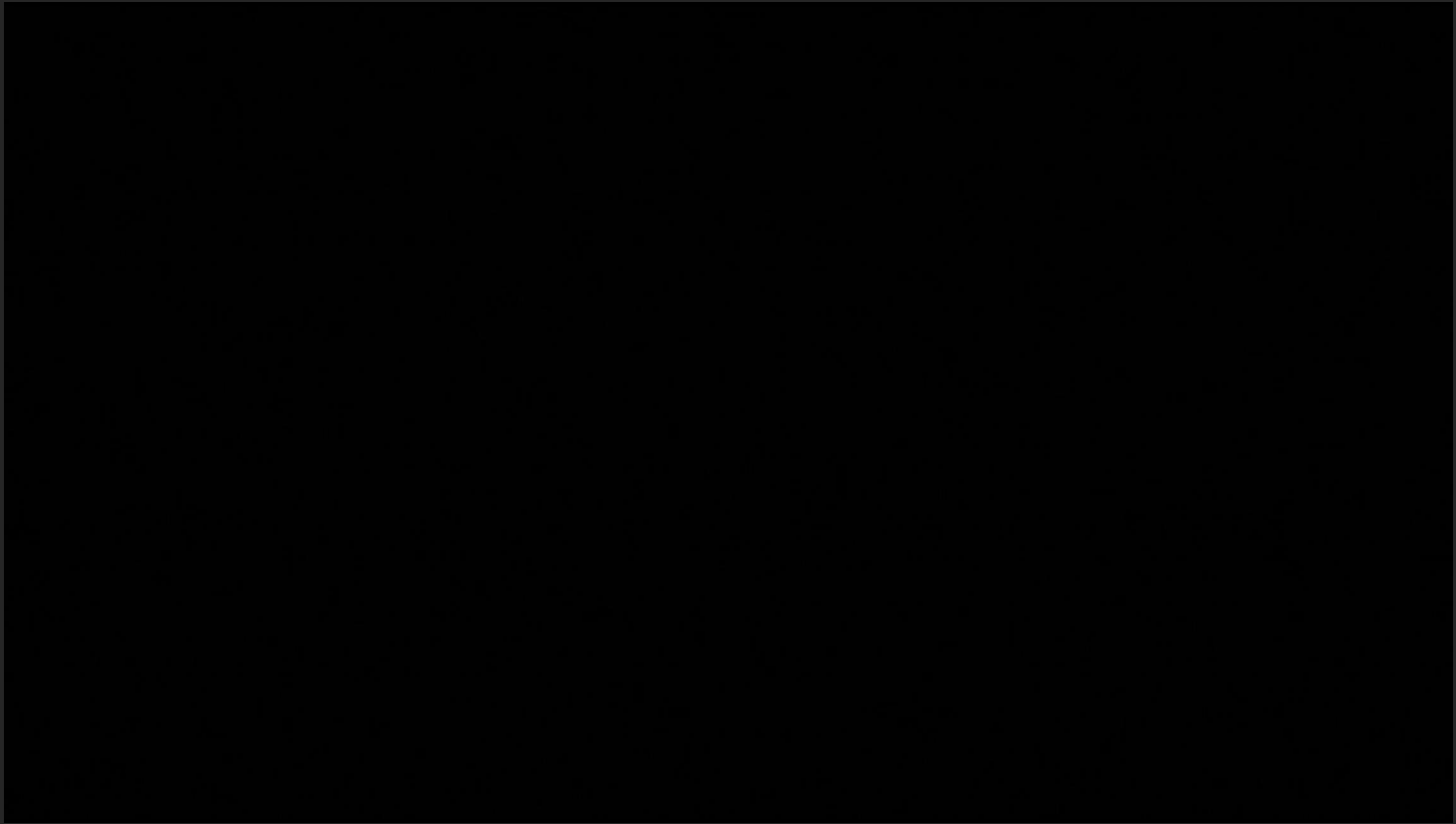
Cr-precipitates

- **Concentration in %**

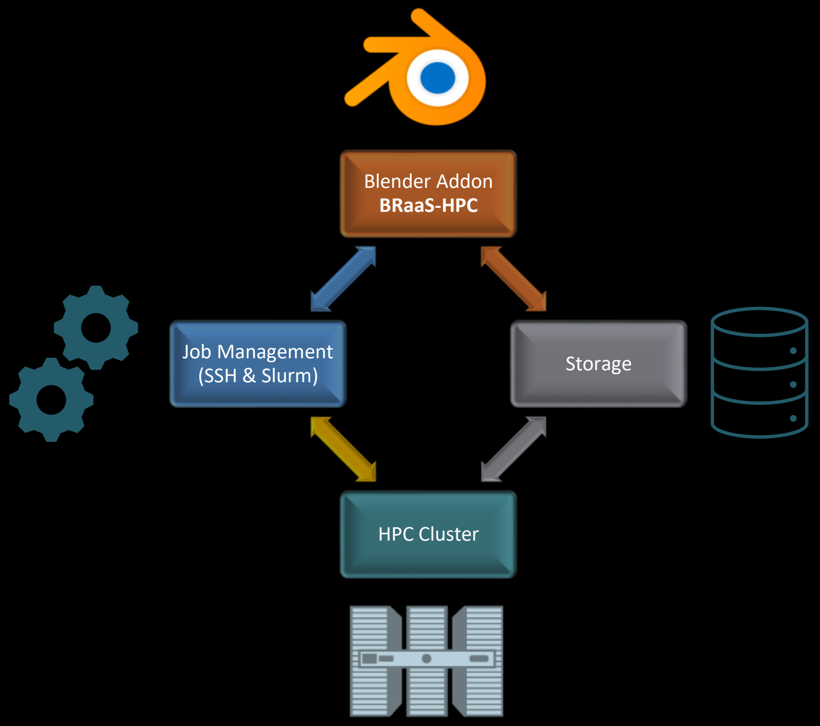
Data Challenges

- Fraunhofer provided: ~200 images (100 for training, 100 for testing).
- Overlapping features of interests.
- Manual analysis of microscopic images is slow and subjective.
- Manual labeling = very time-consuming
- The feature of interests are small and noisy.
- Supervised learning requires labeled data.

SYNTHETIC DATA GENERATION FOR SEM IMAGES (Blender)



RENDERING-AS-A-SERVICE ON HPC CLUSTER



- Distributed rendering using Blender addon and HPC cluster.

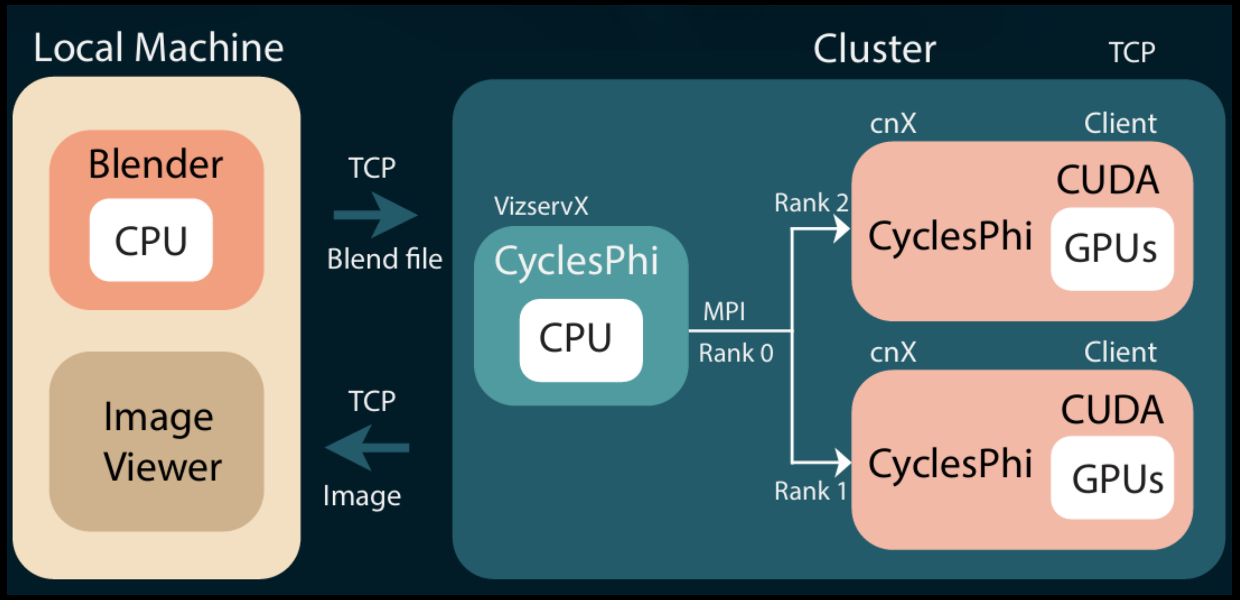


Figure: Distributed rendering using Blender and HPC cluster.

Resource Type	Execution Time per Task	Total time (array Size = 100)	Efficiency
Local CPU (i7-13650HX)	~20 seconds	1980 seconds	Sequential
Cluster CPU	~12 seconds	65 seconds	Parallel
Cluster GPU	~7 seconds	45 seconds	Parallel

[1] **BRaaS-HPC: · GitHub;** Jaros, Strakos. https://github.com/It4innovations/braas-hpc

DATA PREPROCESSING

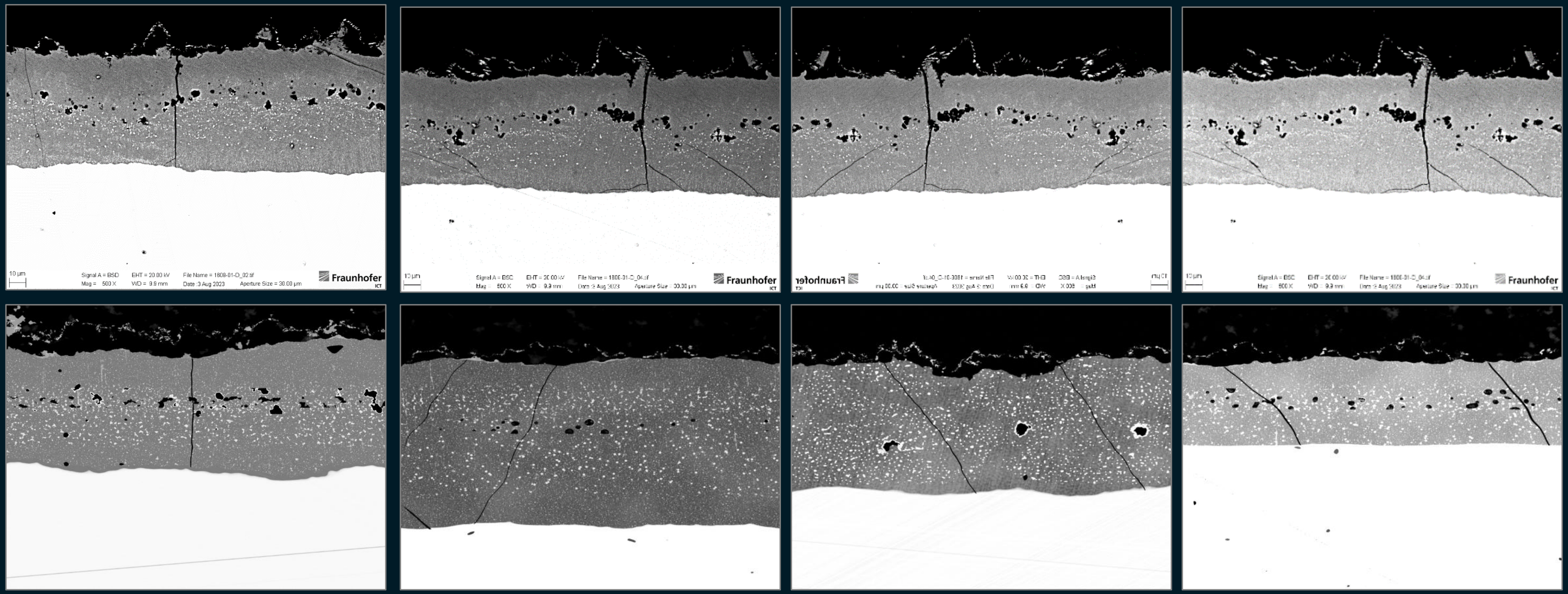


Figure: Example of data augmentation. The **first row** contains example of data augmentation of **real** SEM images, while **second row** shows examples of augmented **synthetic** SEM images.

METHODOLOGY

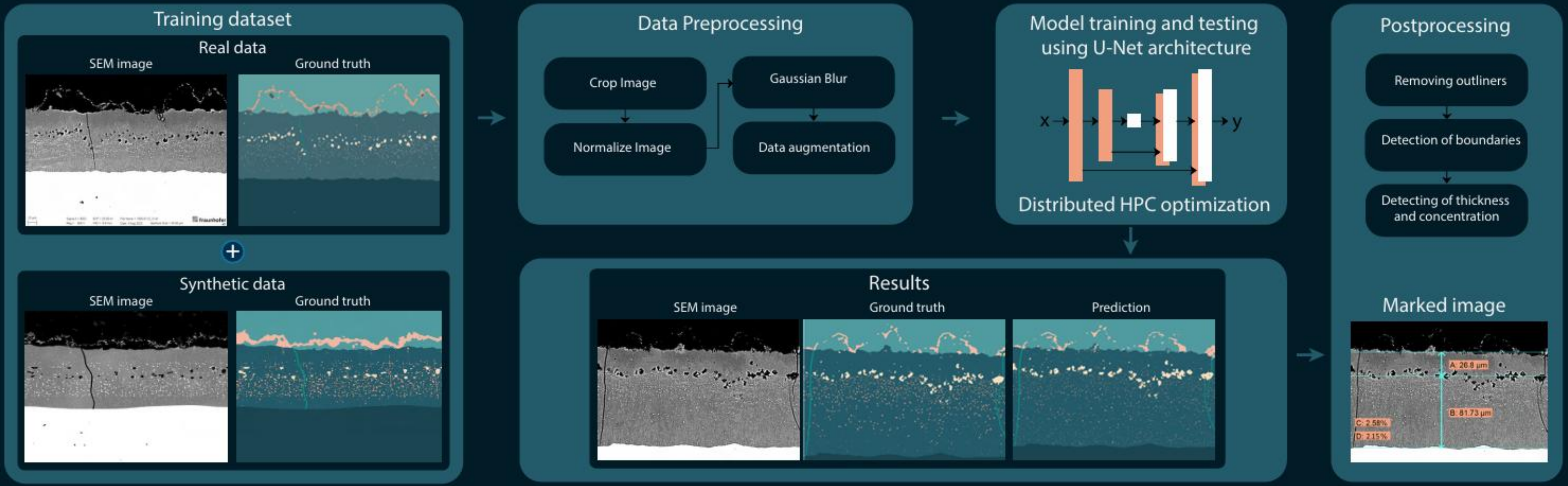
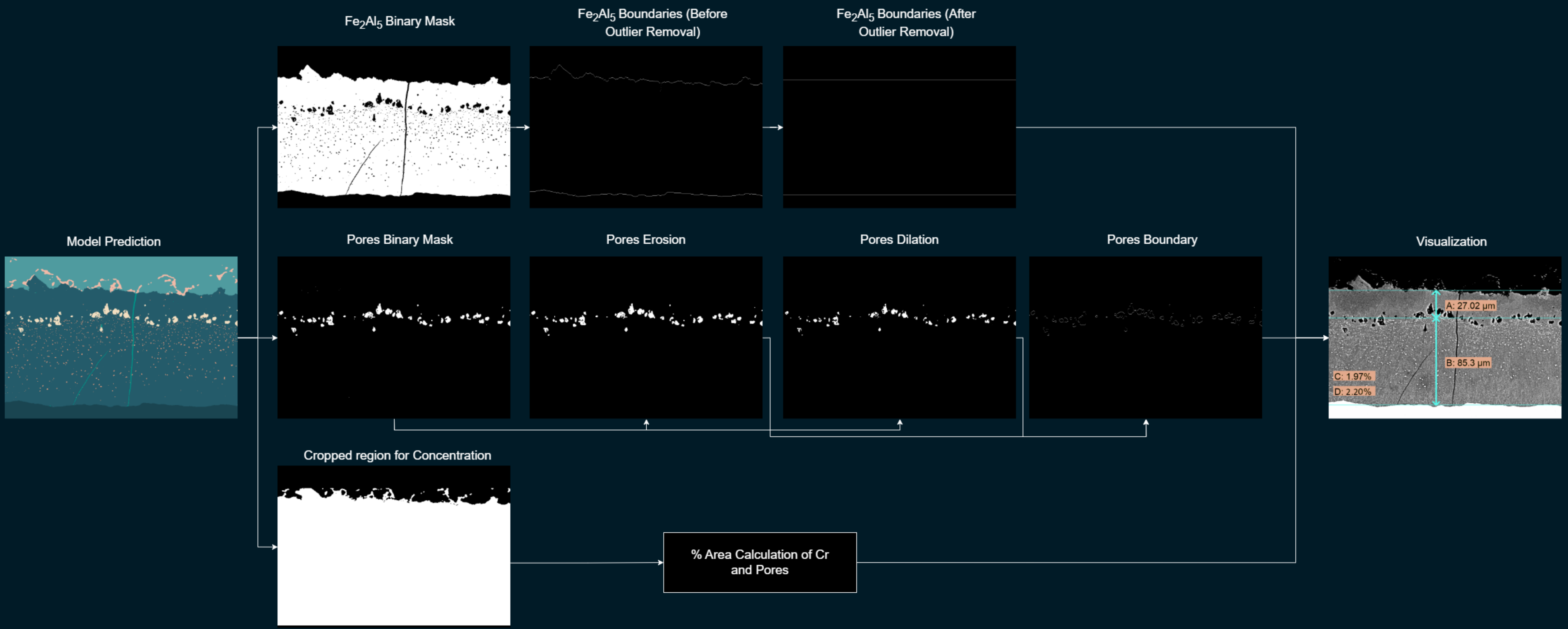


Figure: Workflow for SEM Image Analysis Using U-Net and Distributed HPC Optimization (using DistributedDataParallel).

POSTPROCESSING TO MEASURE FEATURES



RESULTS

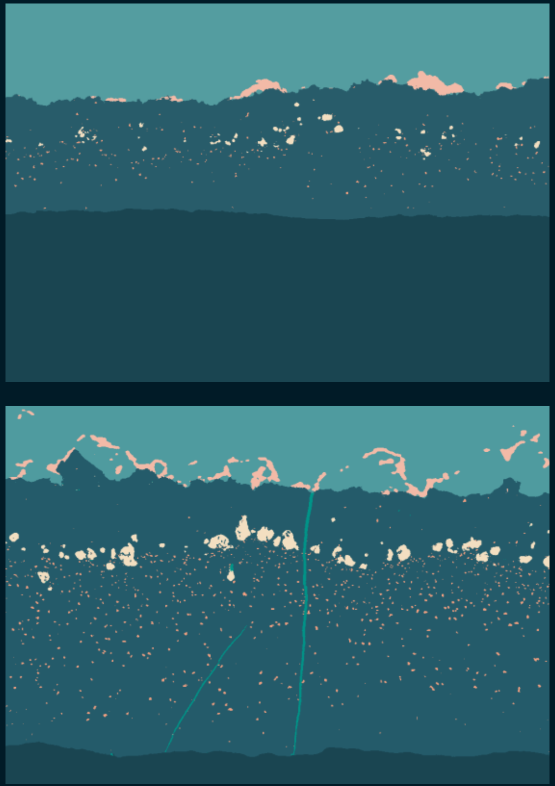


Figure: Post processing on model predictions to analyse features of interest.

Configuration	Training Time (s)	Speedup
Single GPU	9880	1x
8 GPUs	1577	~6.26x

Table: Training Time and Speedup Comparison.

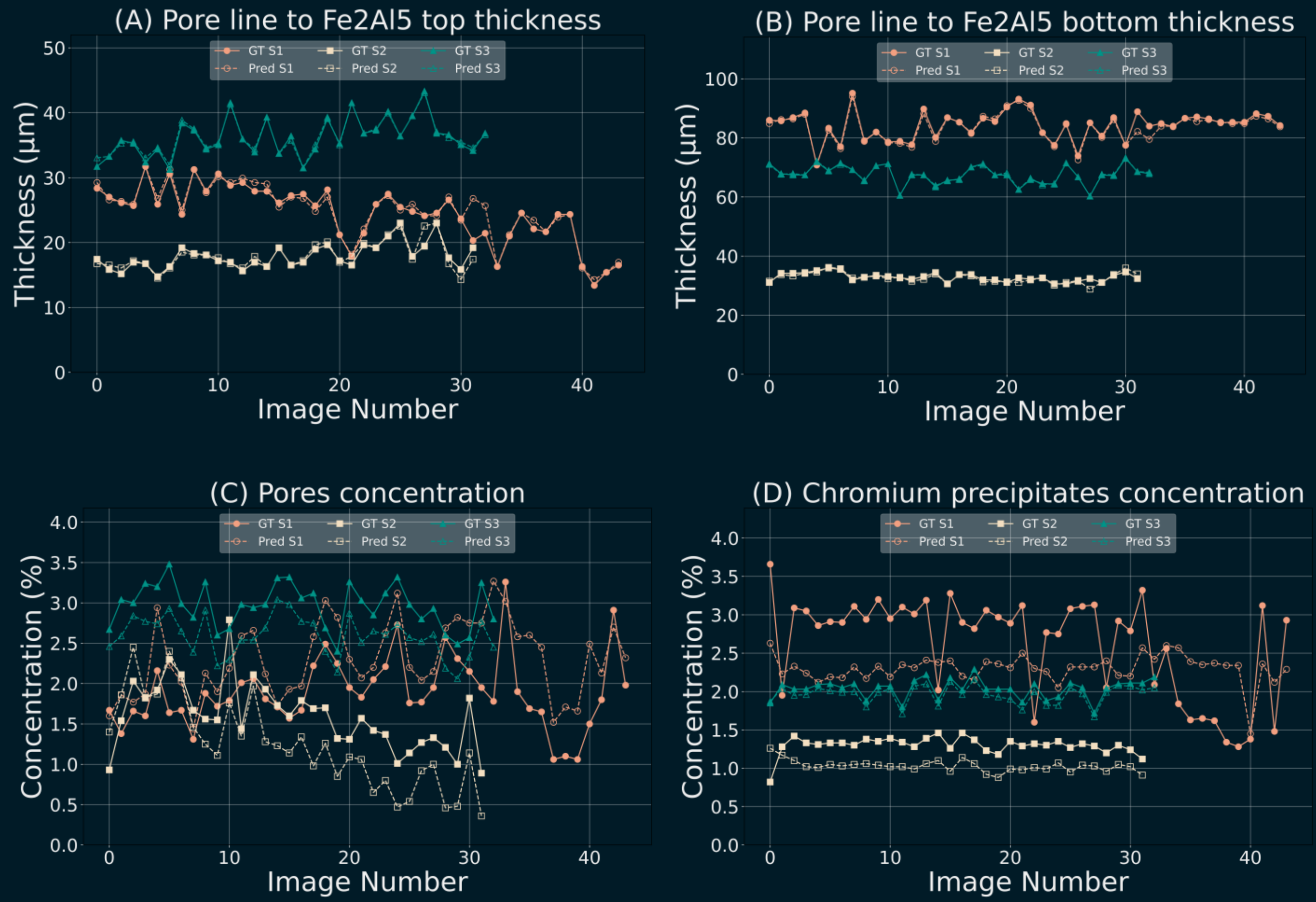


Figure: Comparison of Predicted and Ground Truth Thickness and Concentration for Fe_2Al_5 Top, Fe_2Al_5 Bottom, Pores, and Chromium Precipitate.

Conclusions

Key Takeaways:

- **Synthetic data generation in Blender** can effectively address limitations of small datasets and enables the creation of masks for supervised learning.
- **Deep learning models** demonstrate high accuracy in segmenting coating microstructures.
- **HPC infrastructure** significantly enhances computational efficiency.
- A combined Weighted Dice and Weighted Soft Cross-Entropy (SCCE) **loss function** outperformed other loss strategies, particularly for **classes with imbalance** such as pores and precipitates.
- Among the **tested architectures** (U-Net, DeepLab, and Swin UNETR), U-Net delivered the best overall performance across most feature classes.

Future Work:

- Implement **advanced segmentation architectures**, such as FNOSeg3D, to further improve model accuracy.
- Investigate coatings after **extended heat exposure** (1350 hours at 650 °C in air) to assess long-term performance.
- **Expand the methodology** to include other coating systems for broader applicability.

Thank you

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