# Microstructure Quantification With Deep Learning Encoders Pre-Trained on a Massive Microscopy Dataset

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# Acknowledgements


## Collaborators

Dr. Joshua Stuckner, Dr. Bryan Harder, Dr. Timothy M. Smith,
Dr. Steven M. Arnold, Thomas Ciardi

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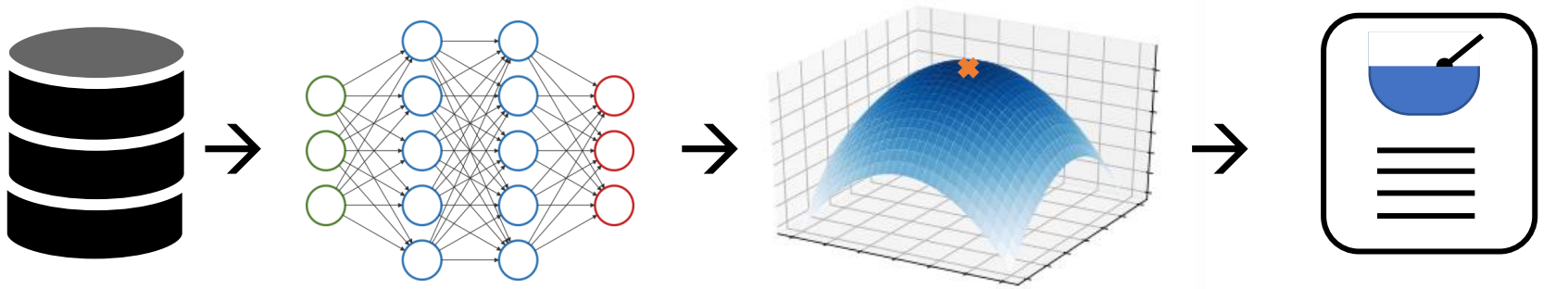
- NASA
  - Aeronautics Research Mission Directorate (ARMD)
    - Transformative Aeronautics Concept Program (TACP)
      - Transformational Tools and Technology ($T^3$)

Processing → Properties
Properties → Processing

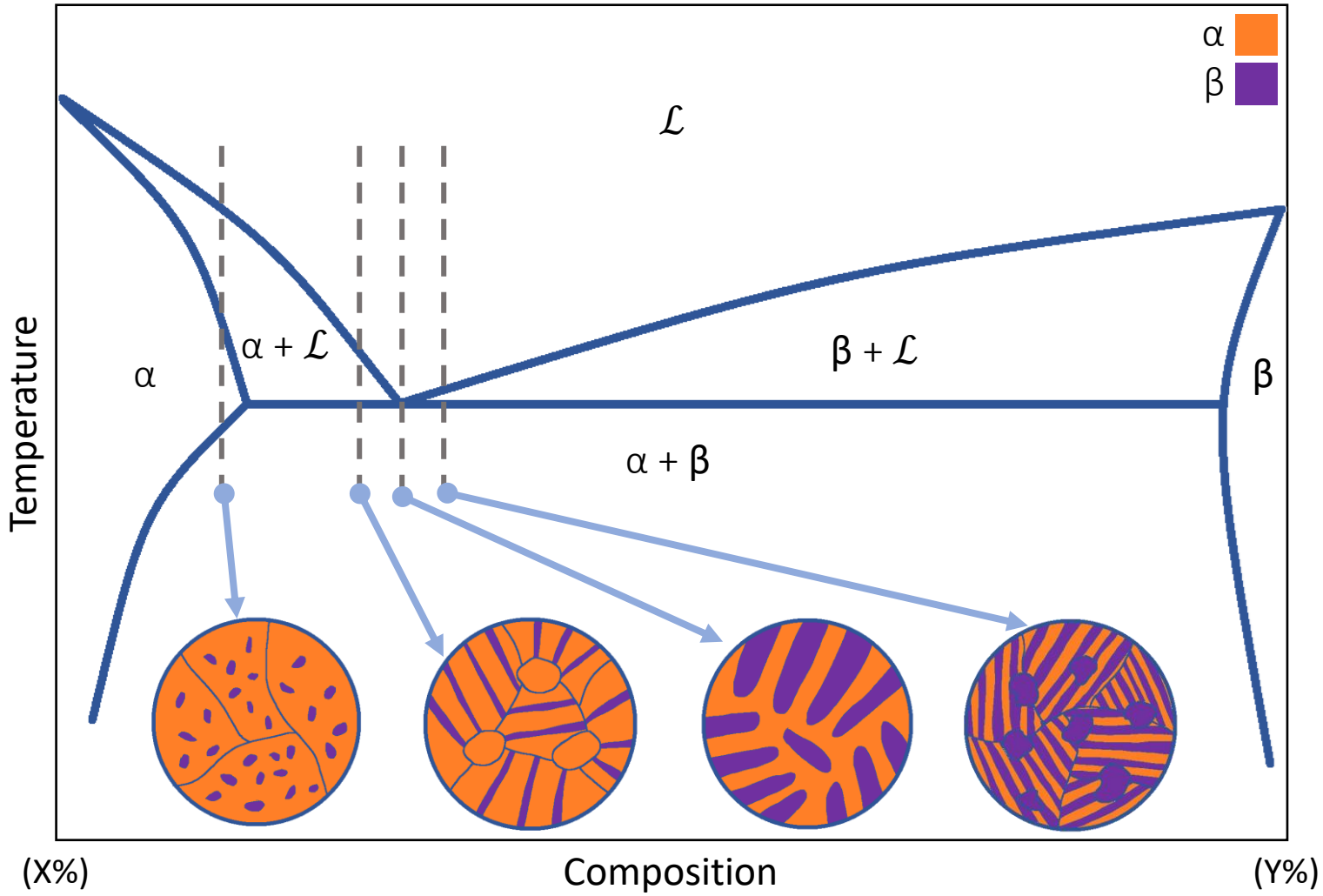
x y

$$y = F(x)$$

processing: $x^* = \text{argmax}(F(x))$



## Phase Diagram

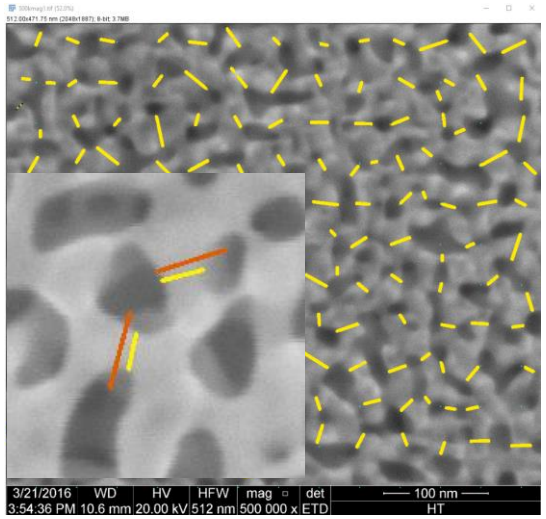


Processing → Structure → Properties
x z y

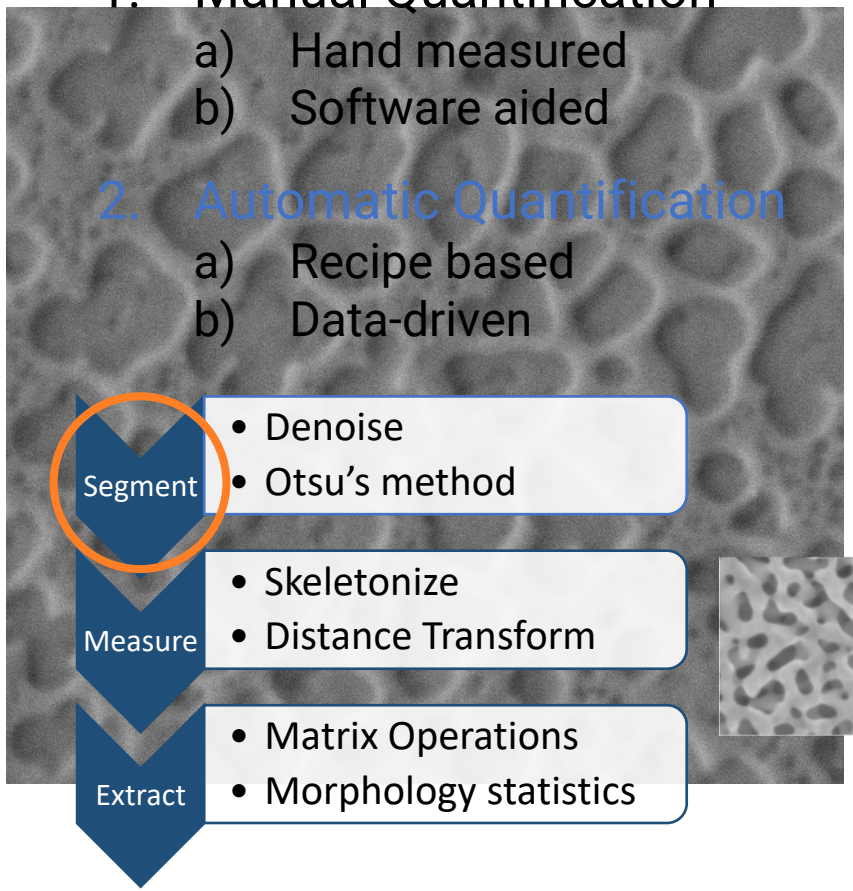
$$y = F(x,z)$$

Problem: How do we quantify the structure

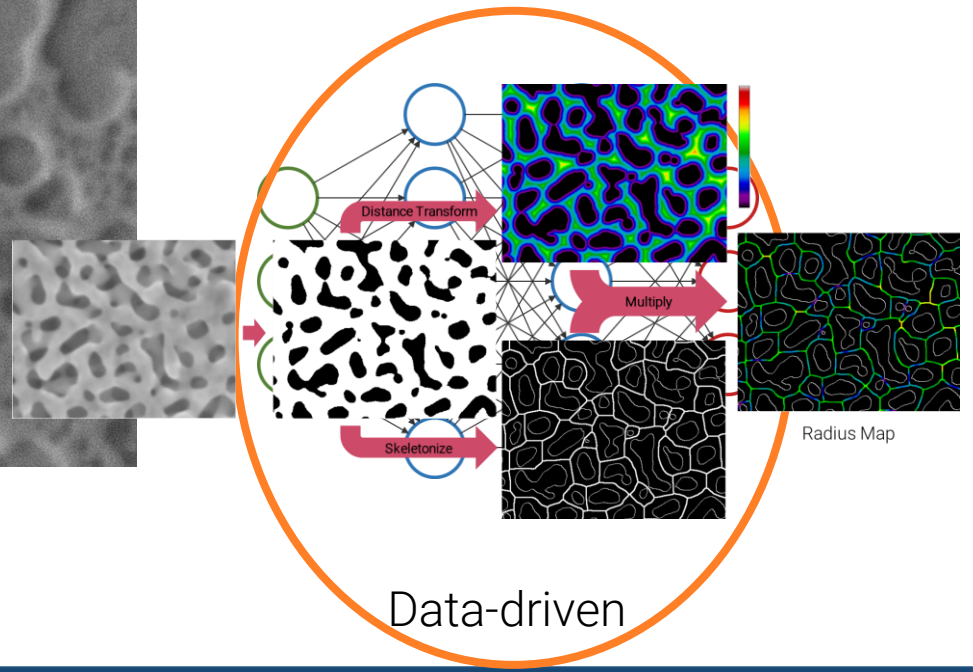
1. Manual Quantification
   a) Hand measured
   b) Software aided
2. Automatic Quantification
   a) Recipe based
   b) Data-driven




Manual

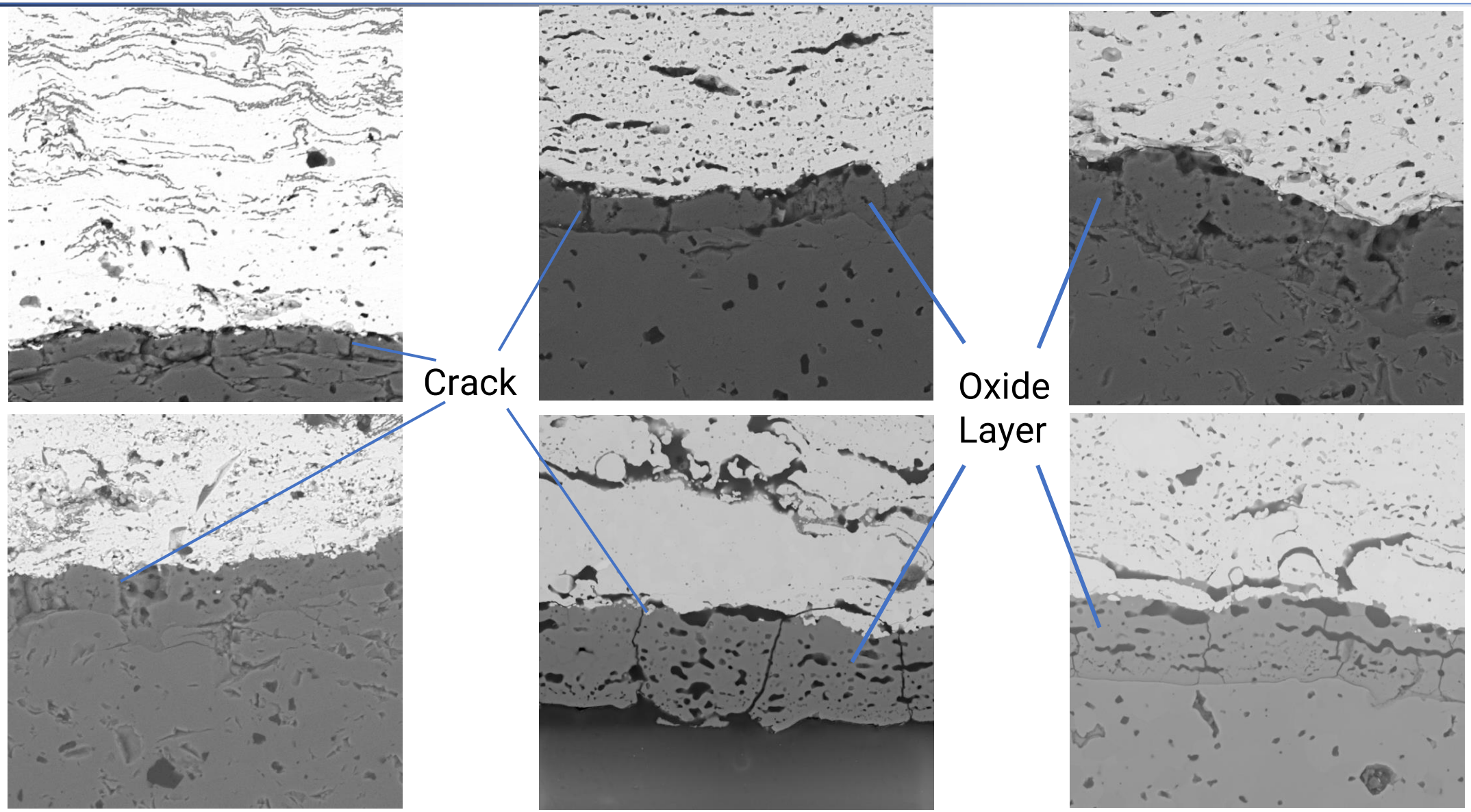


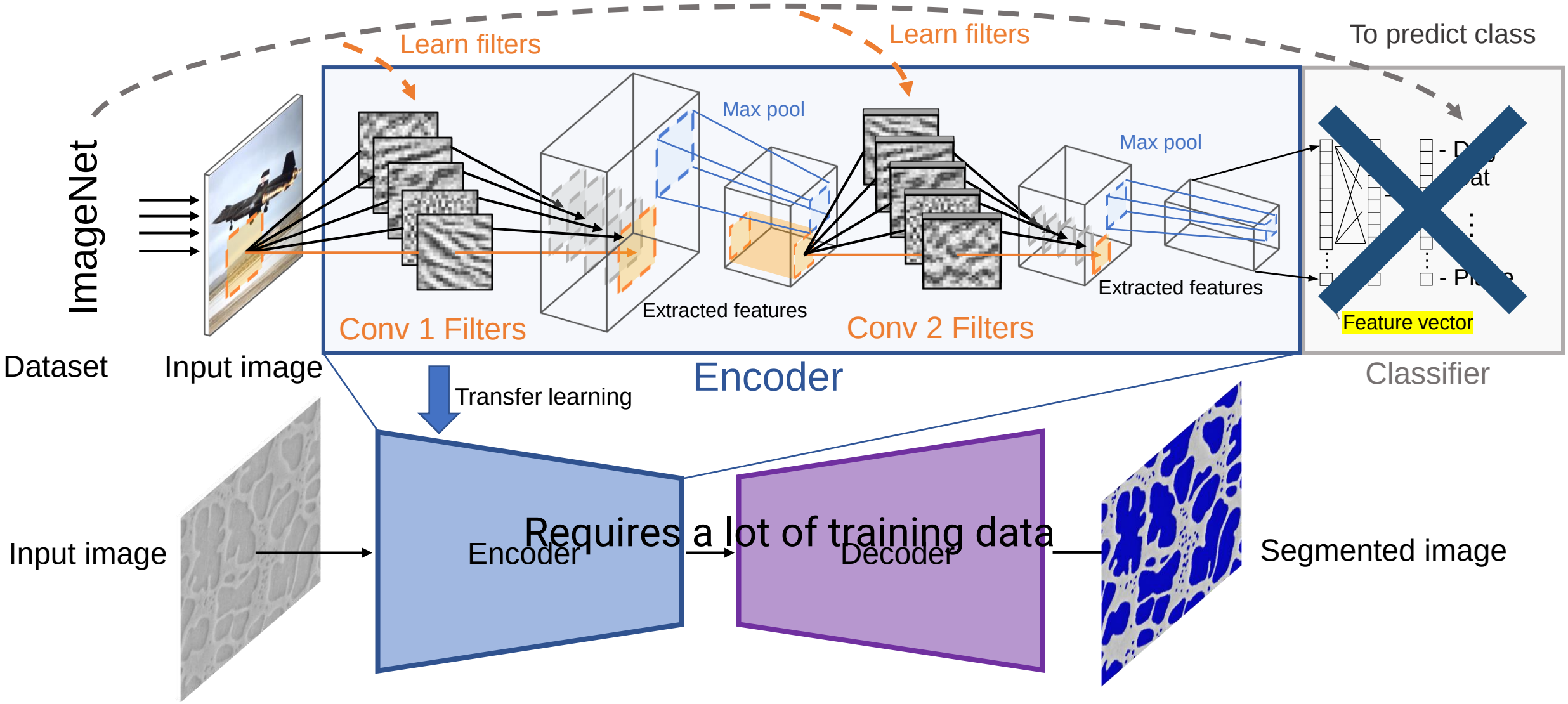

Recipe based

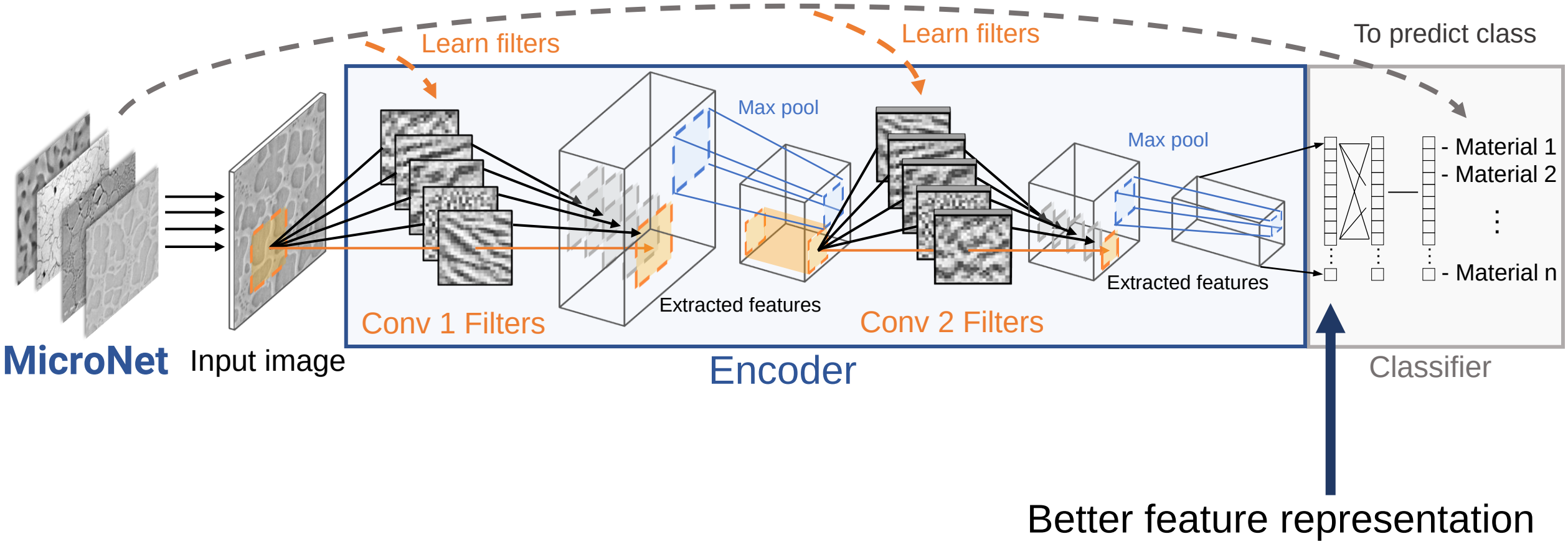


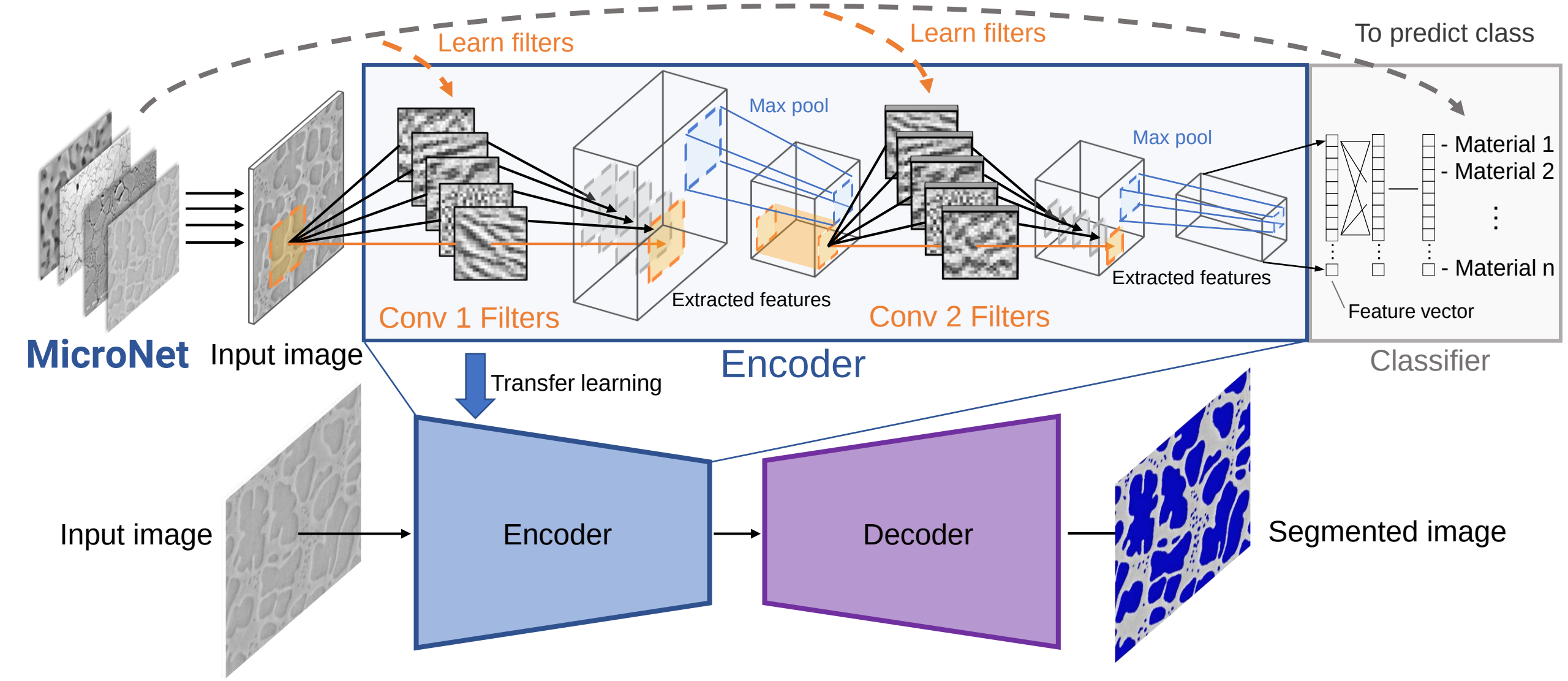

Data-driven

# Background




Learn filters
Learn filters
To predict class
ImageNet
Max pool
Max pool
Extracted features
Extracted features
Conv 1 Filters
Conv 2 Filters
Feature vector
Dataset
Input image
Encoder
Classifier
Transfer learning
Input image
Encoder
Requires a lot of training data
Decoder
Segmented image


Learn filters
Learn filters
To predict class
Max pool
Max pool
- Material 1
- Material 2
- Material n
Extracted features
Extracted features
Conv 1 Filters
Conv 2 Filters
MicroNet
Input image
Encoder
Classifier
Better feature representation


Learn filters
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Feature vector
MicroNet
Input image
Encoder
Classifier
Transfer learning
Input image
Encoder
Decoder
Segmented image

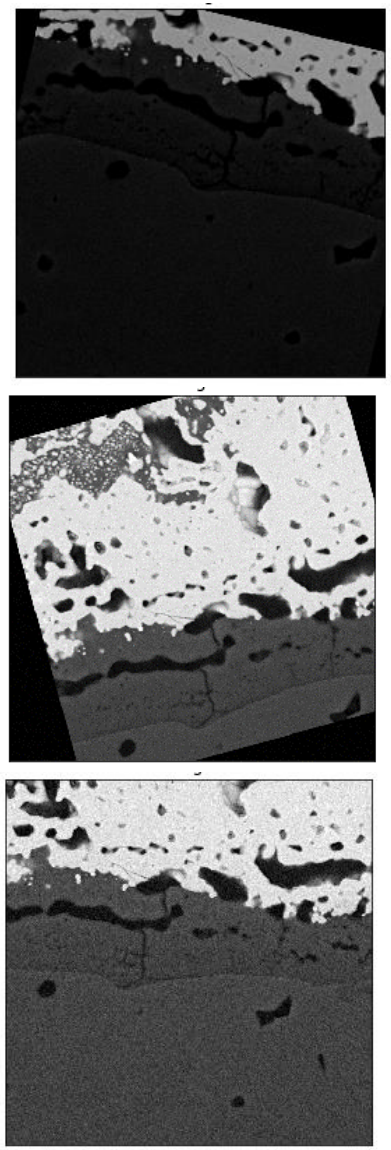
# Classification Training

**Data**
- Classes: 54
- Size: 1057 x 750, 150 GB
- Training set: 108,161
- Validation set: 2700 (50/class)

**Augmentation**
- Random crop, resize, flip, mirror, rotate
- Contrast, CLAHE, Brightness, Gamma, Hue/Saturation
- Gaussian Noise
- Sharpen
- Blur

**Training**
- Early stopping
- Learning rate decay

**Hardware**
- 4 Nvidia Quadro V100 32 GB

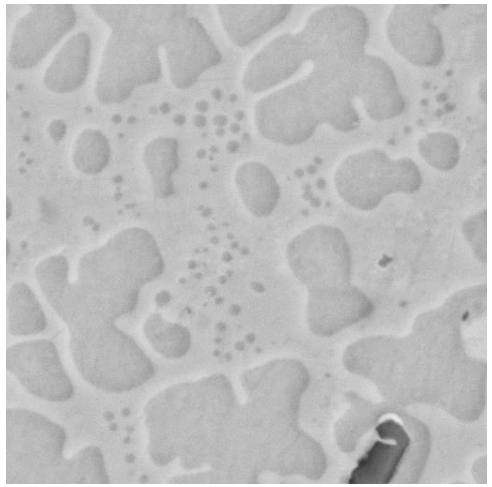


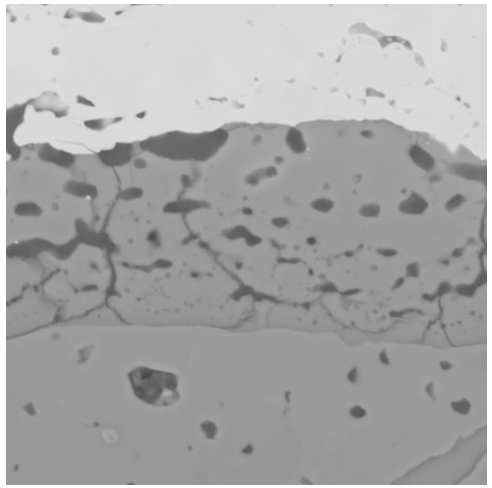
**Encoders**

- resnet18
- resnet34
- resnet50
- resnet101
- resnet152
- resnext50_32x4d
- resnext101_32x4d
- resnext101_32x8d
- resnext101_32x16d
- resnext101_32x32d
- resnext101_32x48d
- dpn68
- dpn68b
- dpn92
- dpn98
- dpn107
- dpn131
- vgg11
- vgg11_bn
- vgg13
- vgg13_bn
- vgg16
- vgg16_bn
- vgg19
- vgg19_bn

**Encoders**

- senet154
- se_resnet50
- se_resnet101
- se_resnet152
- se_resnext50_32x4d
- se_resnext101_32x4d
- densenet121
- densenet169
- densenet201
- densenet161
- inceptionresnetv2
- inceptionv4
- efficientnet-b0
- efficientnet-b1
- efficientnet-b2
- efficientnet-b3
- efficientnet-b4
- efficientnet-b5
- efficientnet-b6
- efficientnet-b7
- mobilenet_v2
- xception





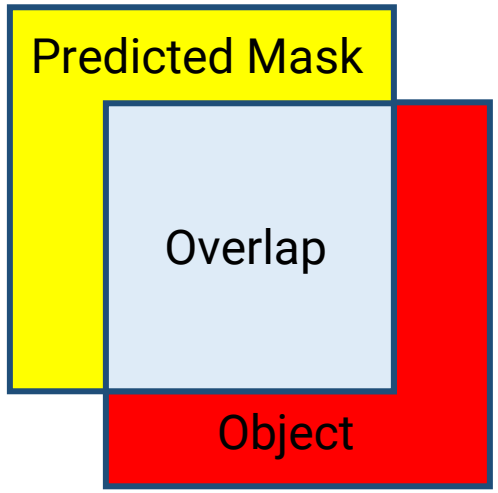
| Experiment | # Train | # Val | # Test |
|---|---|---|---|
| Super-1 | 10 | 4 | 4 |
| Super-2 | 4 | 4 | 4 |
| Super-3 | 1 | 4 | 4 |
| Super-4 | 4 | 4 | 5* |
| EBC-1 | 18 | 3 | 3 |
| EBC-2 | 4 | 3 | 3 |
| EBC-3 | 1 | 3 | 3 |

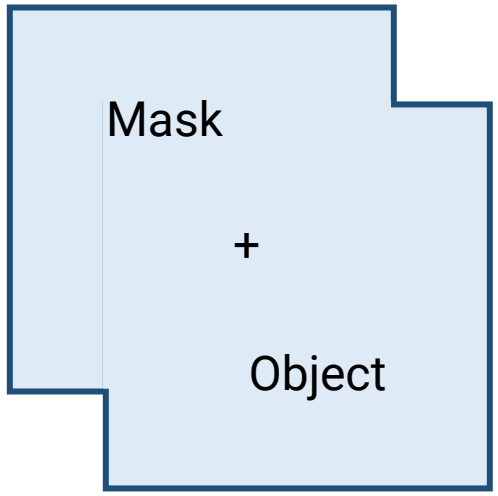
## Decoders

- UNet
- Unet++
- PSPNet
- FPN
- LinkNet
- PAN
- DeepLabV3+

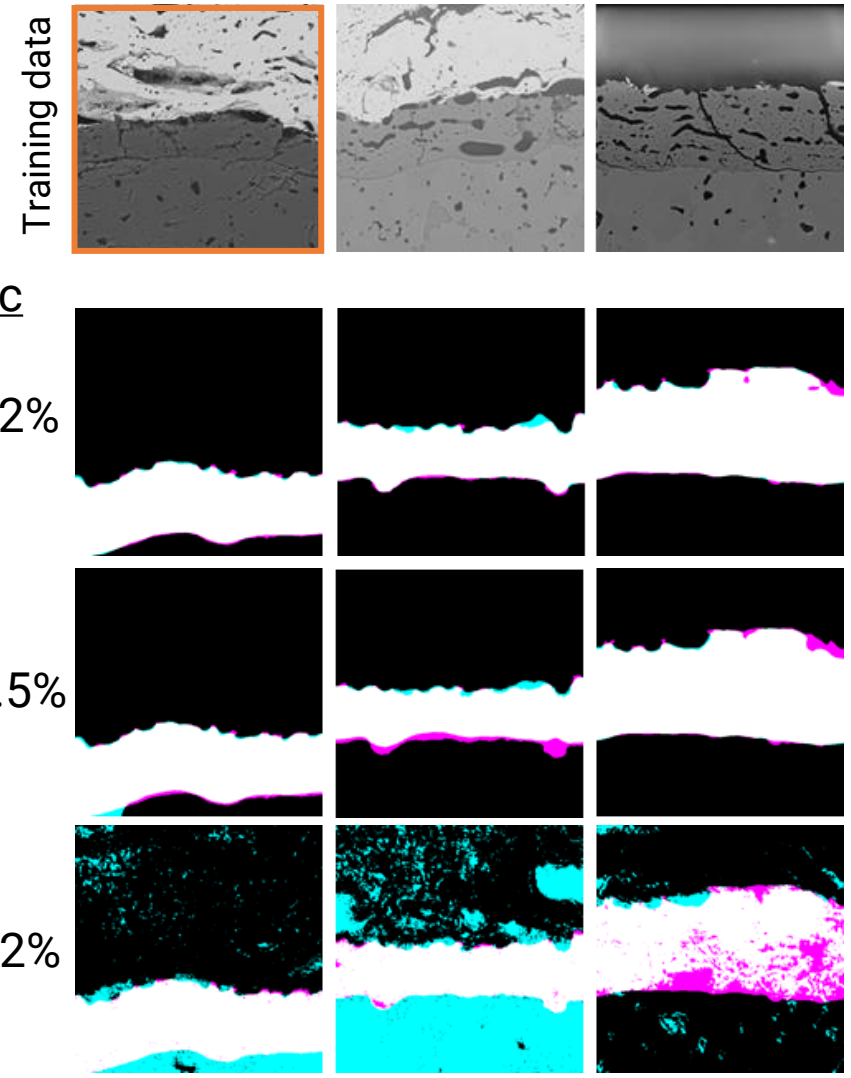
# **Accuracy:** Intersection over union (IoU)

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$



# Segmentation



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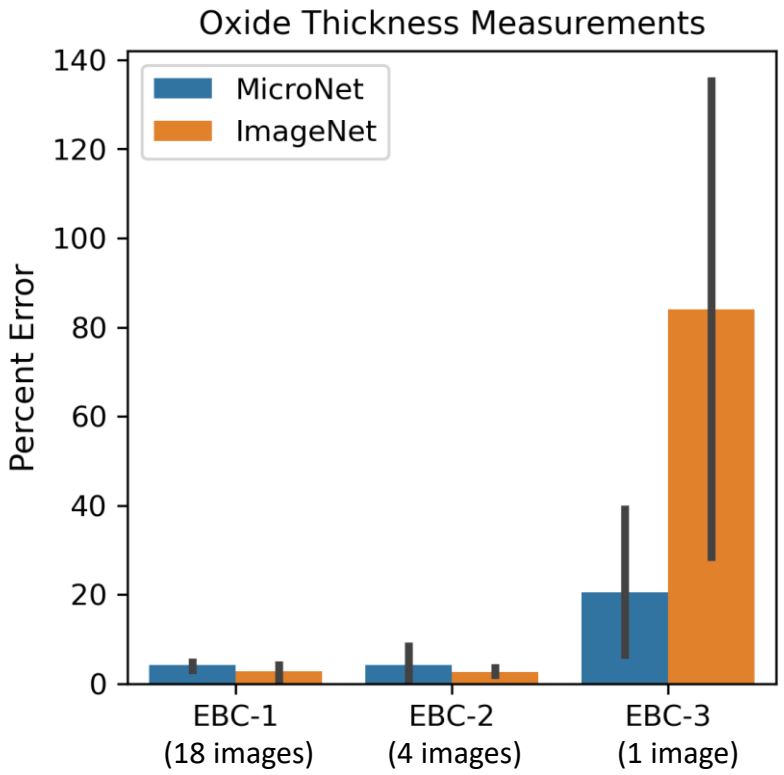
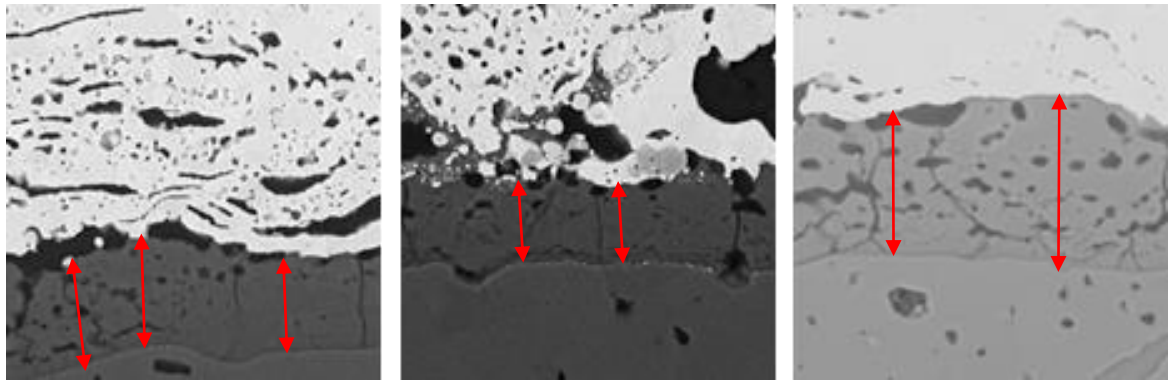
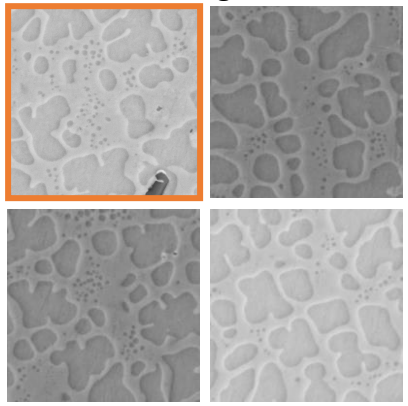


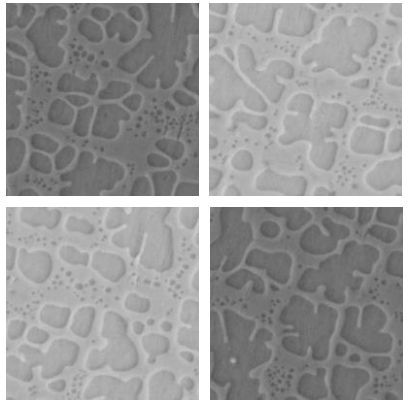



# Segmentation

Training data



Test Data

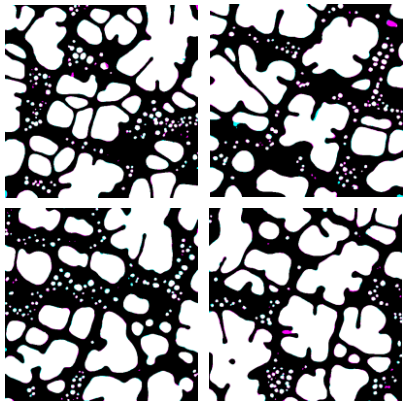


ImageNet

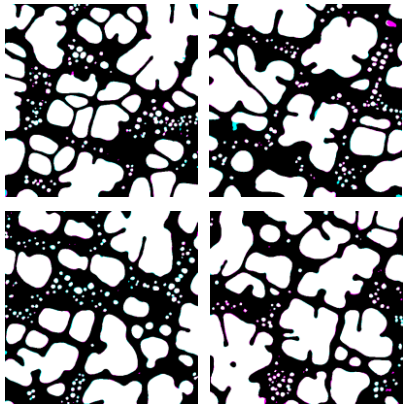
MicroNet

10 Images

96.5% IoU

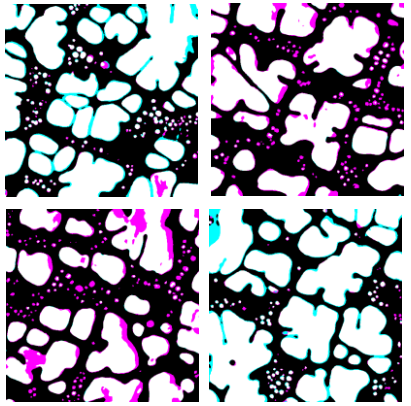


96.4% IoU

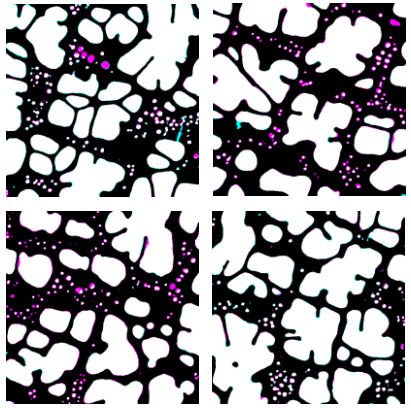


4 Images

88.7% IoU

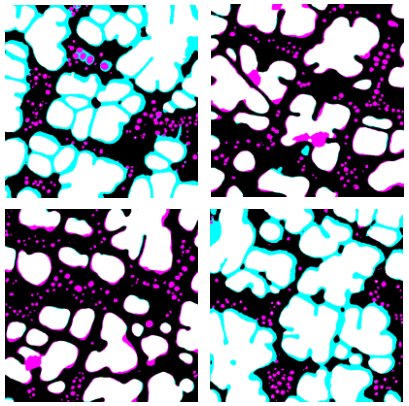


94.2% IoU

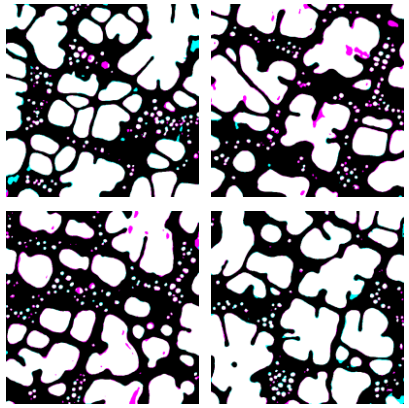


1 Images

74.8% IoU



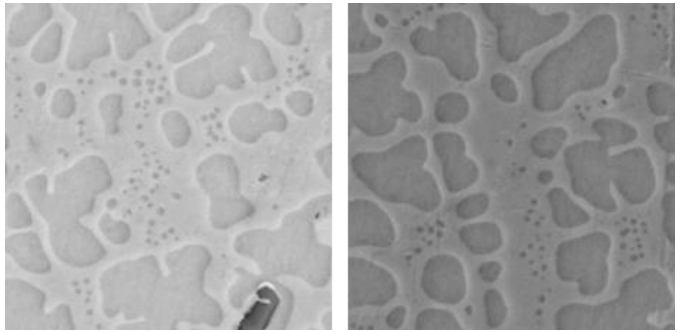
93.0% IoU



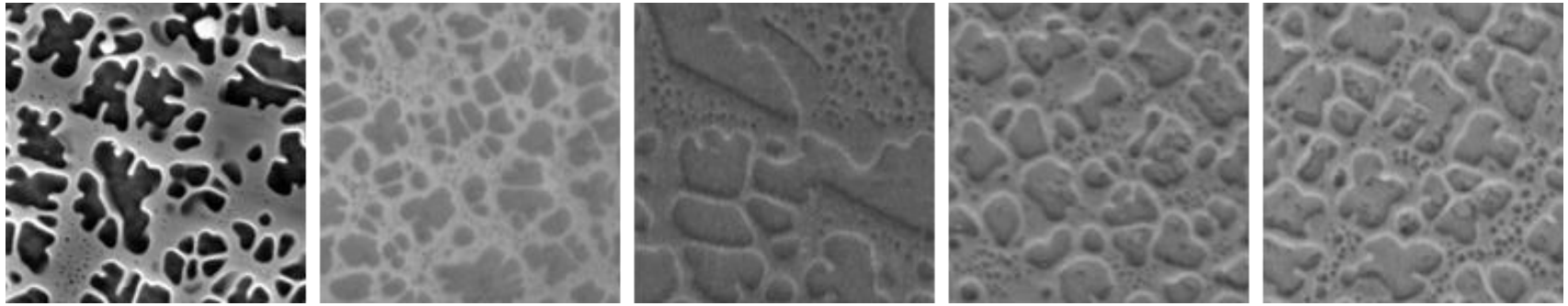
True Positive  True Negative  False Positive  False Negative

# Segmentation

Training data



Test data

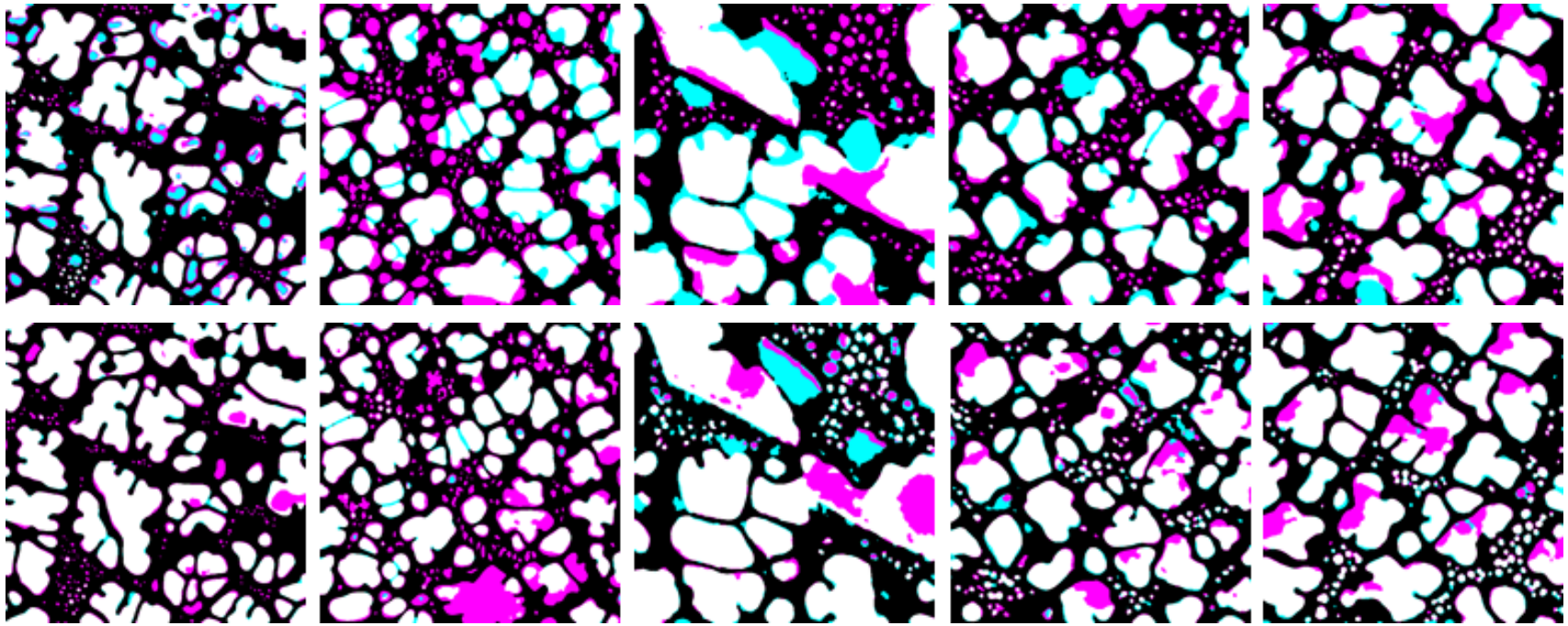


ImageNet

72.5%

MicroNet

78.5%



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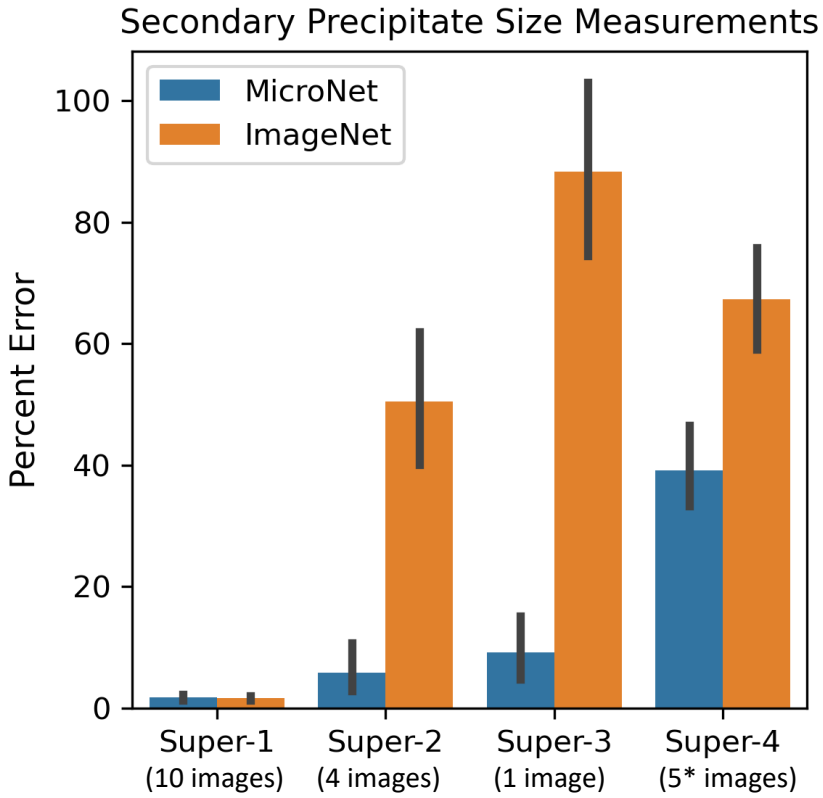
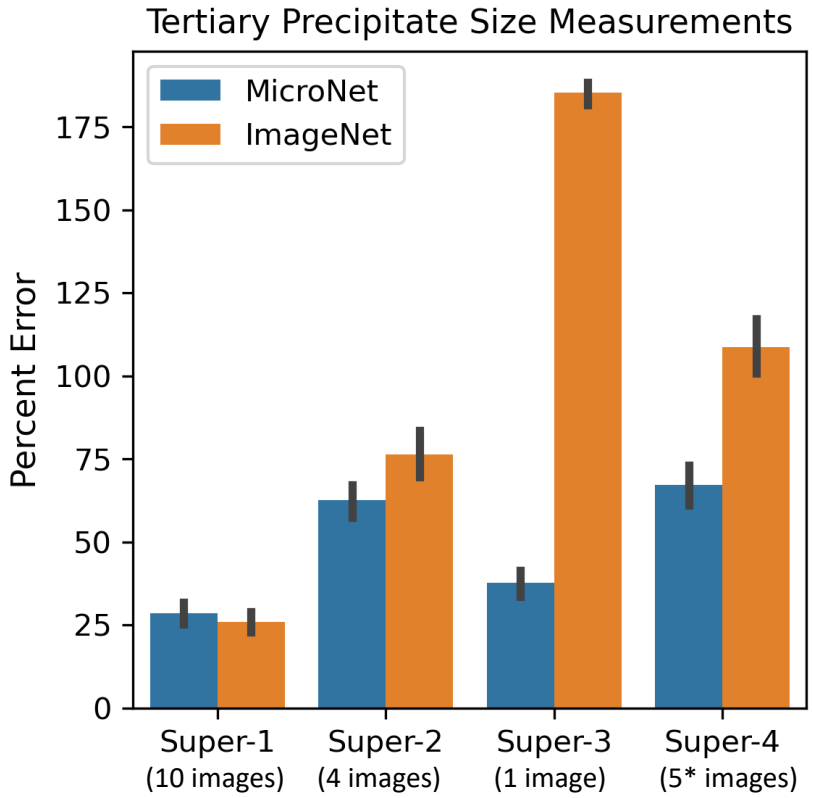
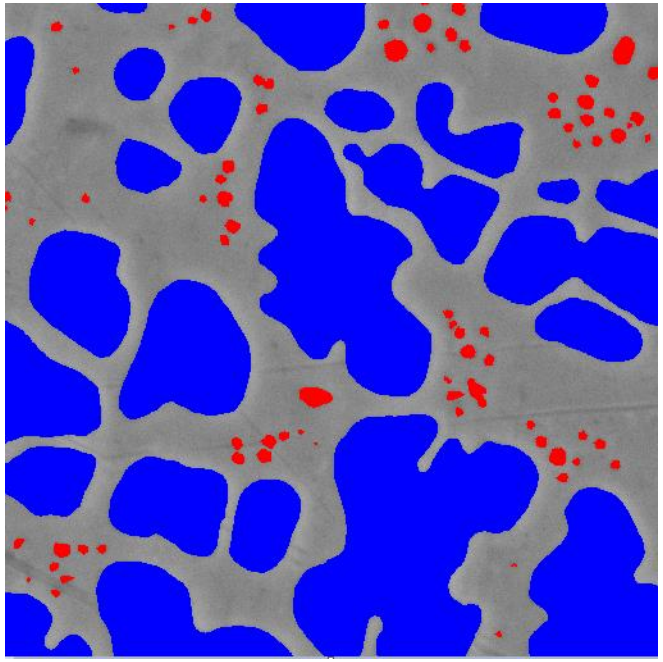
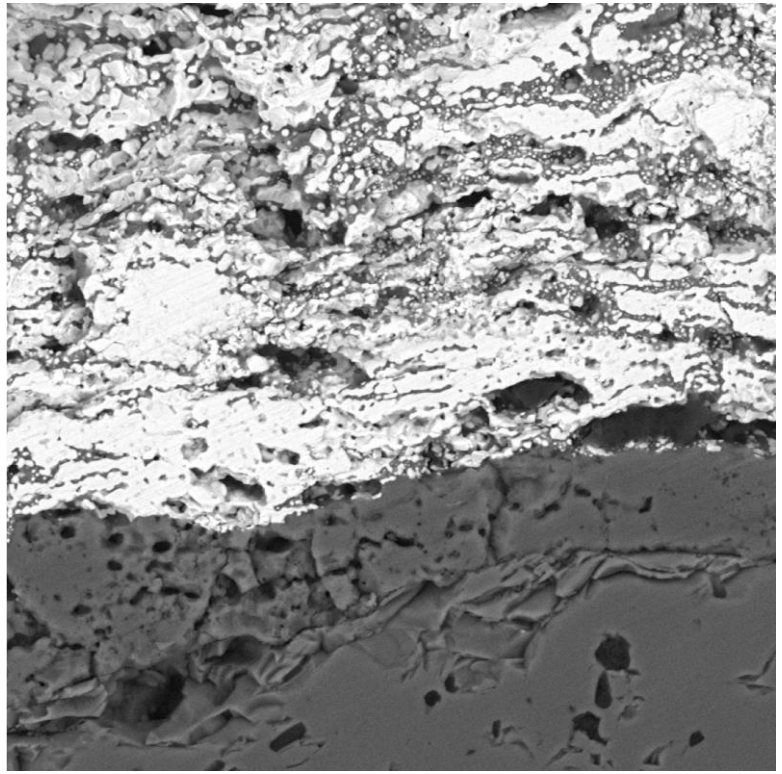
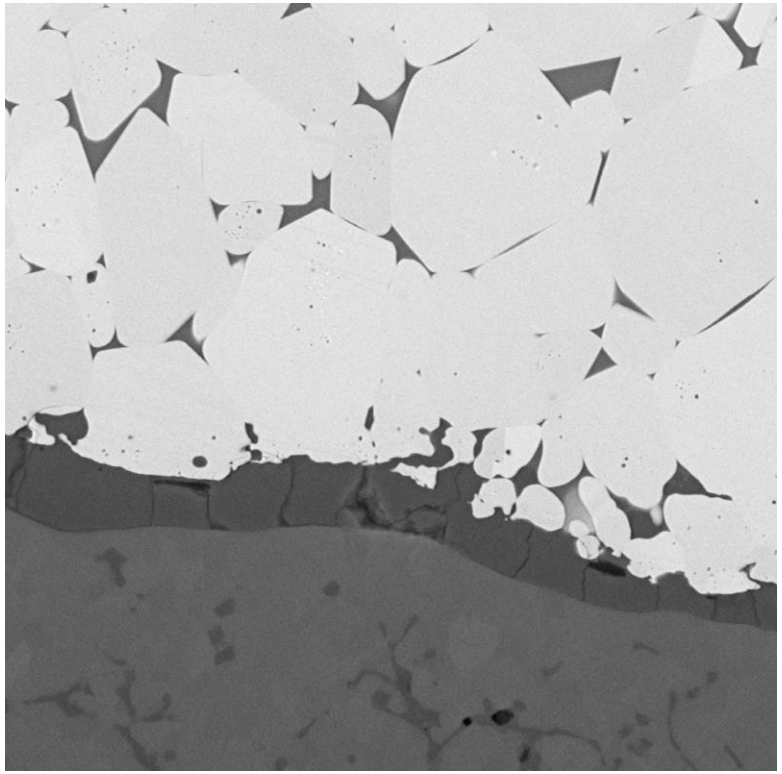
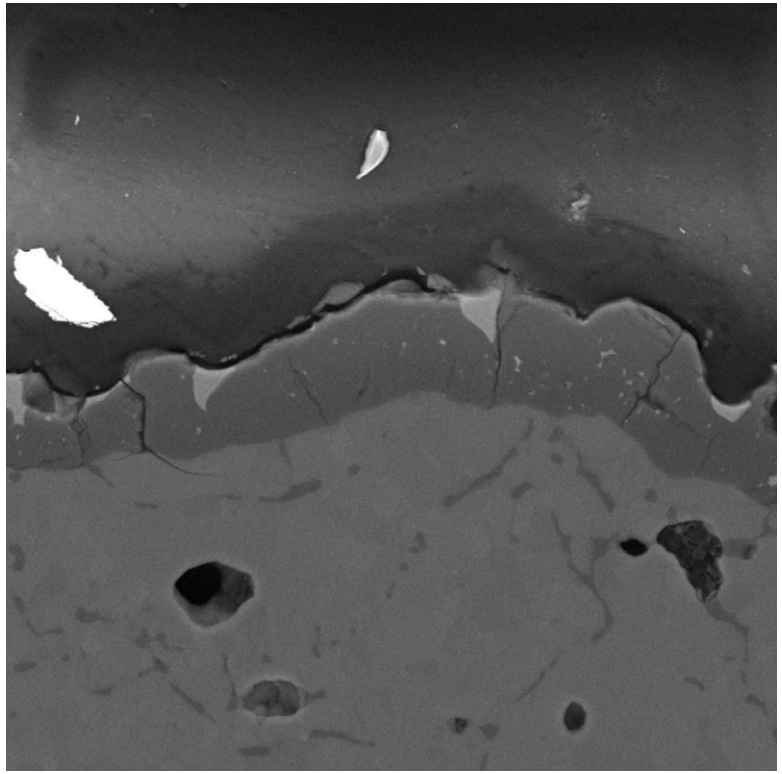


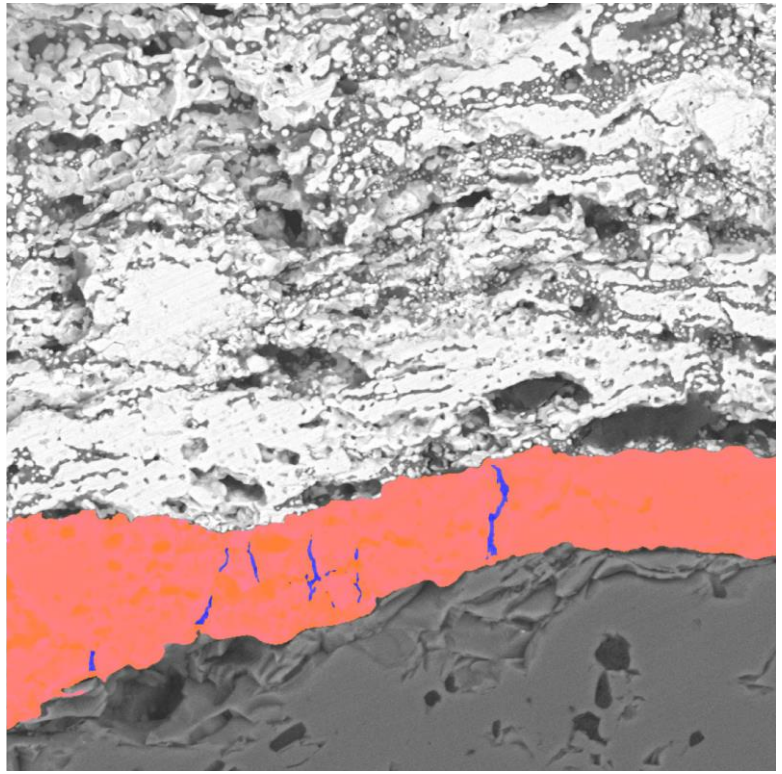



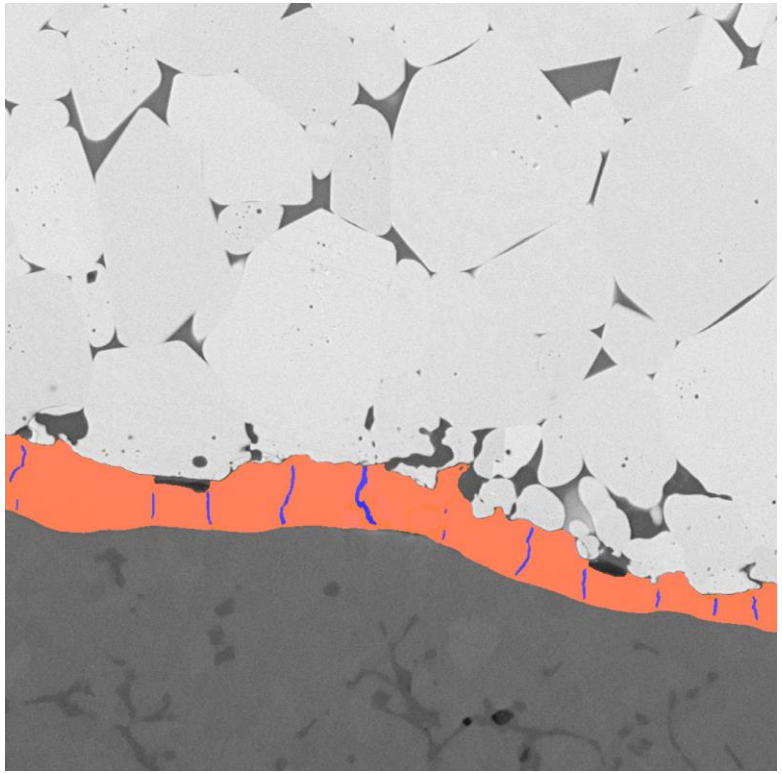


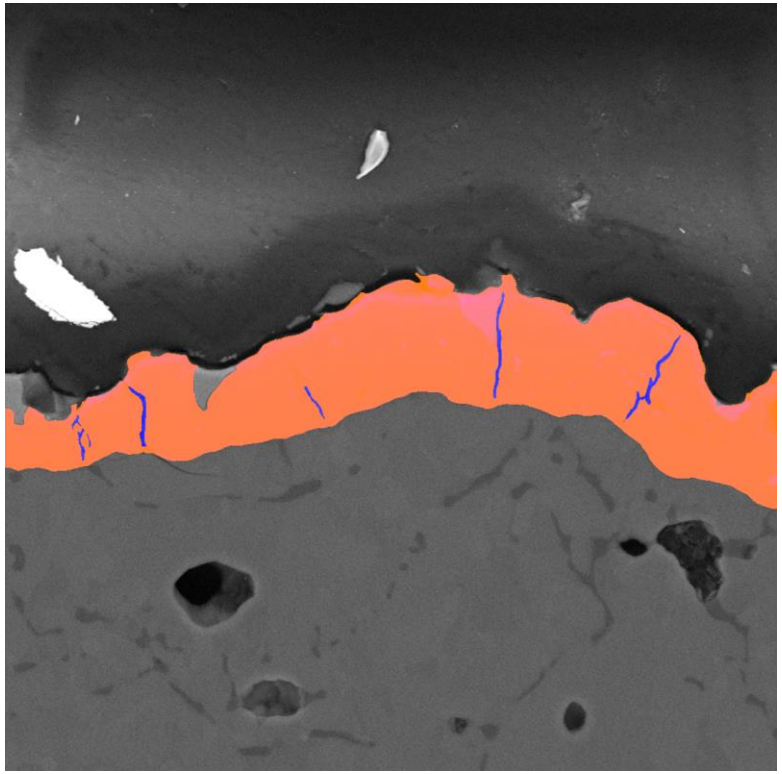




# Applications







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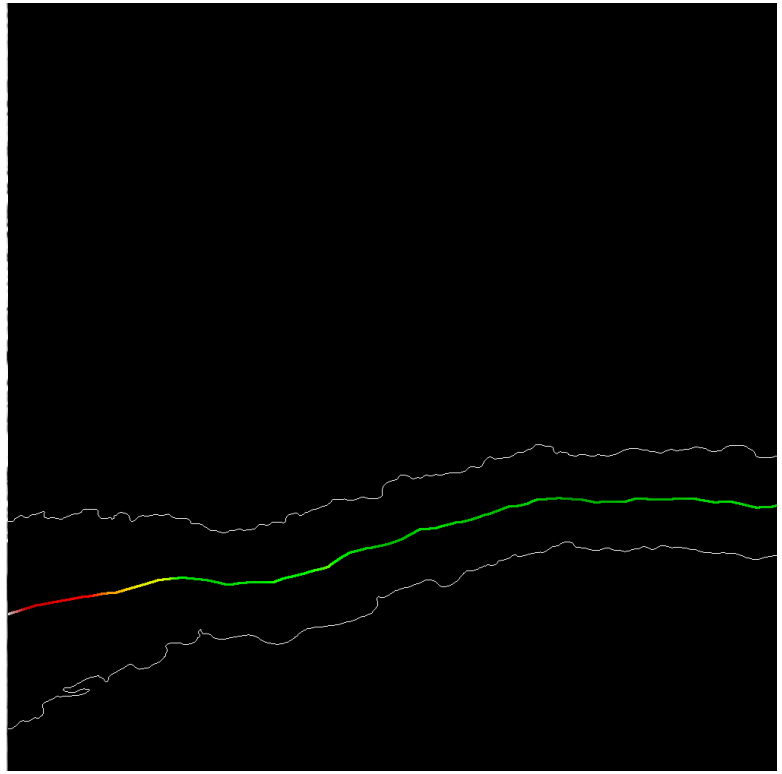

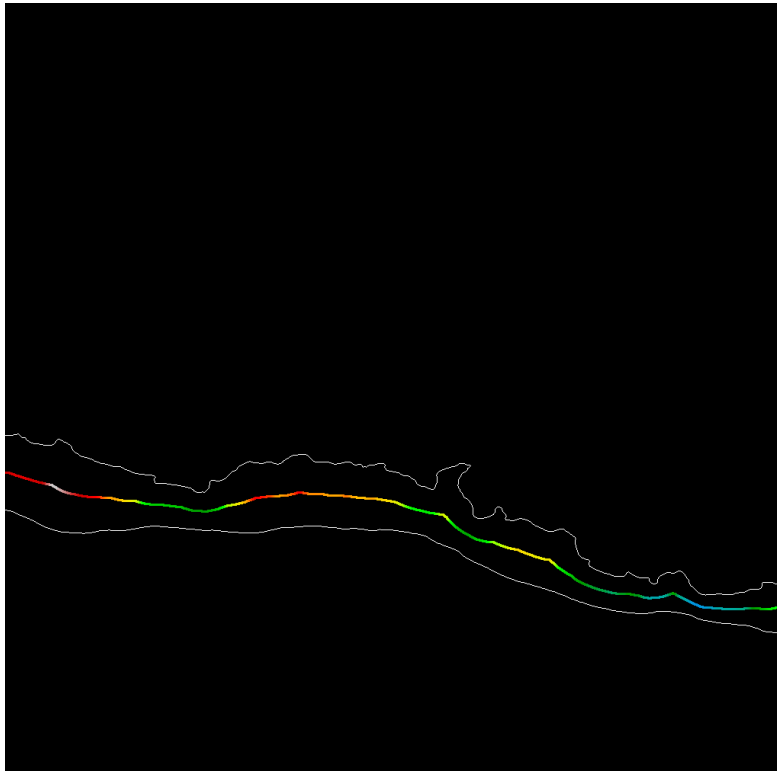

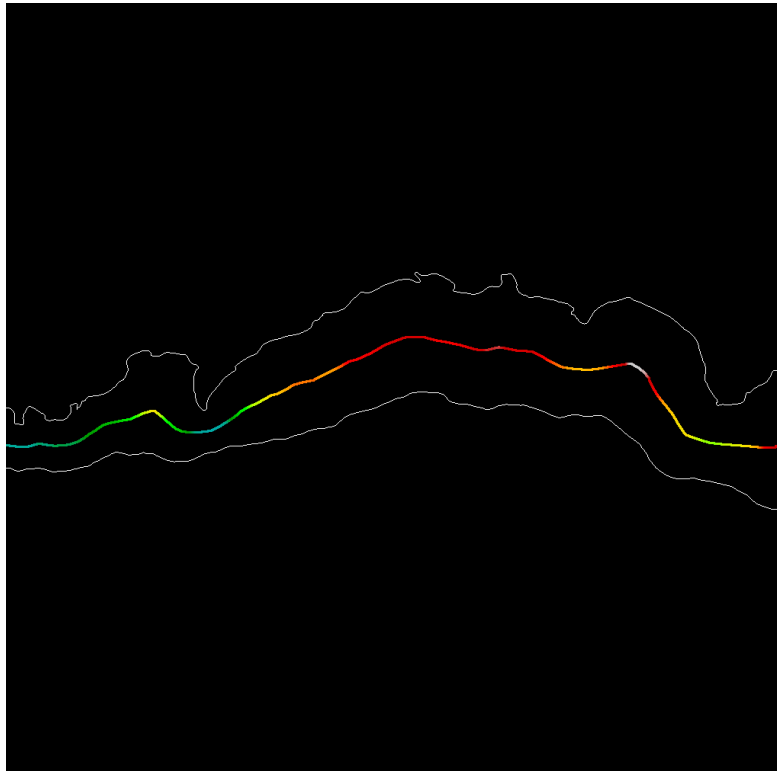

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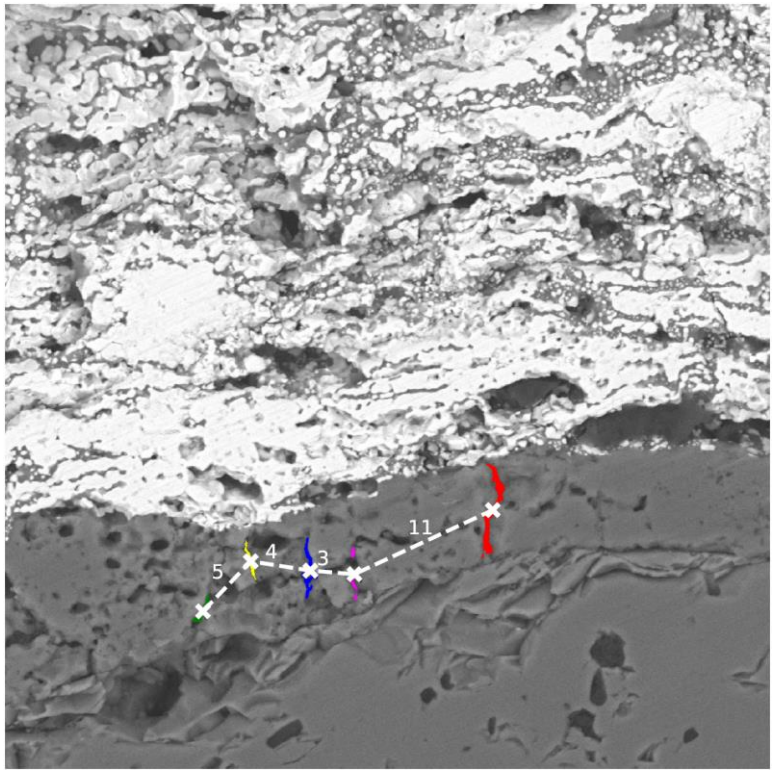
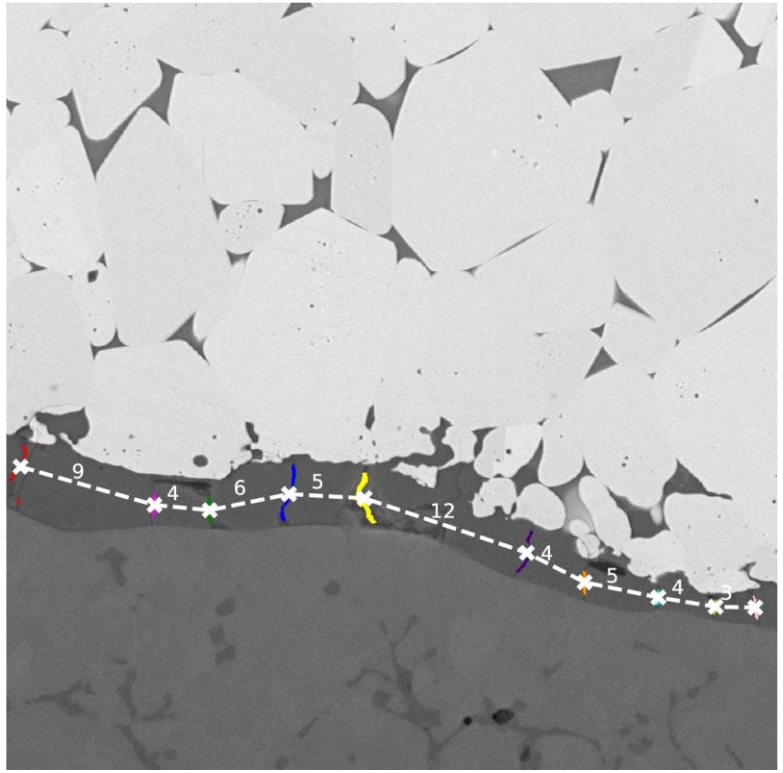
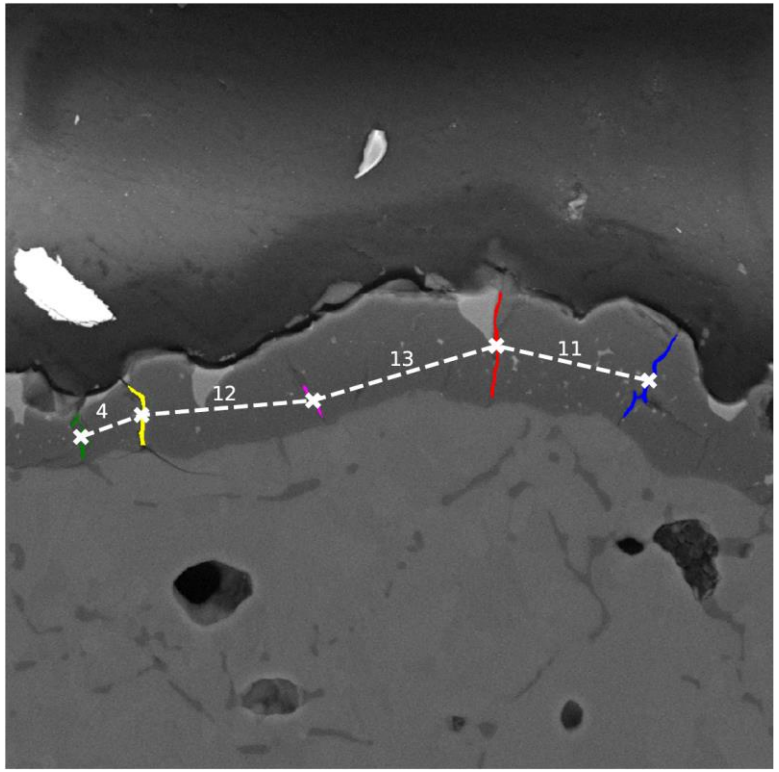
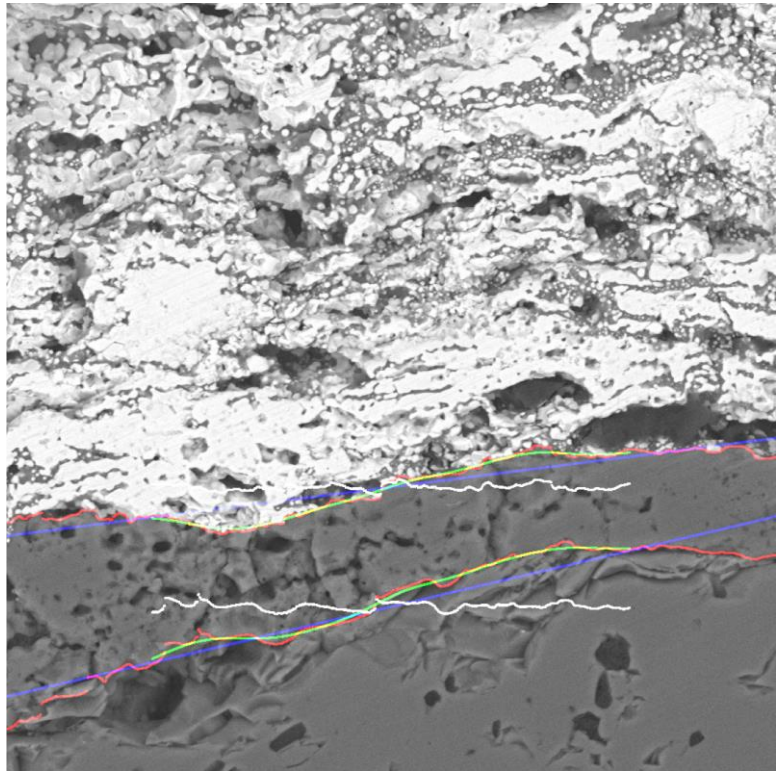
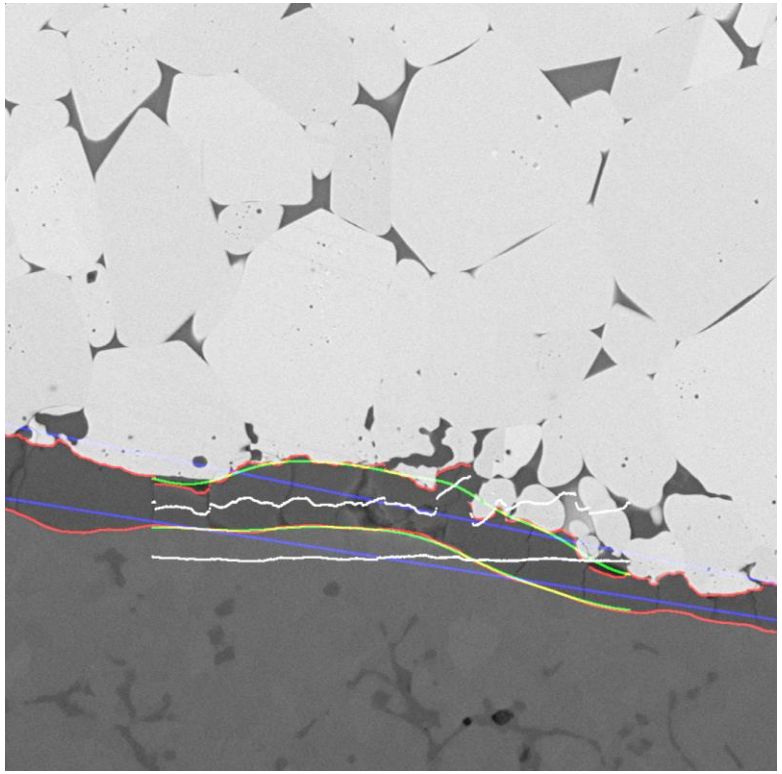


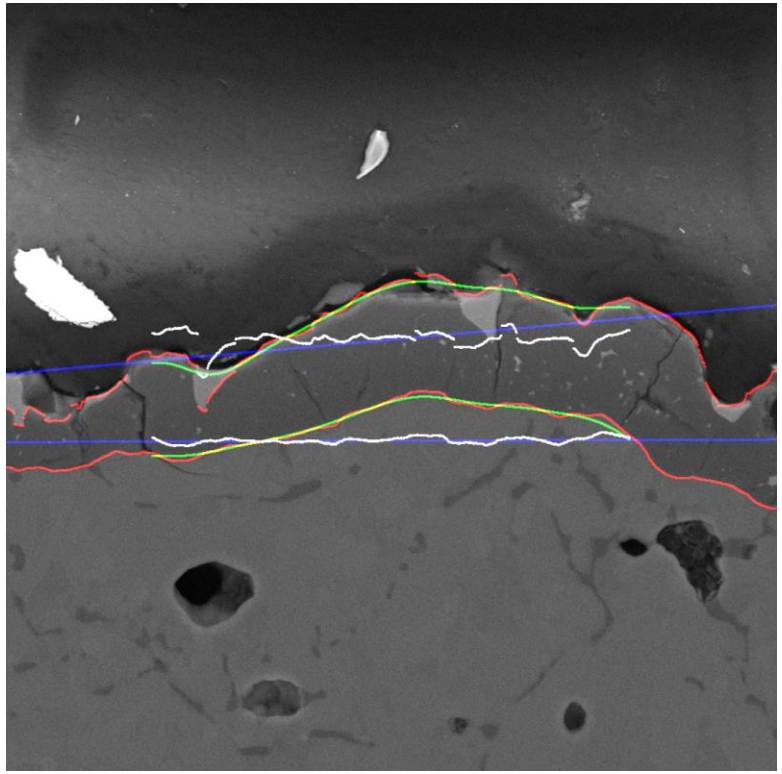



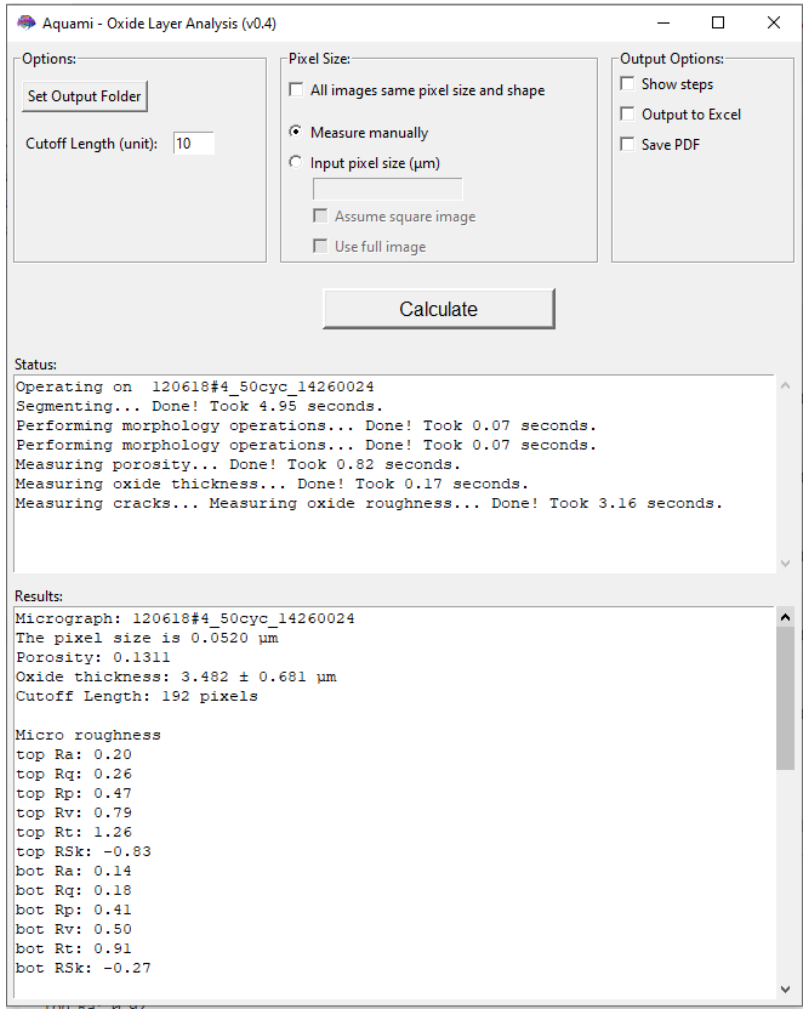
# Applications

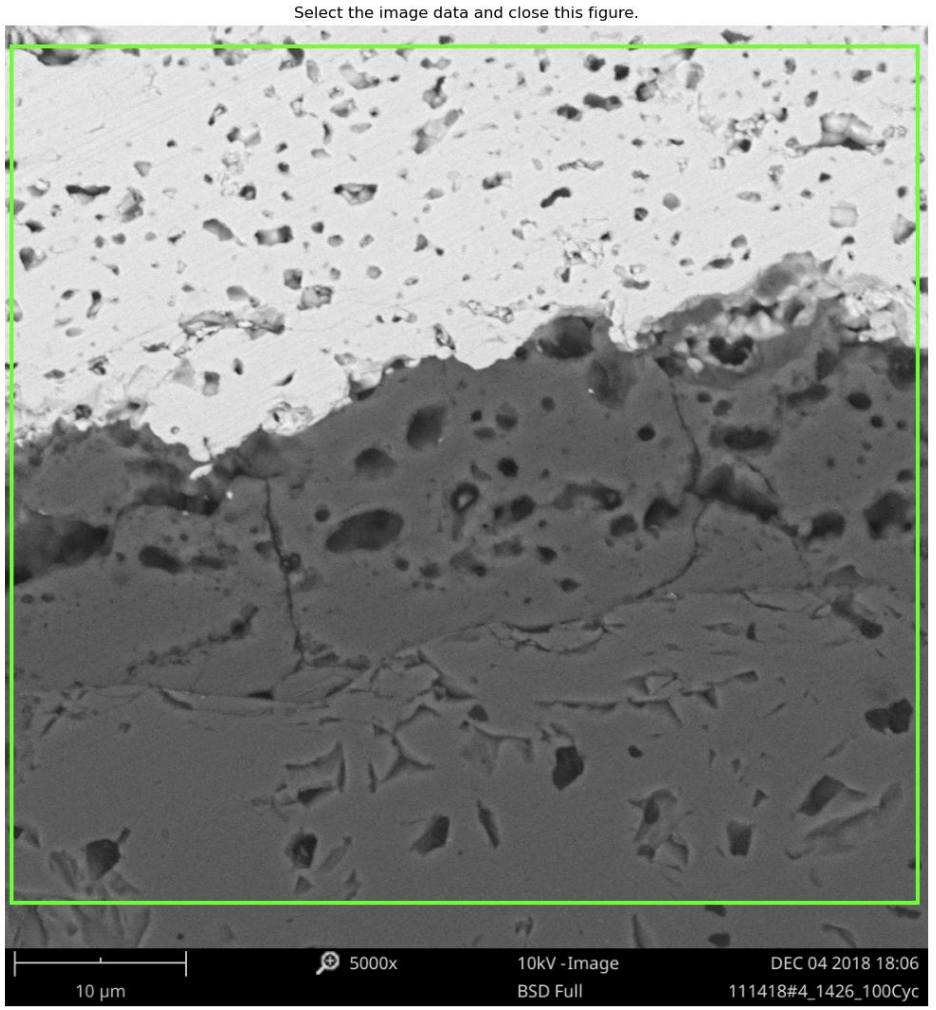




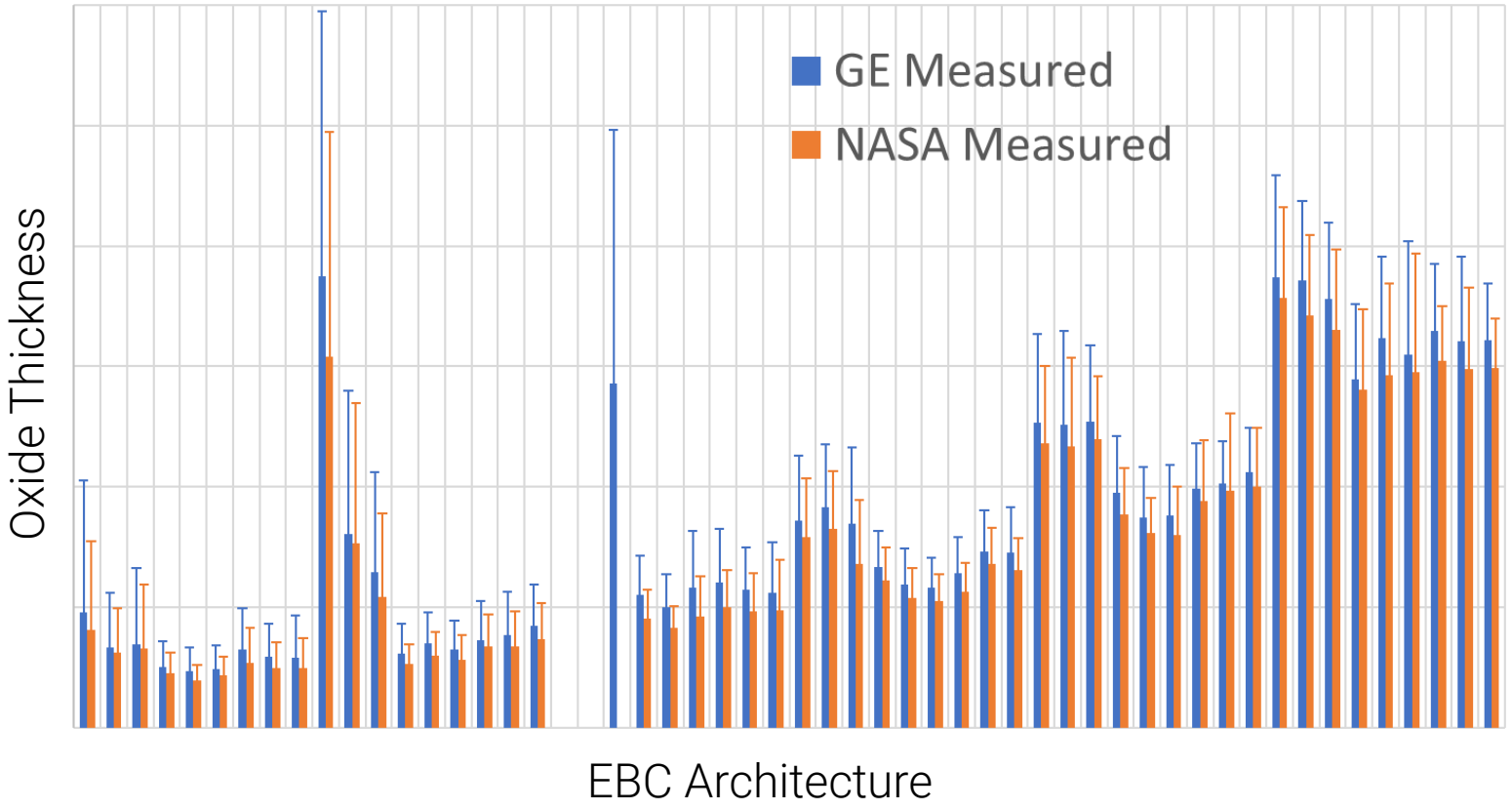


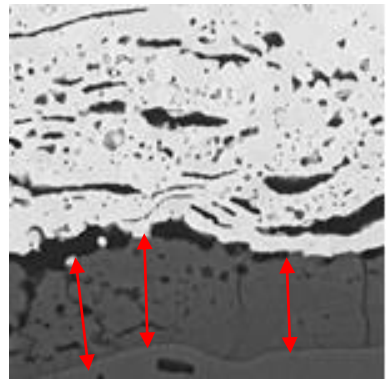
# Open-Source Software GUI

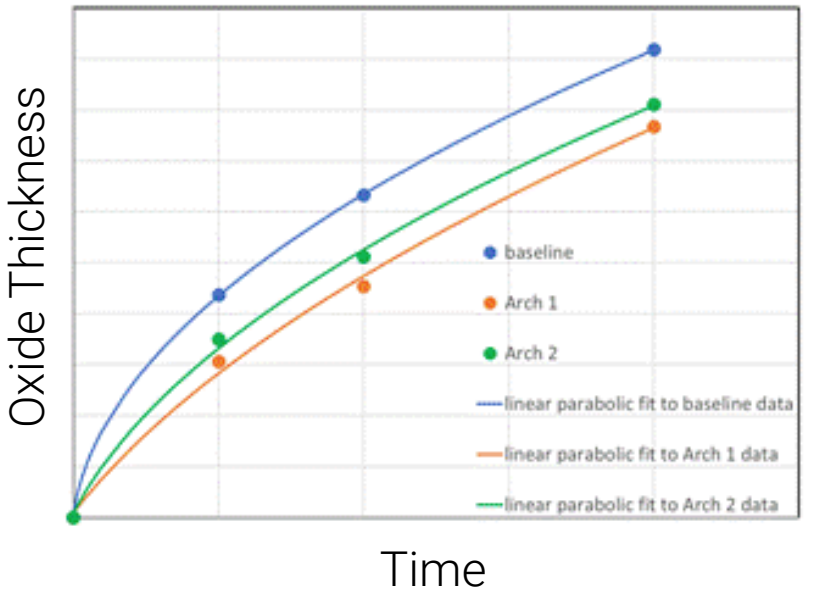


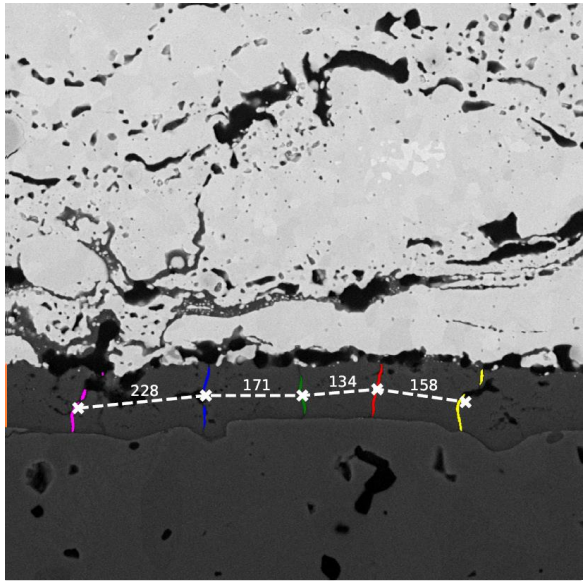
# Applications

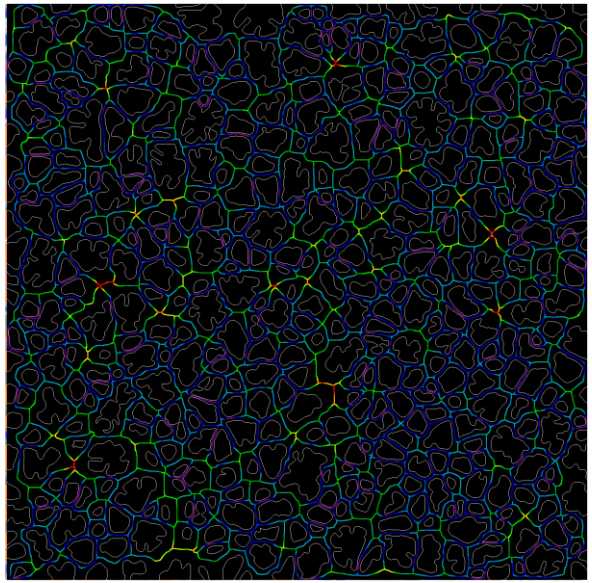


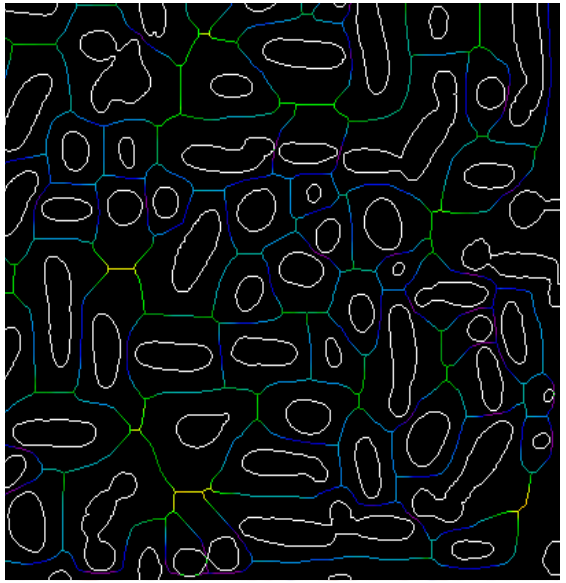



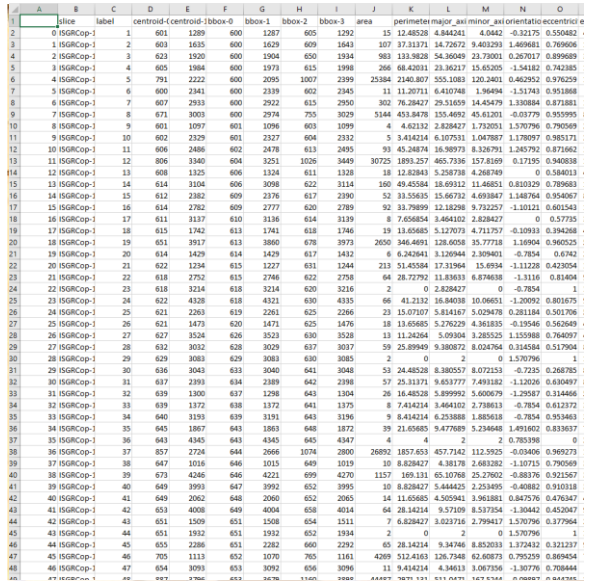


# Applications







| | slice | label | centroid-0 | centroid-1 | bbox-0 | bbox-1 | bbox-2 | bbox-3 | area | perimeter | major_axi | minor_axi | orientatio | eccentricit |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | ISGRCop-1 | 1 | 601 | 1289 | 600 | 1287 | 605 | 1292 | 15 | 12.48528 | 4.844241 | 4.0442 | -0.32175 | 0.550482 |
| 1 | ISGRCop-1 | 2 | 603 | 1635 | 600 | 1629 | 609 | 1643 | 107 | 37.31371 | 14.72672 | 9.401293 | 1.469681 | 0.769606 |
| 2 | ISGRCop-1 | 3 | 623 | 1920 | 600 | 1904 | 650 | 1934 | 983 | 133.9828 | 54.36049 | 23.73001 | 0.267017 | 0.899689 |
| 3 | ISGRCop-1 | 4 | 605 | 1984 | 600 | 1973 | 615 | 1998 | 266 | 68.42031 | 23.36217 | 15.65205 | -1.54182 | 0.742385 |
| 4 | ISGRCop-1 | 5 | 791 | 2222 | 600 | 2095 | 1007 | 2399 | 25384 | 2140.807 | 555.1083 | 120.2401 | 0.462952 | 0.976259 |
| 5 | ISGRCop-1 | 6 | 600 | 2341 | 600 | 2339 | 602 | 2345 | 11 | 11.20711 | 6.410748 | 1.96494 | -1.51743 | 0.951868 |
| 6 | ISGRCop-1 | 7 | 607 | 2933 | 600 | 2922 | 615 | 2950 | 302 | 76.28427 | 29.51659 | 14.45479 | 1.330884 | 0.871881 |
| 7 | ISGRCop-1 | 8 | 671 | 3003 | 600 | 2974 | 755 | 3029 | 5144 | 453.8478 | 155.4692 | 45.61201 | -0.03779 | 0.955995 |
| 8 | ISGRCop-1 | 9 | 601 | 1097 | 601 | 1096 | 603 | 1099 | 4 | 4.62132 | 2.828427 | 1.732051 | 1.570796 | 0.790569 |
| 9 | ISGRCop-1 | 10 | 602 | 2329 | 601 | 2327 | 604 | 2332 | 5 | 3.414214 | 6.107531 | 1.047887 | 1.178097 | 0.985171 |
| 10 | ISGRCop-1 | 11 | 606 | 2486 | 602 | 2478 | 613 | 2495 | 93 | 45.24874 | 16.98973 | 8.326791 | 1.245792 | 0.871662 |
| 11 | ISGRCop-1 | 12 | 806 | 3340 | 604 | 3251 | 1026 | 3449 | 30725 | 1893.257 | 465.7336 | 157.8169 | 0.17195 | 0.940838 |
| 12 | ISGRCop-1 | 13 | 608 | 1325 | 606 | 1324 | 611 | 1328 | 18 | 12.82843 | 5.258738 | 4.268749 | -0 | 0.584013 |
| 13 | ISGRCop-1 | 14 | 614 | 3104 | 606 | 3098 | 622 | 3114 | 160 | 49.45584 | 18.69312 | 11.46851 | 0.810329 | 0.789683 |
| 14 | ISGRCop-1 | 15 | 612 | 2382 | 609 | 2376 | 617 | 2390 | 52 | 33.55635 | 15.66732 | 4.693847 | 1.148764 | 0.954067 |
| 15 | ISGRCop-1 | 16 | 614 | 2782 | 609 | 2777 | 620 | 2789 | 92 | 33.79899 | 12.18298 | 9.732257 | -1.10121 | 0.601543 |
| 16 | ISGRCop-1 | 17 | 611 | 3137 | 610 | 3136 | 614 | 3139 | 8 | 7.656854 | 3.464102 | 2.828427 | 0 | 0.57735 |
| 17 | ISGRCop-1 | 18 | 615 | 1742 | 613 | 1741 | 618 | 1746 | 19 | 13.65685 | 5.127073 | 4.711757 | -0.10933 | 0.394268 |
| 18 | ISGRCop-1 | 19 | 651 | 3917 | 613 | 3860 | 678 | 3973 | 2650 | 346.4691 | 128.6058 | 35.77718 | 1.16904 | 0.960525 |
| 19 | ISGRCop-1 | 20 | 614 | 1429 | 614 | 1429 | 617 | 1432 | 6 | 6.242641 | 3.126944 | 2.309401 | -0.7854 | 0.6742 |
| 20 | ISGRCop-1 | 21 | 622 | 1234 | 615 | 1227 | 631 | 1244 | 213 | 51.45584 | 17.31964 | 15.6934 | -1.11228 | 0.423054 |
| 21 | ISGRCop-1 | 22 | 618 | 2752 | 615 | 2746 | 622 | 2758 | 64 | 28.72792 | 11.83633 | 6.874638 | -1.3116 | 0.81404 |
| 22 | ISGRCop-1 | 23 | 618 | 3214 | 618 | 3214 | 620 | 3216 | 2 | 0 | 2.828427 | 0 | -0.7854 | 1 |
| 23 | ISGRCop-1 | 24 | 622 | 4328 | 618 | 4321 | 630 | 4335 | 66 | 41.2132 | 16.84038 | 10.06651 | -1.20092 | 0.801675 |
| 24 | ISGRCop-1 | 25 | 621 | 2263 | 619 | 2261 | 625 | 2266 | 23 | 15.07107 | 5.814167 | 5.029478 | 0.281184 | 0.501706 |
| 25 | ISGRCop-1 | 26 | 621 | 1473 | 620 | 1471 | 625 | 1476 | 18 | 13.65685 | 5.276229 | 4.361835 | -0.19546 | 0.562649 |
| 26 | ISGRCop-1 | 27 | 627 | 3524 | 626 | 3523 | 630 | 3528 | 13 | 11.24264 | 5.09304 | 3.285525 | 1.155988 | 0.764097 |
| 27 | ISGRCop-1 | 28 | 632 | 3032 | 628 | 3029 | 637 | 3037 | 59 | 25.89949 | 9.380872 | 8.024764 | 0.314584 | 0.517904 |
| 28 | ISGRCop-1 | 29 | 629 | 3083 | 629 | 3083 | 630 | 3085 | 2 | 0 | 2 | 0 | 1.570796 | 1 |
| 29 | ISGRCop-1 | 30 | 636 | 3043 | 633 | 3040 | 641 | 3048 | 53 | 24.48528 | 8.380557 | 8.072153 | -0.7235 | 0.268785 |
| 30 | ISGRCop-1 | 31 | 637 | 2393 | 634 | 2389 | 642 | 2398 | 57 | 25.31371 | 9.651777 | 7.491182 | -1.12026 | 0.630497 |
| 31 | ISGRCop-1 | 32 | 639 | 1300 | 637 | 1298 | 643 | 1304 | 26 | 16.48528 | 5.899992 | 5.600679 | -1.29587 | 0.314466 |
| 32 | ISGRCop-1 | 33 | 639 | 1372 | 638 | 1372 | 641 | 1375 | 8 | 7.414214 | 3.464102 | 2.738613 | -0.7854 | 0.612372 |
| 33 | ISGRCop-1 | 34 | 640 | 3193 | 639 | 3191 | 643 | 3196 | 9 | 8.414214 | 6.253888 | 1.885618 | -0.7854 | 0.953463 |
| 34 | ISGRCop-1 | 35 | 645 | 1867 | 643 | 1863 | 648 | 1872 | 39 | 21.65685 | 9.477689 | 5.234648 | 1.491602 | 0.833637 |
| 35 | ISGRCop-1 | 36 | 643 | 4345 | 643 | 4345 | 645 | 4347 | 4 | 4 | 2 | 2 | 0.785398 | 0 |
| 36 | ISGRCop-1 | 37 | 857 | 2724 | 644 | 2666 | 1074 | 2800 | 26892 | 1857.653 | 457.7142 | 112.5925 | -0.03406 | 0.969273 |
| 37 | ISGRCop-1 | 38 | 647 | 1016 | 646 | 1015 | 649 | 1019 | 10 | 8.828427 | 4.38178 | 2.683282 | -1.10715 | 0.790569 |
| 38 | ISGRCop-1 | 39 | 673 | 4246 | 646 | 4221 | 699 | 4270 | 1157 | 169.131 | 65.10768 | 25.27602 | -0.88376 | 0.921567 |
| 39 | ISGRCop-1 | 40 | 649 | 3993 | 647 | 3992 | 652 | 3995 | 10 | 8.828427 | 5.444425 | 2.253495 | -0.40882 | 0.910318 |
| 40 | ISGRCop-1 | 41 | 649 | 2062 | 648 | 2060 | 652 | 2065 | 14 | 11.65685 | 4.505941 | 3.961881 | 0.847576 | 0.476347 |
| 41 | ISGRCop-1 | 42 | 653 | 4008 | 649 | 4004 | 658 | 4014 | 64 | 28.14214 | 9.57109 | 8.537354 | -1.30442 | 0.452047 |
| 42 | ISGRCop-1 | 43 | 651 | 1509 | 651 | 1508 | 654 | 1511 | 7 | 6.828427 | 3.023716 | 2.799417 | 1.570796 | 0.377964 |
| 43 | ISGRCop-1 | 44 | 651 | 1932 | 651 | 1932 | 652 | 1934 | 2 | 0 | 2 | 0 | 1.570796 | 1 |
| 44 | ISGRCop-1 | 45 | 655 | 2286 | 651 | 2282 | 660 | 2292 | 65 | 28.14214 | 9.34746 | 8.852033 | 1.372432 | 0.321237 |
| 45 | ISGRCop-1 | 46 | 705 | 1113 | 652 | 1070 | 765 | 1161 | 4269 | 512.4163 | 126.7348 | 62.60873 | 0.795259 | 0.869454 |
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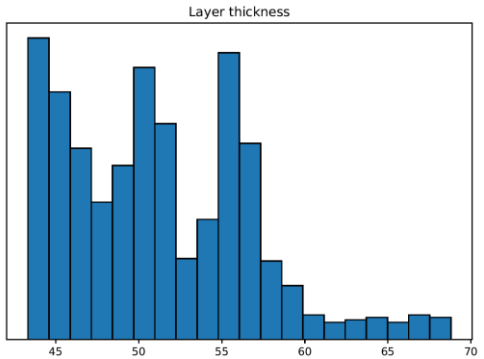
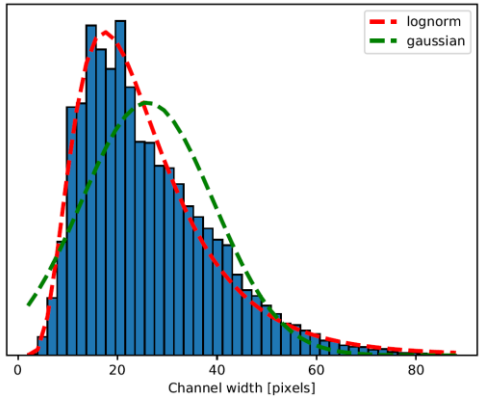
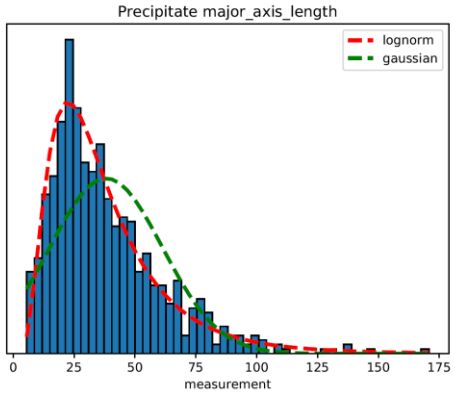
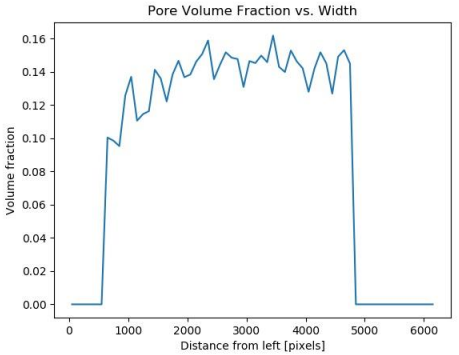


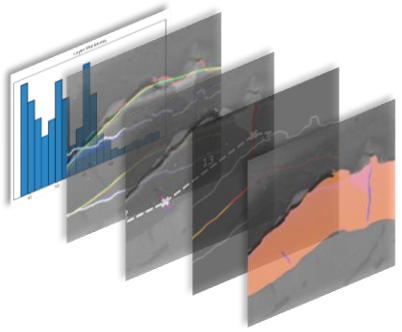



# Applications

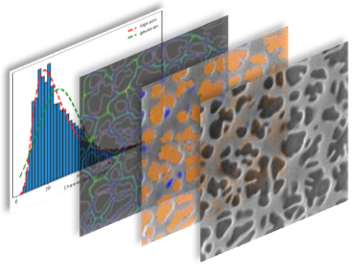
Microscopy Aware AI

MicroNet

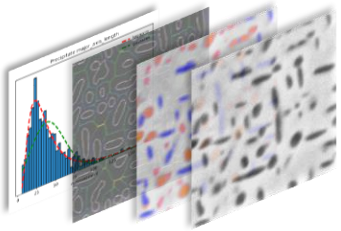
Environmental Barrier Coatings
- Quantifies: thickness, roughness, crack spacing



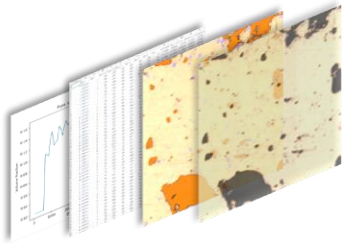
Ni-Superalloys
- Quantifies: area fraction, size, spacing, morphology



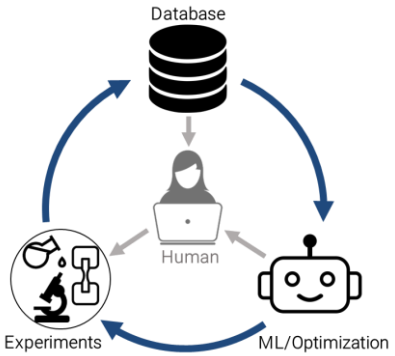
Inconel 718
- Quantifies: area fraction, size, aspect ratio, eccentricity



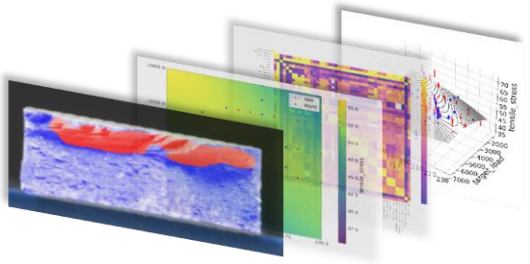
GRCop
- Quantifies: area fraction, aspect ratio, eccentricity
- Quantify massive Robomet datasets



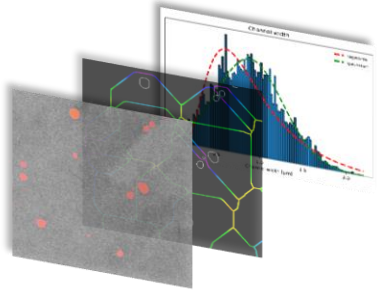
JARAMIS



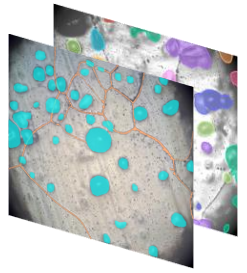

SLS Core Stage Welds
- Quantifies: defect features
- Link process feedback to defects
- Improve process window



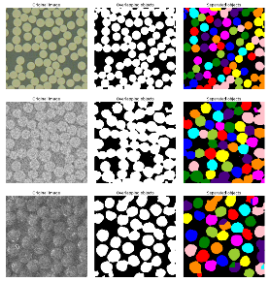
ODS Alloys



Wind tunnel Icing

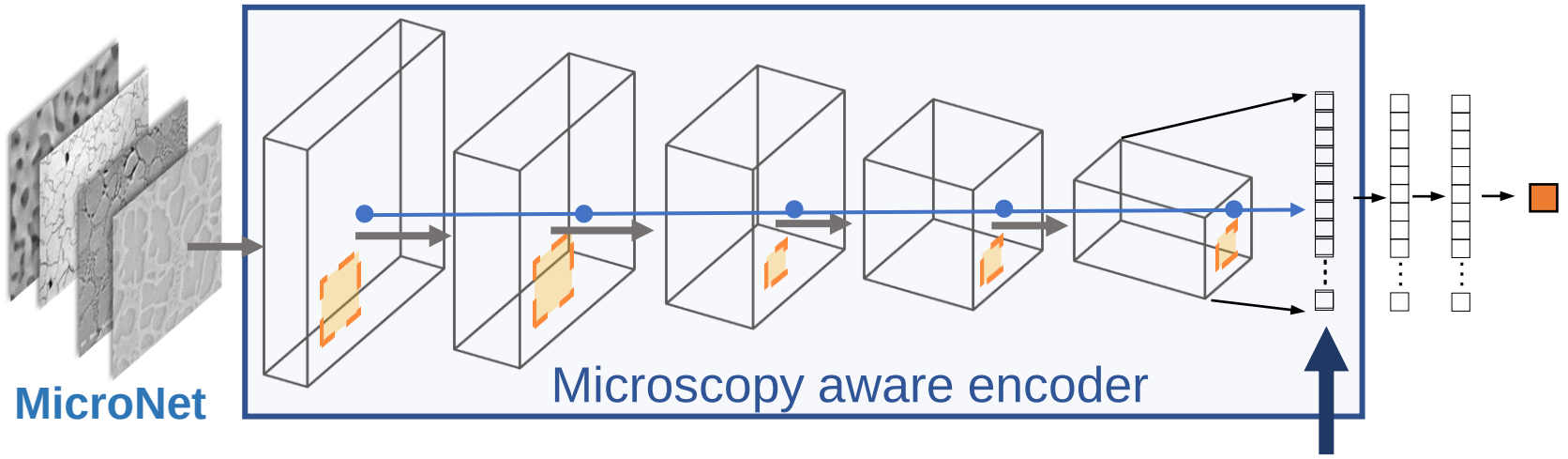


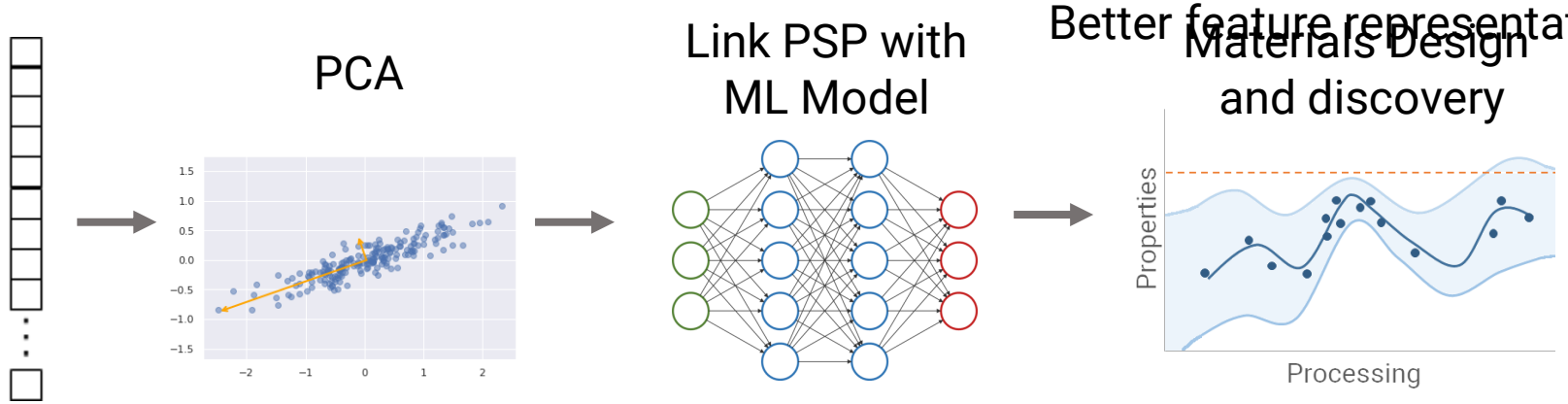
Composite Fibers



AI/ML Microstructure Toolkit
- with ASM International
- Automatically featurize ANY microstructure
- Used to establish PSPP relationships

# Applications

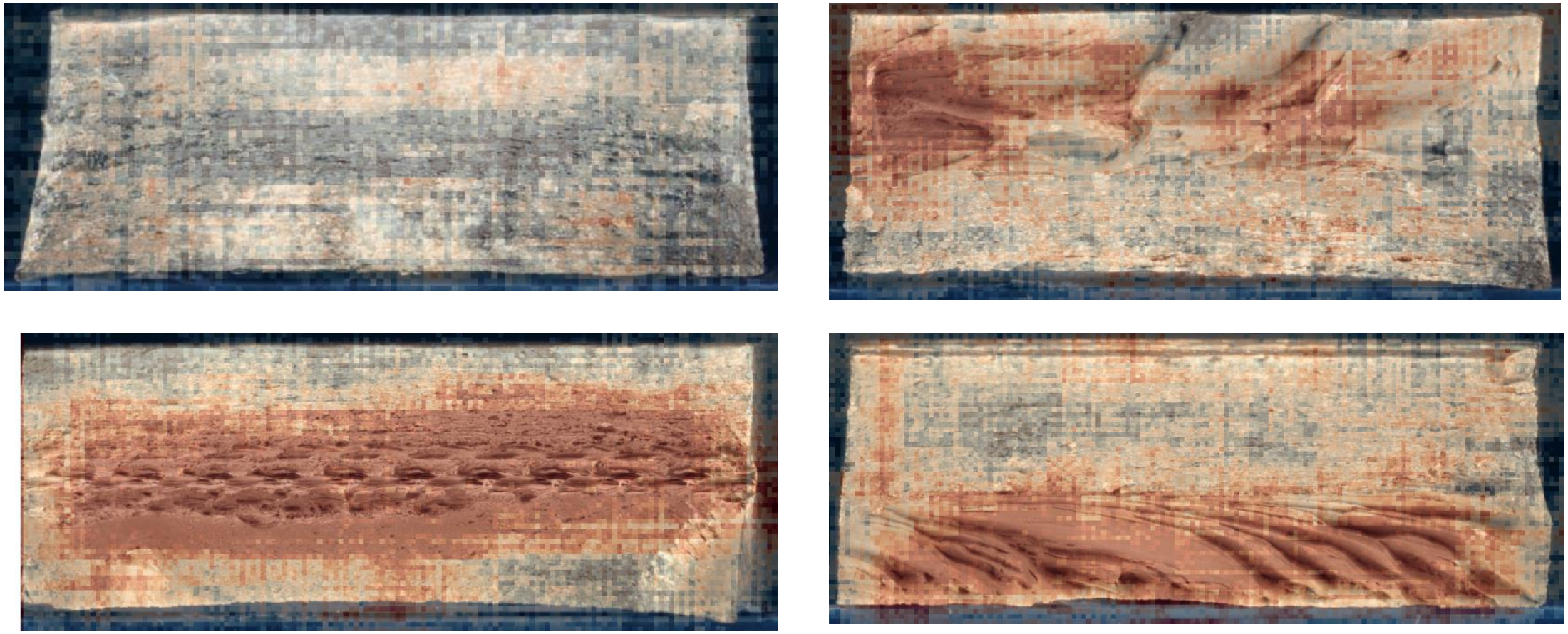


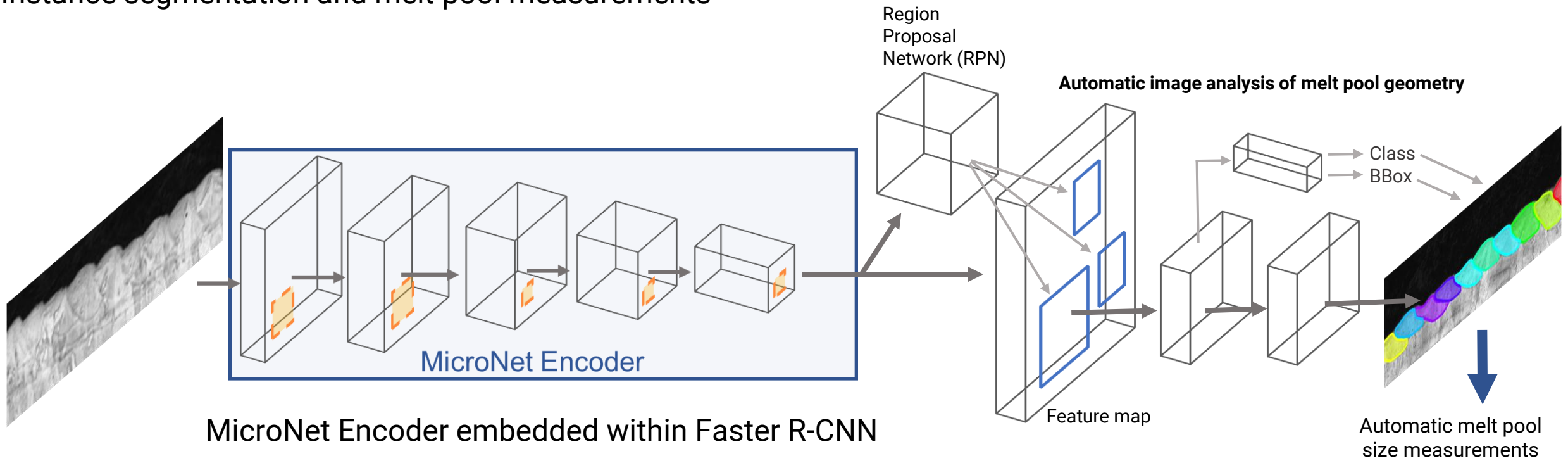


1. R. Noraas, et al., “Structural Material Property Tailoring Using Deep Neural Networks,” in *AIAA Scitech 2019 Forum*, 2019, p. 1703.
2. M. Larmuseau, et al., “Compact representations of microstructure images using triplet networks,” npj Comput. Mater., vol. 6, no. 1, 2020
3. B. L. DeCost, et al., “High throughput quantitative metallography for complex microstructures using deep learning: A case study in ultrahigh carbon steel,” Microsc. Microanal., vol. 25, 2019

## Direct regression and patch prediction



## Instance segmentation and melt pool measurements




MicroNet Encoder embedded within Faster R-CNN

1. Cohn, Ryan, et al. "Instance segmentation for direct measurements of satellites in metal powders and automated microstructural characterization from image data." JOM 73.7 (2021): 2159-2172.
2. He, Kaiming, et al. "Mask r-cnn." Proceedings of the IEEE international conference on computer vision. 2017.

- General microstructure aware pre-trained encoders
  - Higher accuracy with less training data
  - More robust to changes in imaging and sample conditions
- Automatically extract microstructure features to establish processing-structure-processing relationships
- Can easily be applied to any computer vision architecture that utilizes pre-trained CNNs
- All code and models are open-source and easy to use with examples

# Code