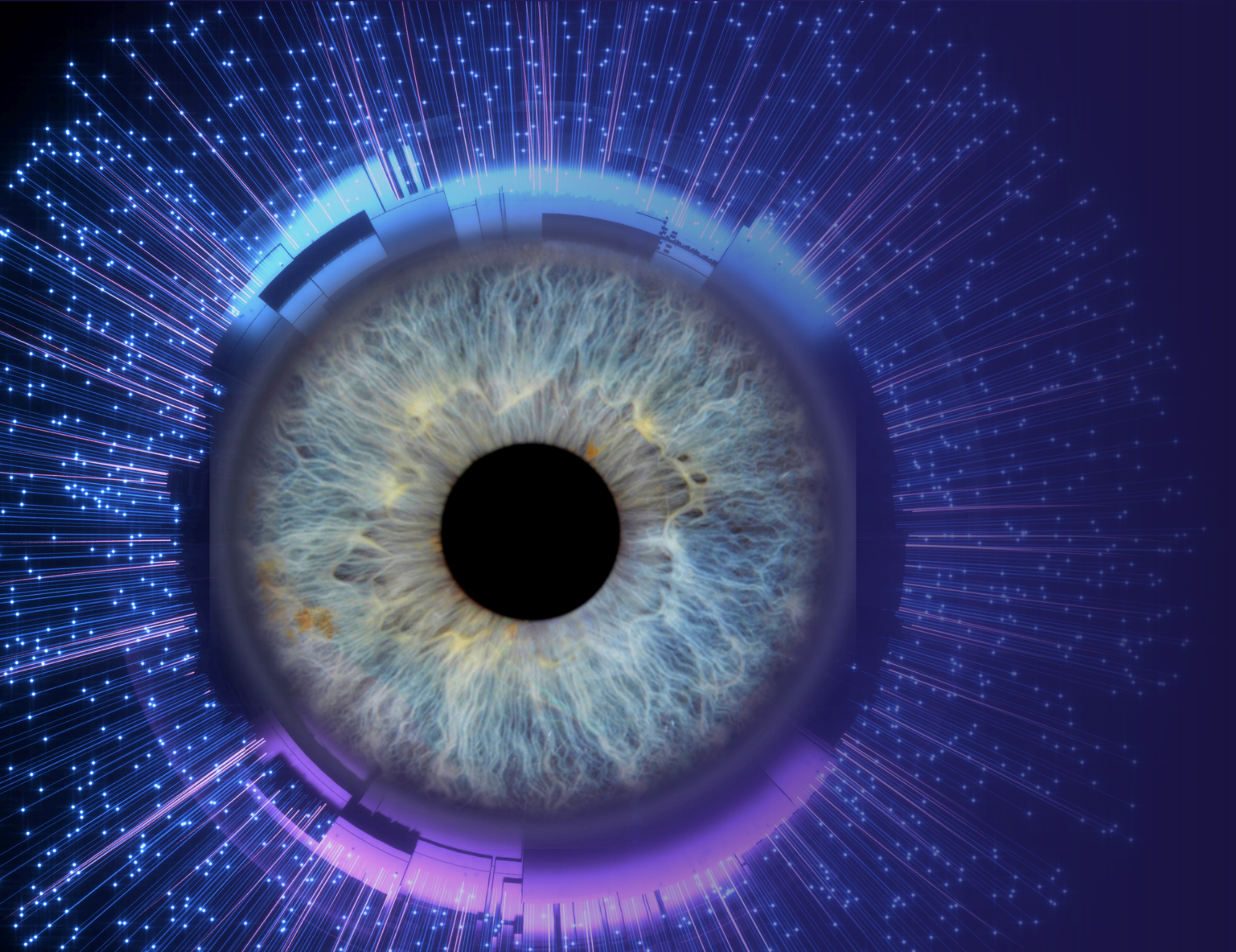
Computer Vision Methods for Fractographic Defect Detection in Titanium and Aluminum Alloys



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Motivation:

- **Additive Manufacturing (AM):**

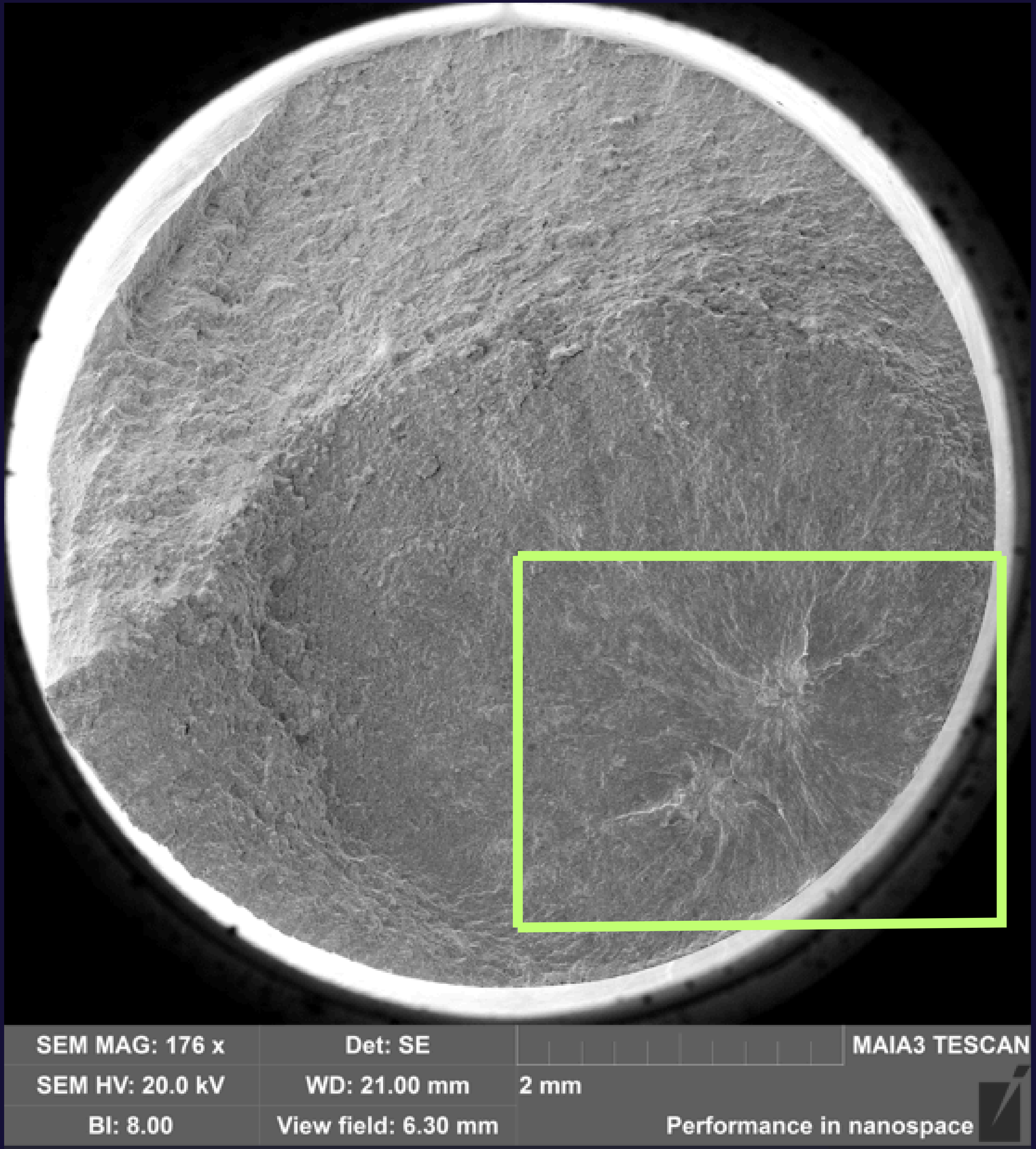
A modern fabrication technique that builds parts layer by layer directly from digital 3D models, enabling lightweight structures and complex geometries that are difficult or impossible to produce with traditional manufacturing.
-Key in aerospace, biomedical, automotive.

- **Challenges :**

– Process-induced defects: porosity, roughness, residual stress
– Leads to fatigue cracks → initiation → propagation → fracture
- Manual Fractography is time consuming, where experts are required to examine the fracture surfaces.

Fatigue Crack Propagation:

- Cracks initiate at defects or surface irregularities.
- They grow progressively
  Propagation continues until final fracture occurs.



our contribution:

- Develop a fully automated Computer Vision pipeline for analyzing SEM images.

- Detect, segment, and measure fatigue-induced cracks in titanium & aluminum alloys.

- Replace manual fractographic inspection with a faster, objective, and reproducible solution.

Provide two main outputs:

- Visual results → Heatmaps, contours, crack phases

- Quantitative reports → Areas, statistics and data.

Dataset:

- The dataset consists of high-resolution SEM images of fracture surfaces.
- Contains specimens from additively manufactured titanium and aluminum alloys.
- Divided into:

01 SLM Ti-6Al-4V → Produced using **Selective Laser Melting.**

02 EBM Ti-6Al-4V → Produced using **Electron Beam Melting.**

Proposed Approach & Workflow:

01 Preprocessing & Inner-shape extraction

02 Heatmap generation

03 Crack zone detection

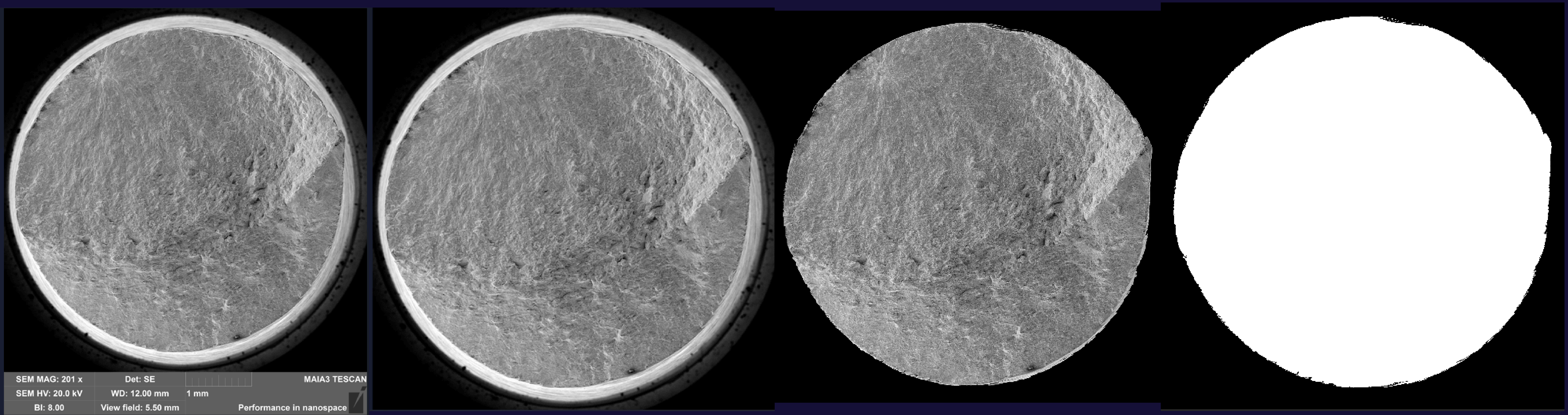
04 Multi-phase contour extraction

05 Quantitative analysis

Preprocessing & Inner-Shape Extraction

1. Convert SEM images from TIFF → PNG.
2. Crop and normalize images into square format.
3. Use CLAHE, Gaussian smoothing, and Canny edge detection.
4. Generate binary masks and isolate the specimen.

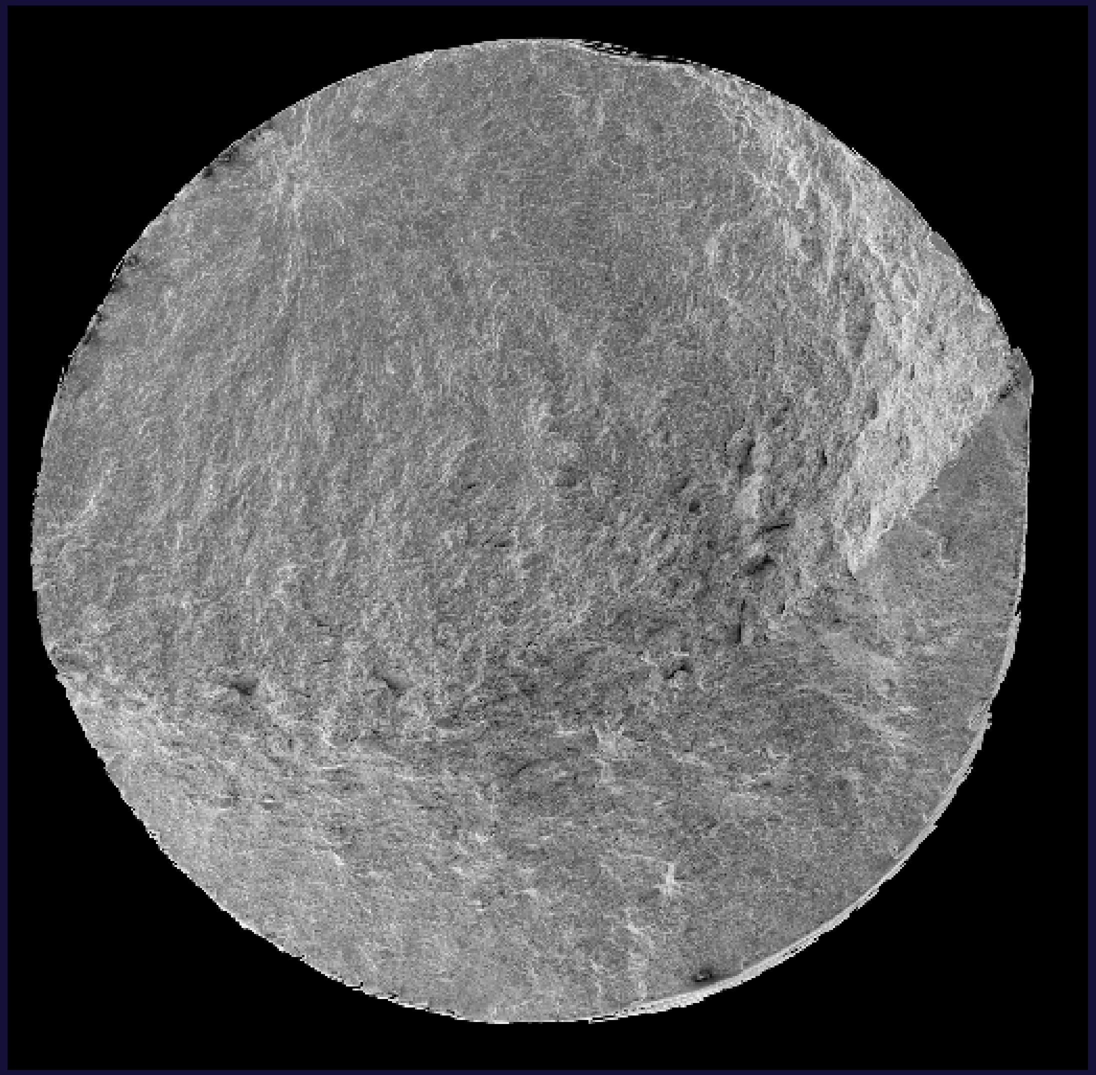
“This ensures we focus only on the relevant fracture area”.

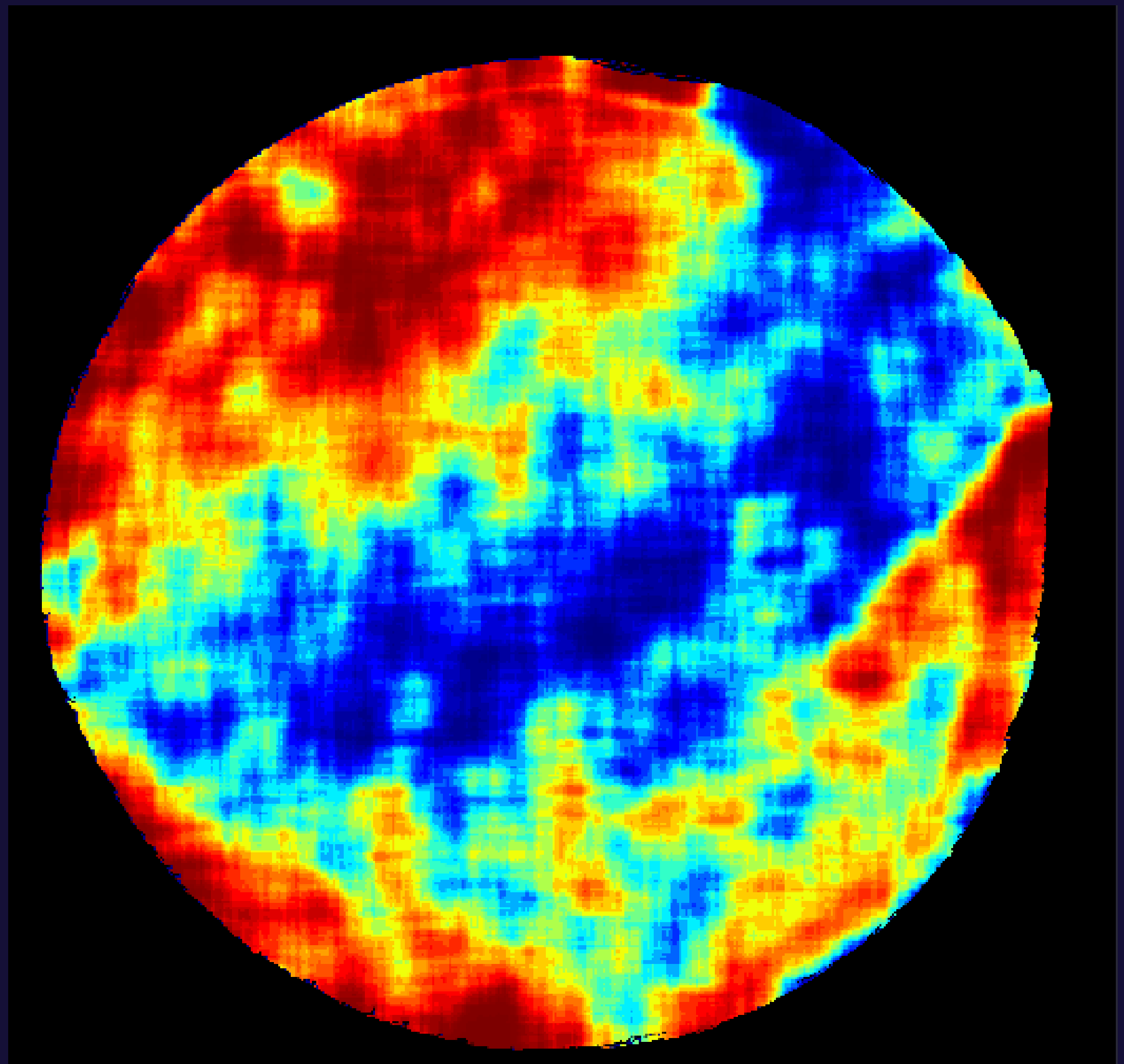


Heatmap Generation:

1. Convert to grayscale → smooth → detect gradients.
2. Use Sobel operator to highlight structural transitions.
3. Apply sliding-window averaging + histogram equalization.
4. Generate color heatmaps using JET colormap.

this is Enhance visibility of cracks and microstructural changes.”

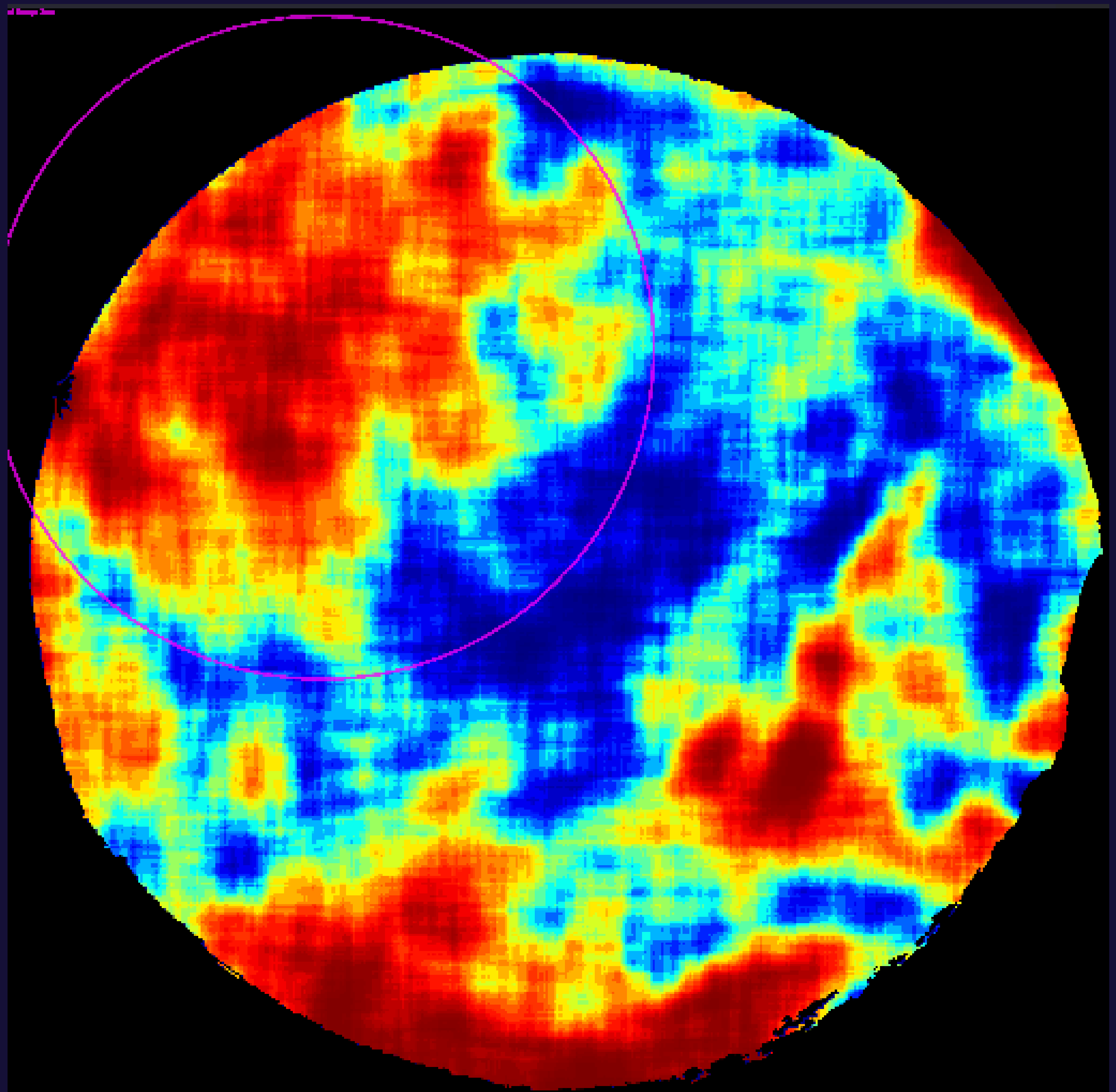




Crack Zone Detection:

Goal: Automatically locate the primary crack region.

1. Convert heatmaps to HSV color space for robust segmentation.
2. Use color thresholds to detect high-stress regions (red/orange areas).
3. Apply centroid-inclusion logic to ensure detected cracks are inside high-stress zones.



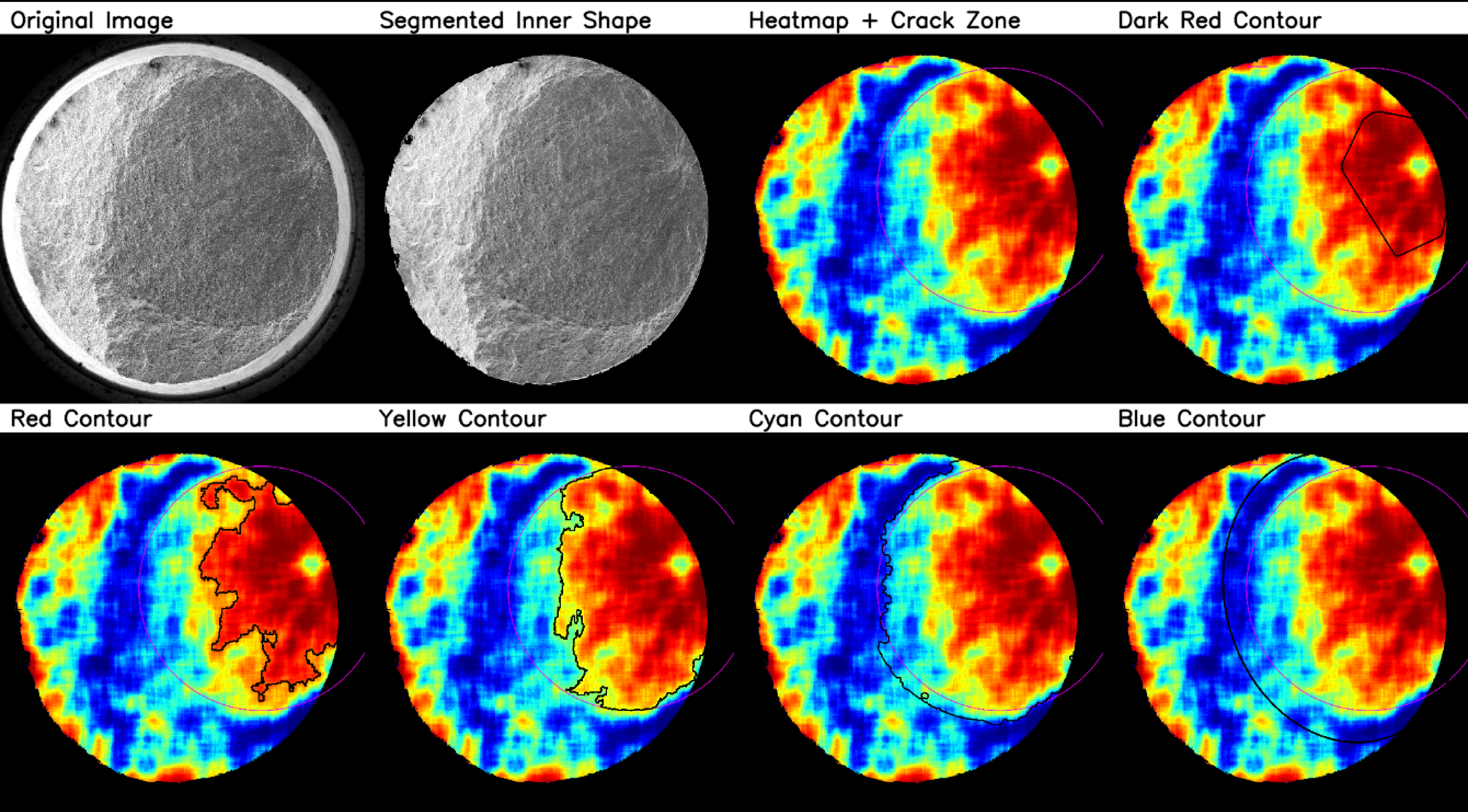
Multi-Phase Contour Extraction:

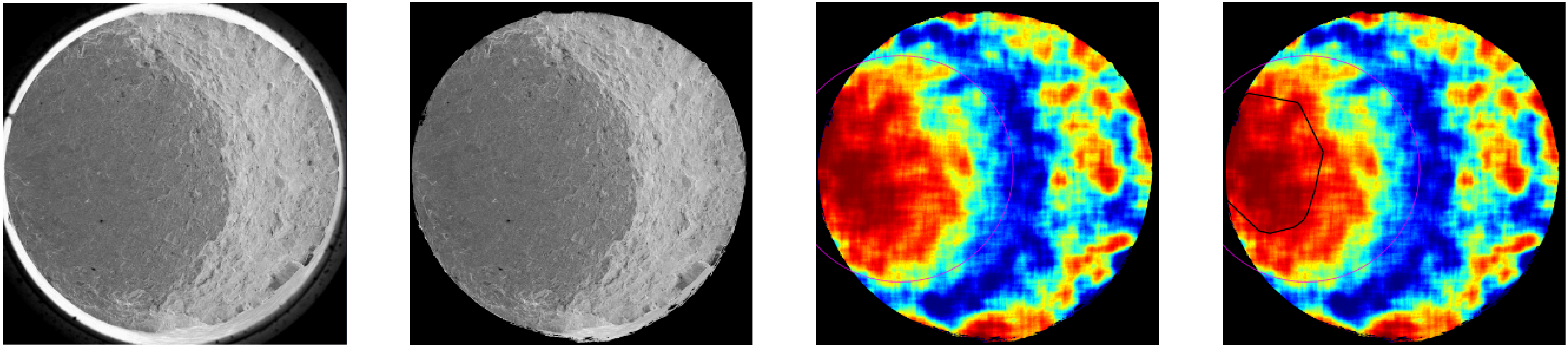
Goal: Separate and analyze five crack-growth phases based on heatmap colors:

1. Dark Red → Crack initiation
2. Red → Early propagation
3. Yellow → Intermediate fatigue growth
4. Cyan → Advanced propagation
5. Blue → Final failure

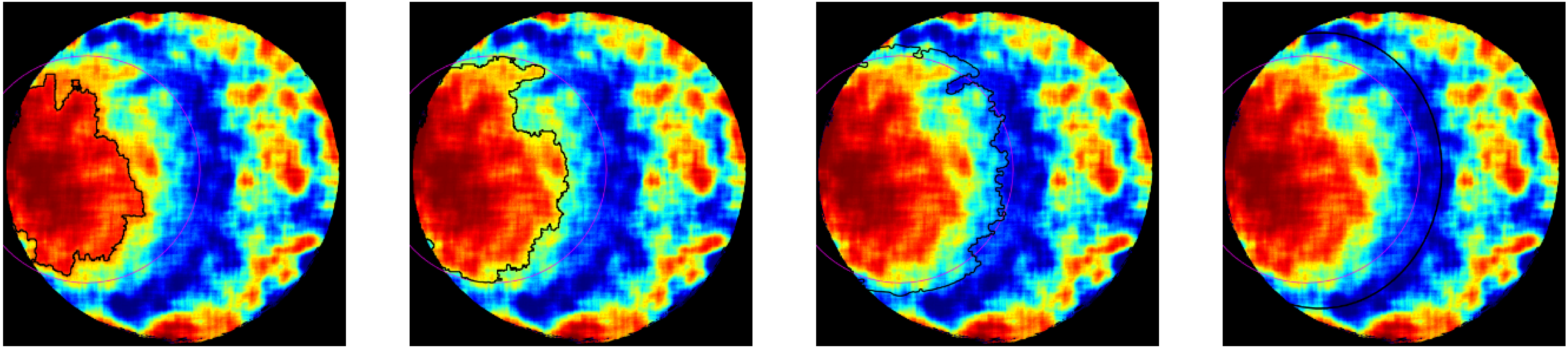
- Fit contours with convex hulls, splines, or ellipses depending on phase complexity.

"This step captures the entire fracture history from initiation to failure."


Original Image
Segmented Inner Shape
Heatmap + Crack Zone
Dark Red Contour
Red Contour
Yellow Contour
Cyan Contour
Blue Contour



Original Image | Segmented Shape | Heatmap + Crack Zone | Dark Red Contour



Red Contour | Yellow Contour | Cyan Contour | Blue Contour

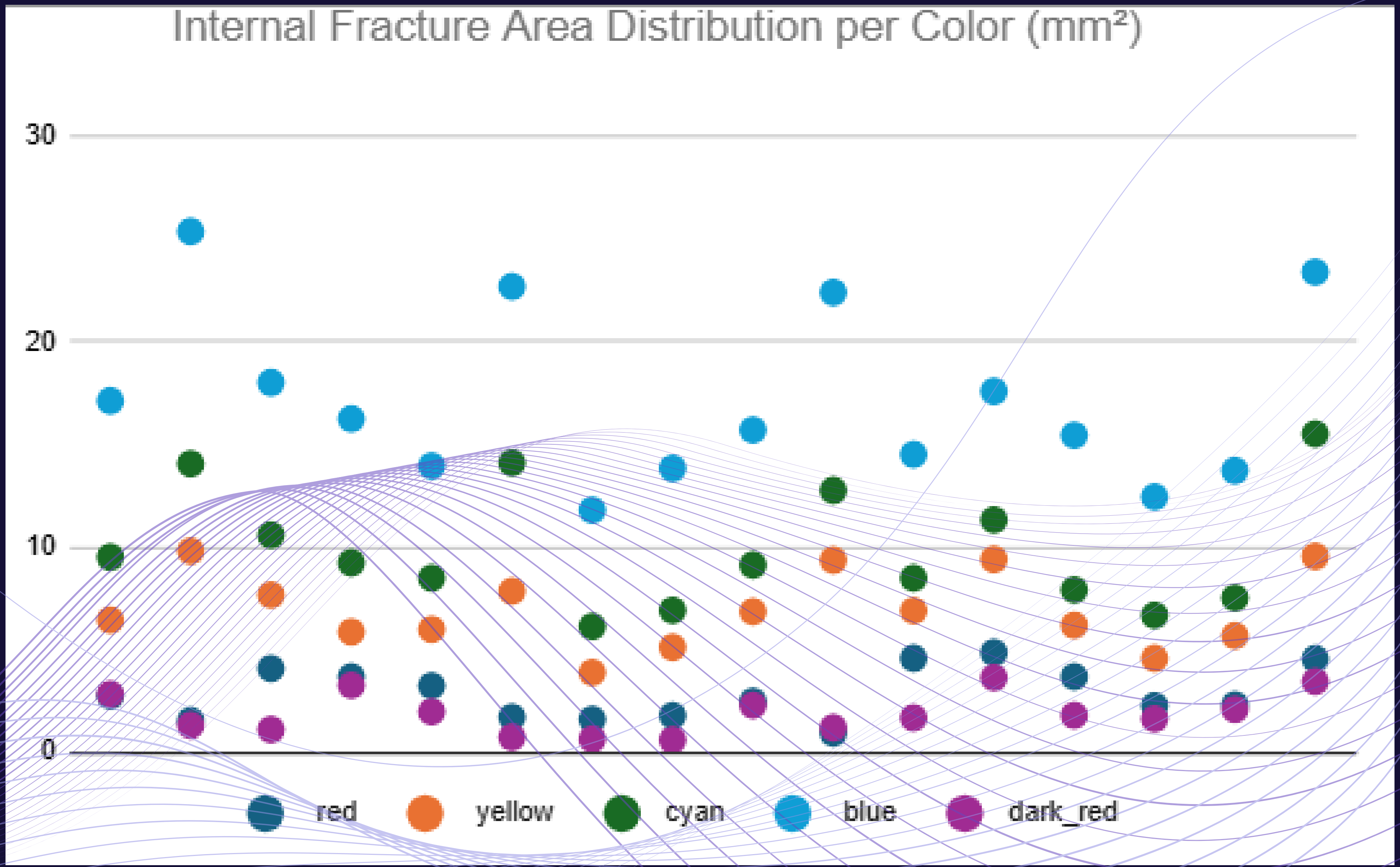
Quantitative Analysis:

Goal: Convert visual crack data into numerical measurements.

- Calibrate using pixel-to-micrometer scaling:
- 1 pixel ≈ 1.34 µm.
- Compute crack area for each phase → output in pixels & µm².
- Save results into structured CSV files with per-specimen statistics.
- Enables comparisons, reproducibility, and statistical modeling.

Specimen	Dark Red	Red	Yellow	Cyan	Blue
Specimen 1	2.041	1.911	3.987	6.276	8.764
Specimen 2	1.275	1.605	4.574	8.603	11.702
Specimen 3	1.939	2.289	6.433	9.228	11.714
Specimen 4	2.286	2.202	4.980	7.845	12.903
Specimen 5	1.720	2.304	5.159	8.525	13.527
Specimen 6	6.186	8.192	16.310	28.685	33.875
Specimen 7	1.892	2.176	4.660	6.984	10.065
Specimen 8	0.728	1.288	2.074	3.211	5.214
Specimen 9	1.262	1.393	2.521	3.980	6.750
AVG	1.93	2.81	7.16	12.13	15.92
STDV	1.64	2.12	6.26	11.54	12.84

Table 2: Area of each crack-growth phase in mm^2 for selected specimens



Conclusion:

In this project, we developed a fully automated computer vision framework that analyzes SEM images of additively manufactured alloys. It detects, segments, and quantifies cracks across different growth phases using heatmap-based analysis. The pipeline generates both visual and numerical results, ensuring accuracy, consistency, and reproducibility.

Future Work:

- Integrate deep learning

Use models like U-Net and Mask R-CNN to improve segmentation accuracy.

- 3D fracture analysis

Extend the framework to study surface roughness & crack curvature in 3D.

- Real-time monitoring

Adapt the pipeline for in-situ defect detection during additive manufacturing.

- Benchmark datasets

Build large, standardized datasets for research & industrial use.

Thank You!