Deep Active Learning for Segmentation of Biodegradable Bone Implants in High Resolution Synchrotron Radiation Microtomograms

Bashir Kazimi[1], Julian Moosmann[1], Sahar Kakavand[2], Ivo Baltruschat[2] and Philipp Heuser[2]

[1] Institute of Materials Physics, Helmholtz-Zentrum Hereon
[2] Deutsches Elektronen-Synchrotron DESY

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bashir.kazimi@hereon.de
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Project

- **Universal Segmentation Framework (UniSeF)**: Funded by Helmholtz AI
- PETRA III @DESY
  - Storage ring based X-ray sources for high energy photons
  - Multiple beamlines
- P05 Imaging Beamline
  - Micro and Nano tomography
  - Used for different applications
  - Problem:
    - Preprocessing and annotation
    - Segmentation and postprocessing
    - ➔ Very time-consuming
  - **Proposed Solution:**
    - An easy-to-use, guided, interactive and iterative framework for data annotation and deep learning based segmentation
    - A browser-based service
      - Available for diverse tasks by users at the beamline

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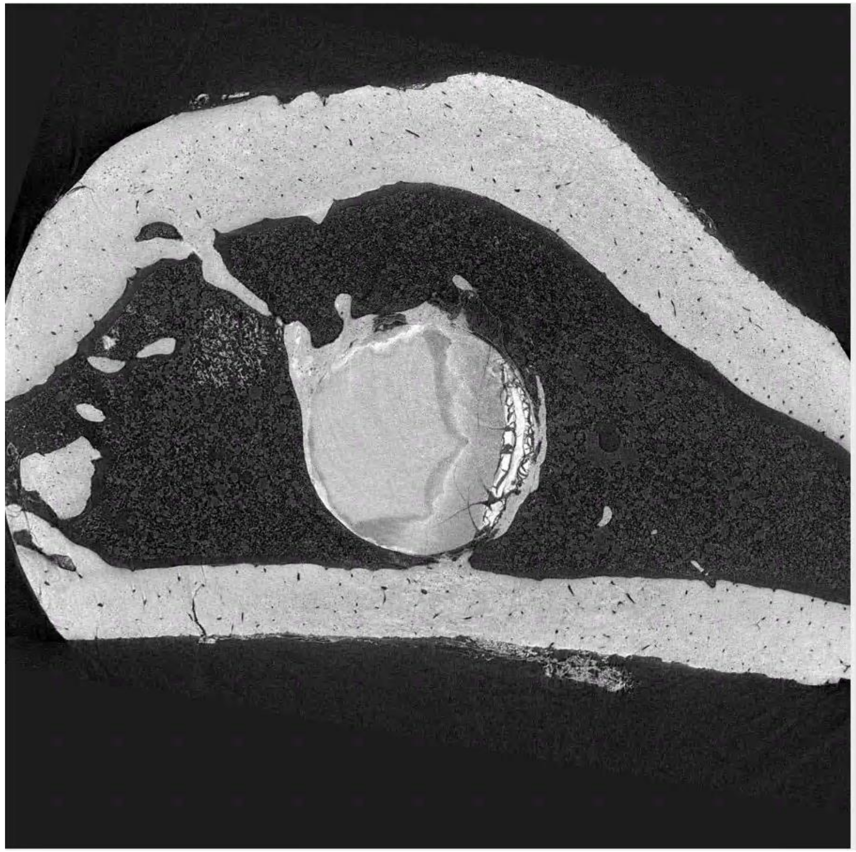
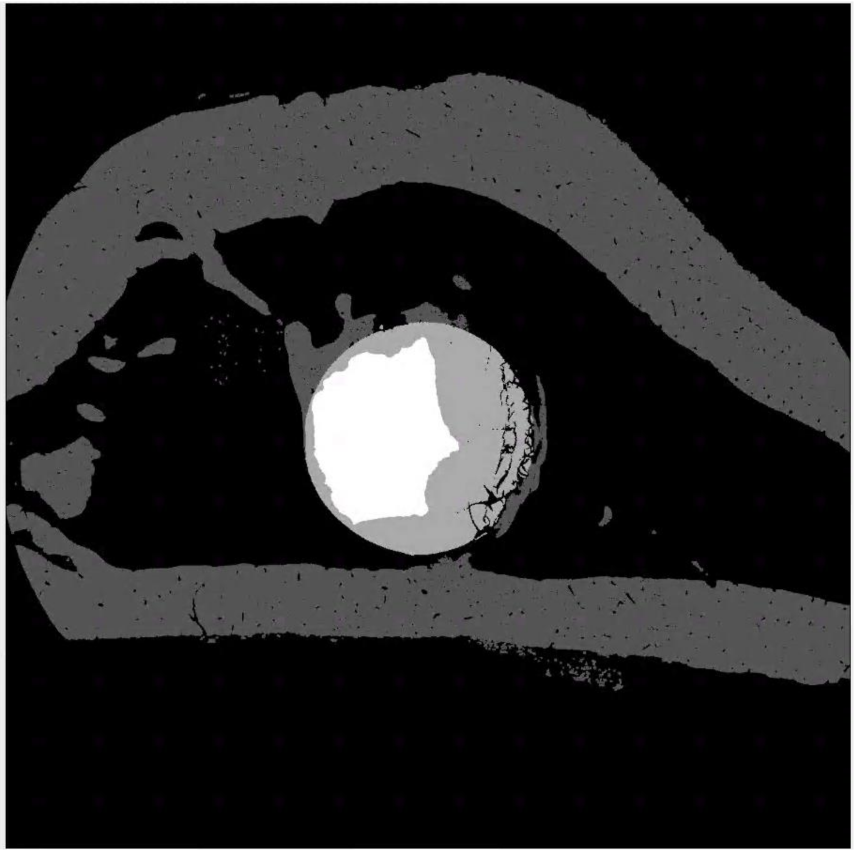
Current Talk

- **Segmentation of biodegradable implants in SRµCT data**



Image



Segmentation Mask

Background

Bone

Corroded Screw

Screw

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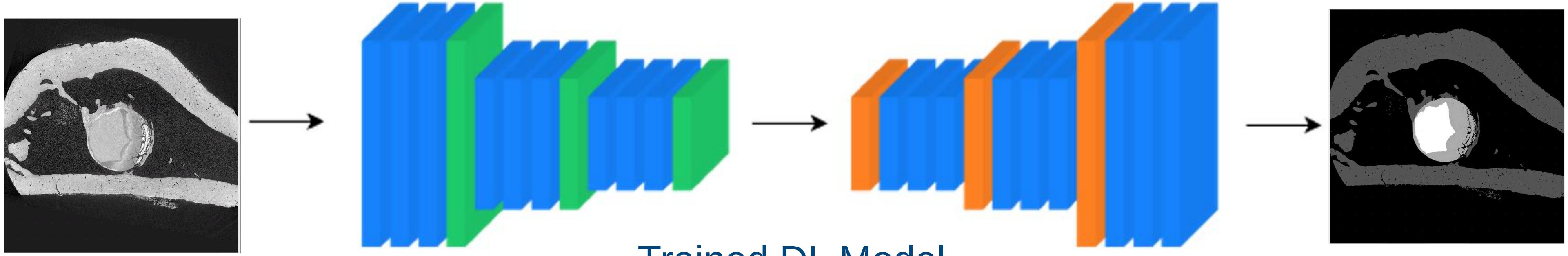
Methods

- ➢ **Supervised Deep Learning with Annotated Datasets**



Input Image

Trained DL Model

Learned segmentation mask

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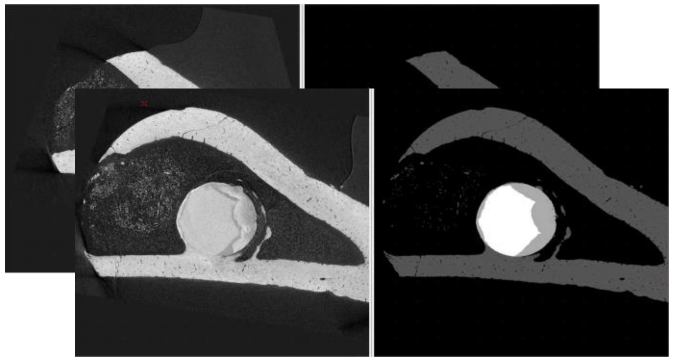
Challenges

- Lots of annotations required !!!



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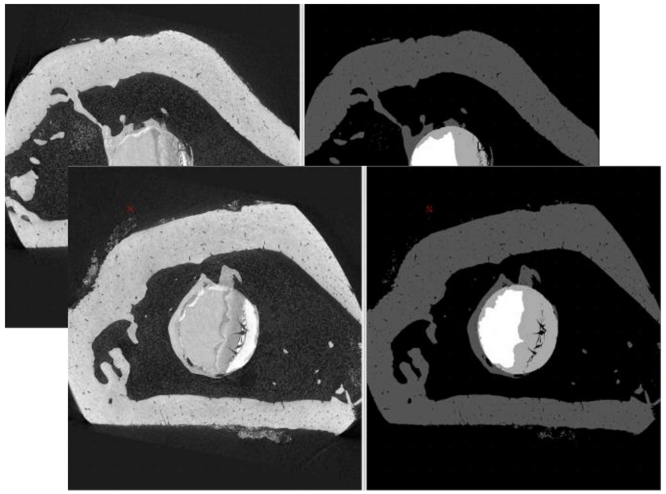
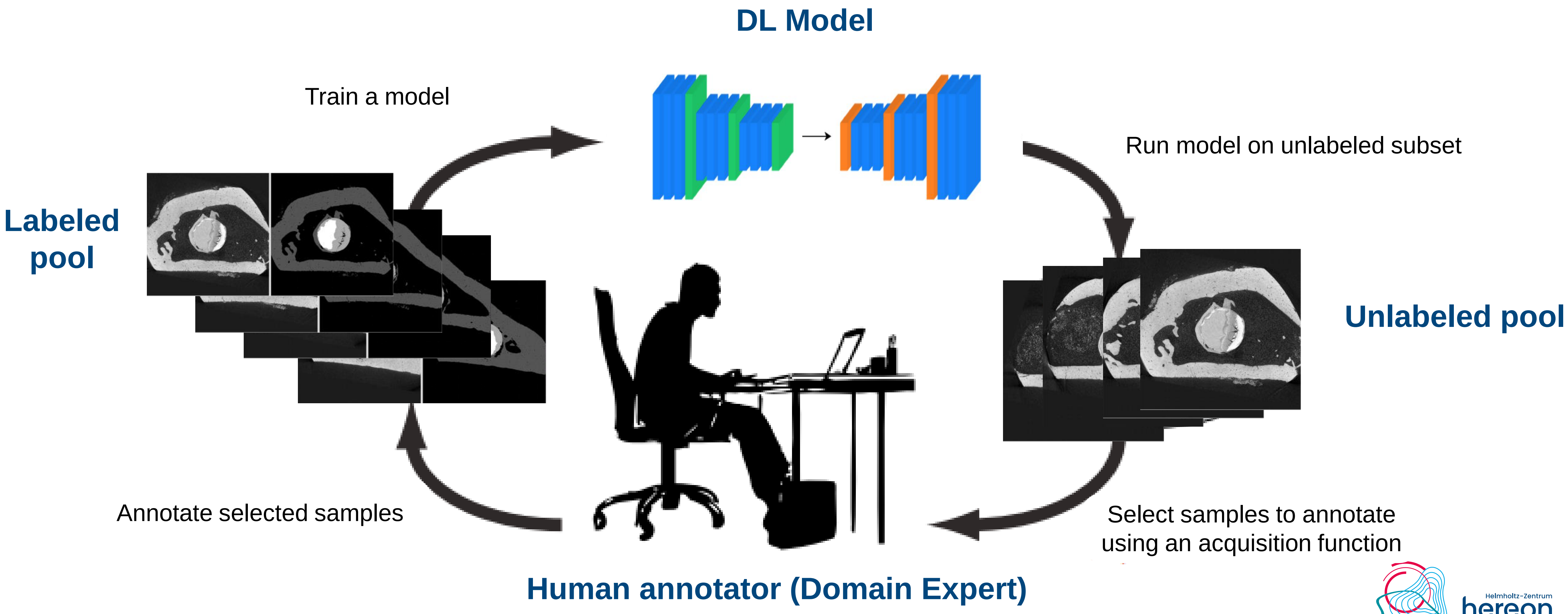


Solution

- Deep Active Learning



Acquisition Functions

- **Random:**
  - K random unlabeled images selected and annotated
- **Softmax Confidence:**
  - Sum of highest probabilities for all pixels is calculated

$$S_I^{\mathrm{CONF}} = \sum_i^I \max p(y_{i,C} | x_i; \theta_{\mathrm{SEG}})$$

  - K samples with the least confidence scores are selected for annotation

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Acquisition Functions

- **Coreset**
  - Use labeled samples c^i as cluster centers
  - Calculated pairwise distance between c^i and unlabeled samples u^j
  - Select K samples with the smallest distance from their closest cluster centers
- Other functions (explained in Appendix):
  - Softmax Entropy
  - Maximum Representation
  - Monte Carlo Dropout
  - Softmax Margin
  - Cost Effective Active Learning (CEAL)

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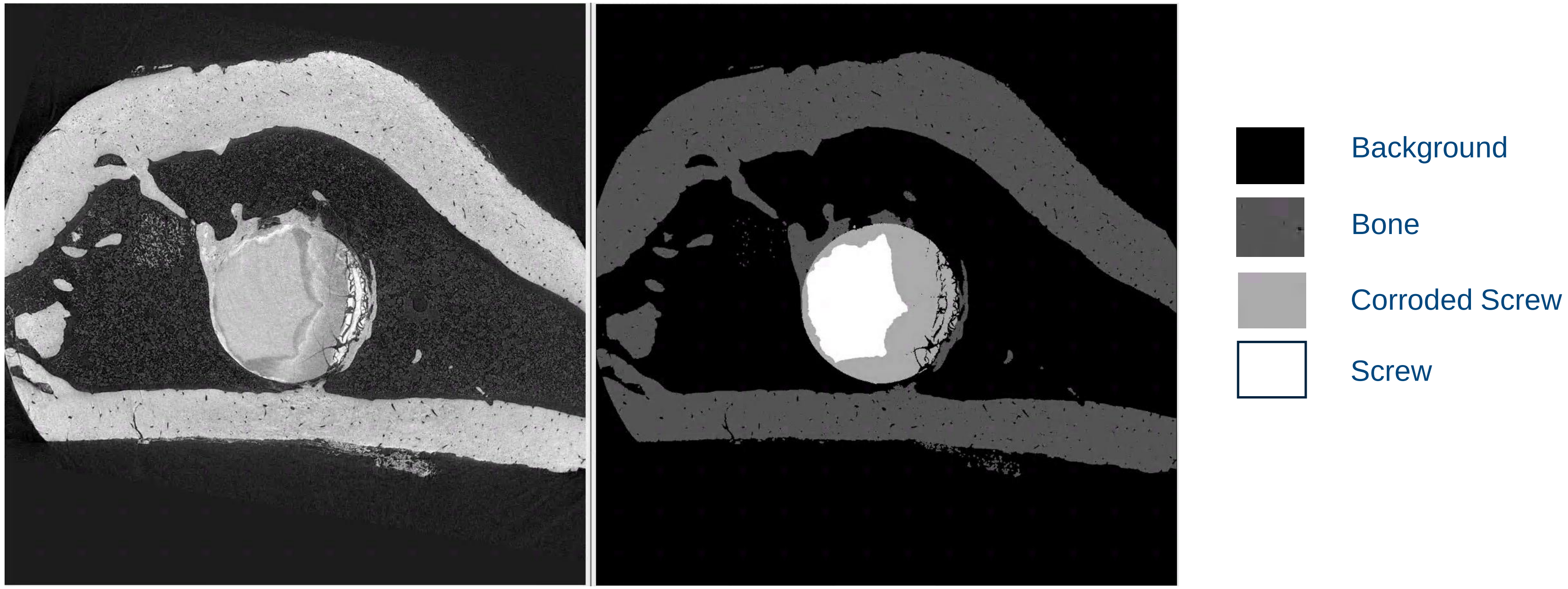
Experiments: Dataset

- 6878 images for training
- 5591 images for validation
- 6000 images for testing



Image

Segmentation Mask

Experiments: Setup

- Python + PyTorch
- High Resolution Network (HRNet) [Sun et al., 2019]
- 10 active learning rounds
- 8 images selected for annotation in each round
- Model evaluated on test set after each round

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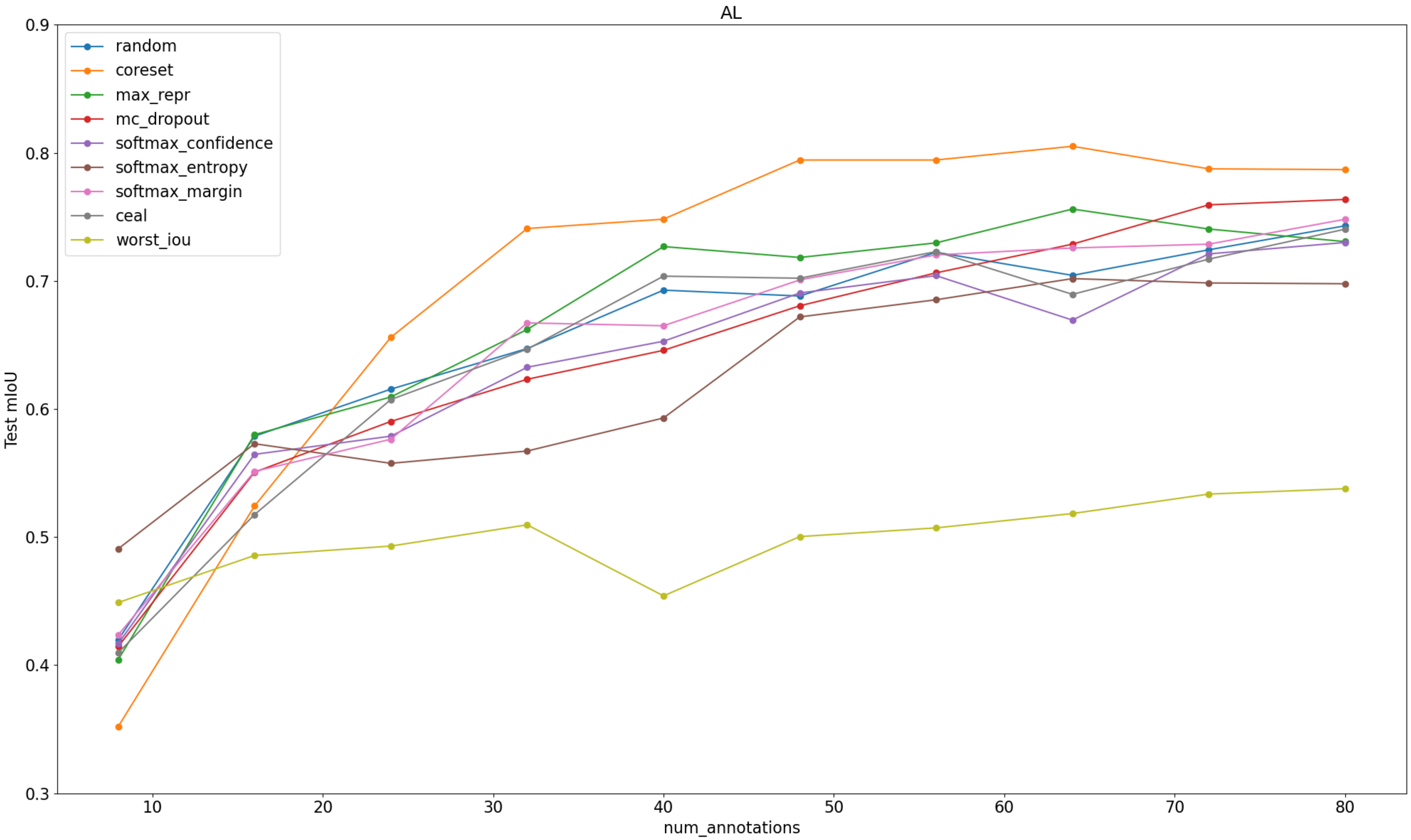
Experiments: Results



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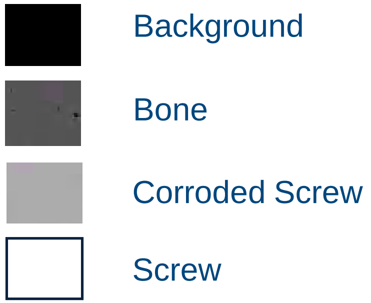
Experiments: Results

Acquisition Function	Test mIoU Score
Coreset	0,8051
Random	0,743
Maximum Representation	0,7561
Softmax Margin	0,7481
Monte Carlo Dropout	0,7636
Softmax Confidence	0,73
CEAL	0,7404
Softmax Entropy	0,7018
Worst IoU Score	0,5378
Fully Suppervised	0,829070518

Experiments: Results



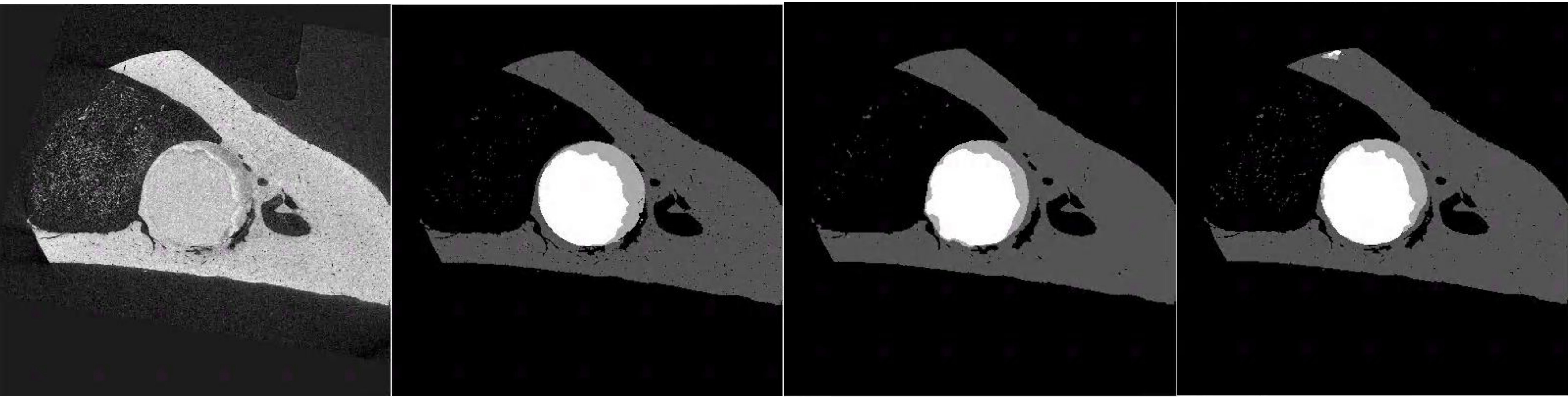


Image | Segmentation Mask | Active Learning (Coreset) | Full Supervised Learning

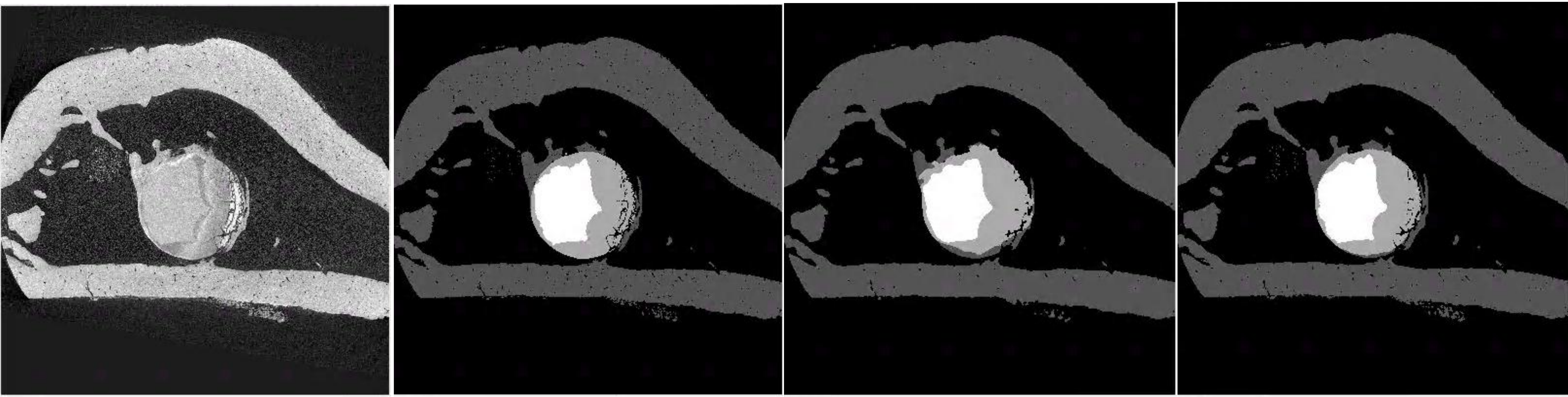
Experiments: Results

Background

Bone

Corroded Screw

Screw



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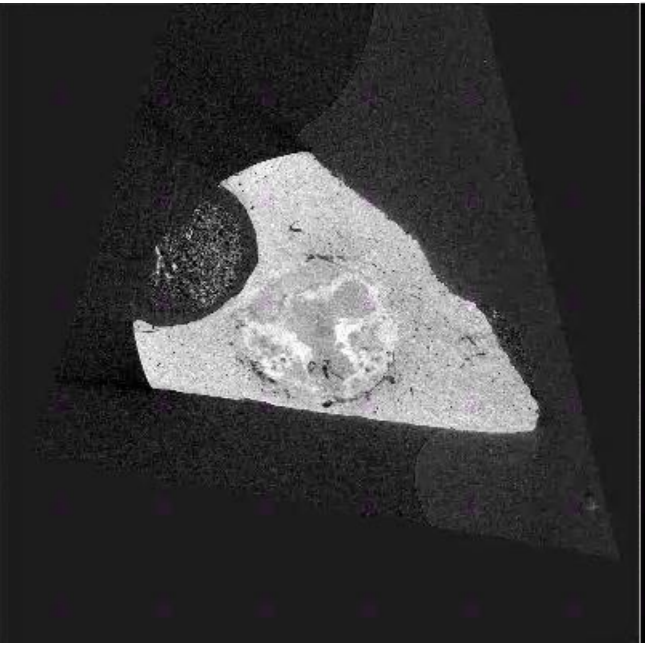

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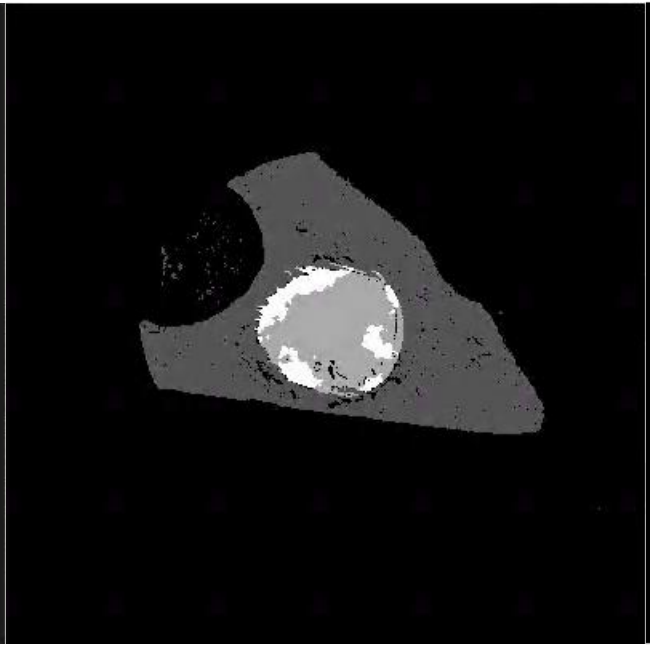
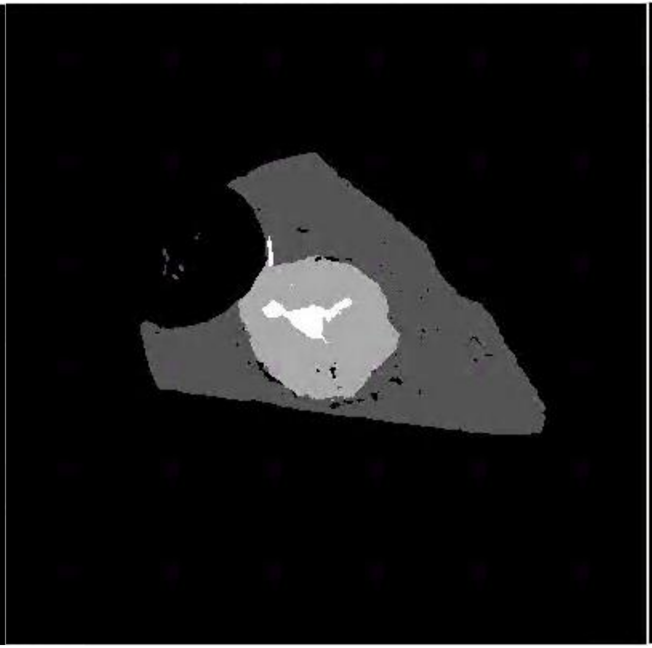
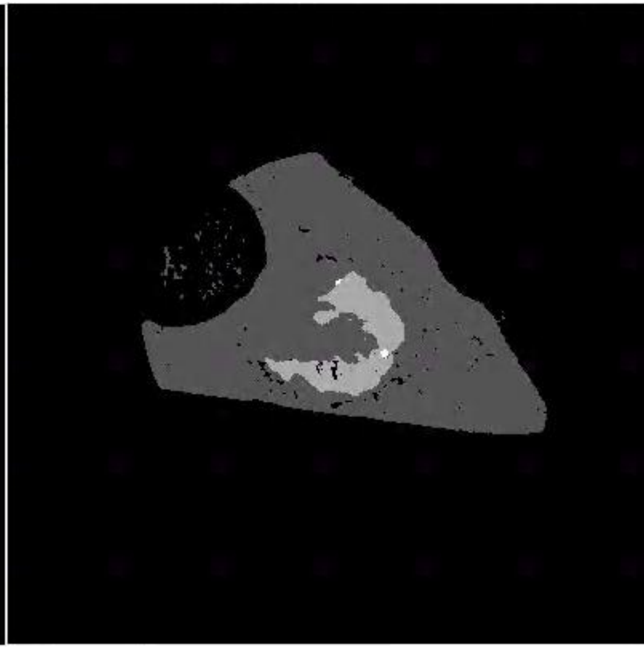


Segmentation Mask



Active Learning (Coreset)



Full Supervised Learning

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Experiments: Results

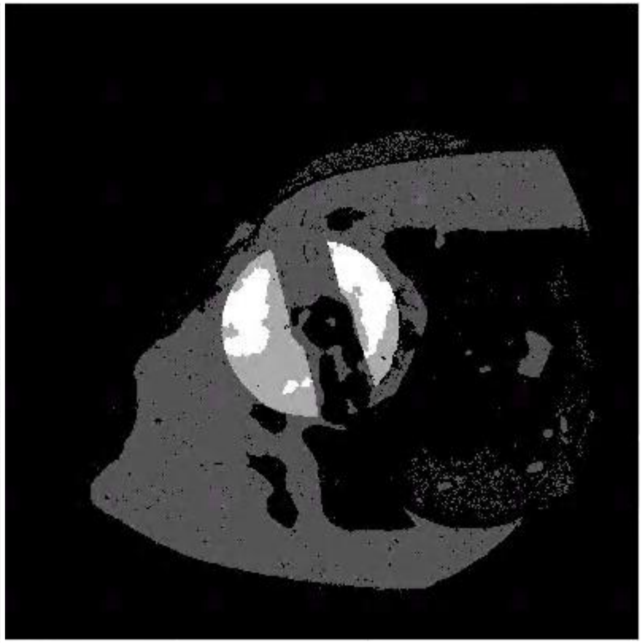
Background

Bone

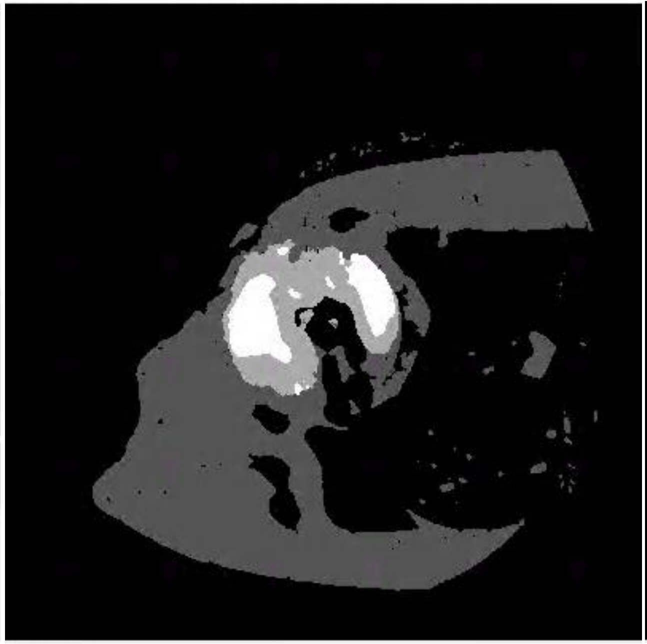
Corroded Screw

Screw

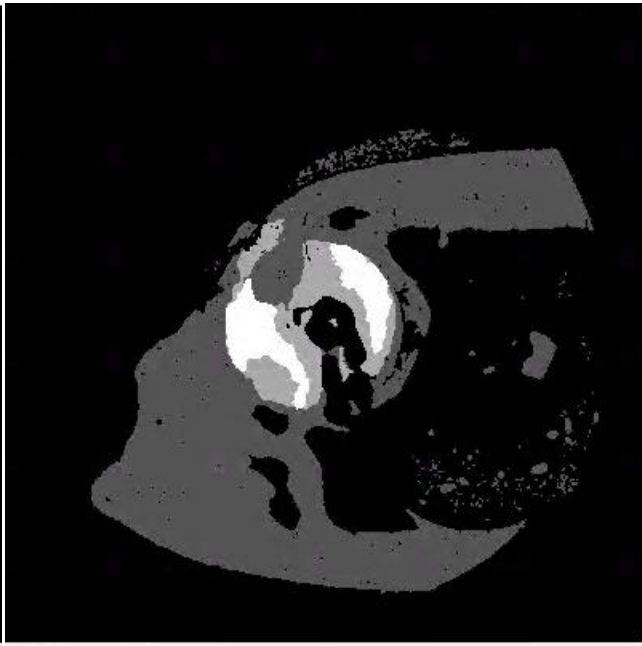
Image



Segmentation Mask



Active Learning (Coreset)



Full Supervised Learning

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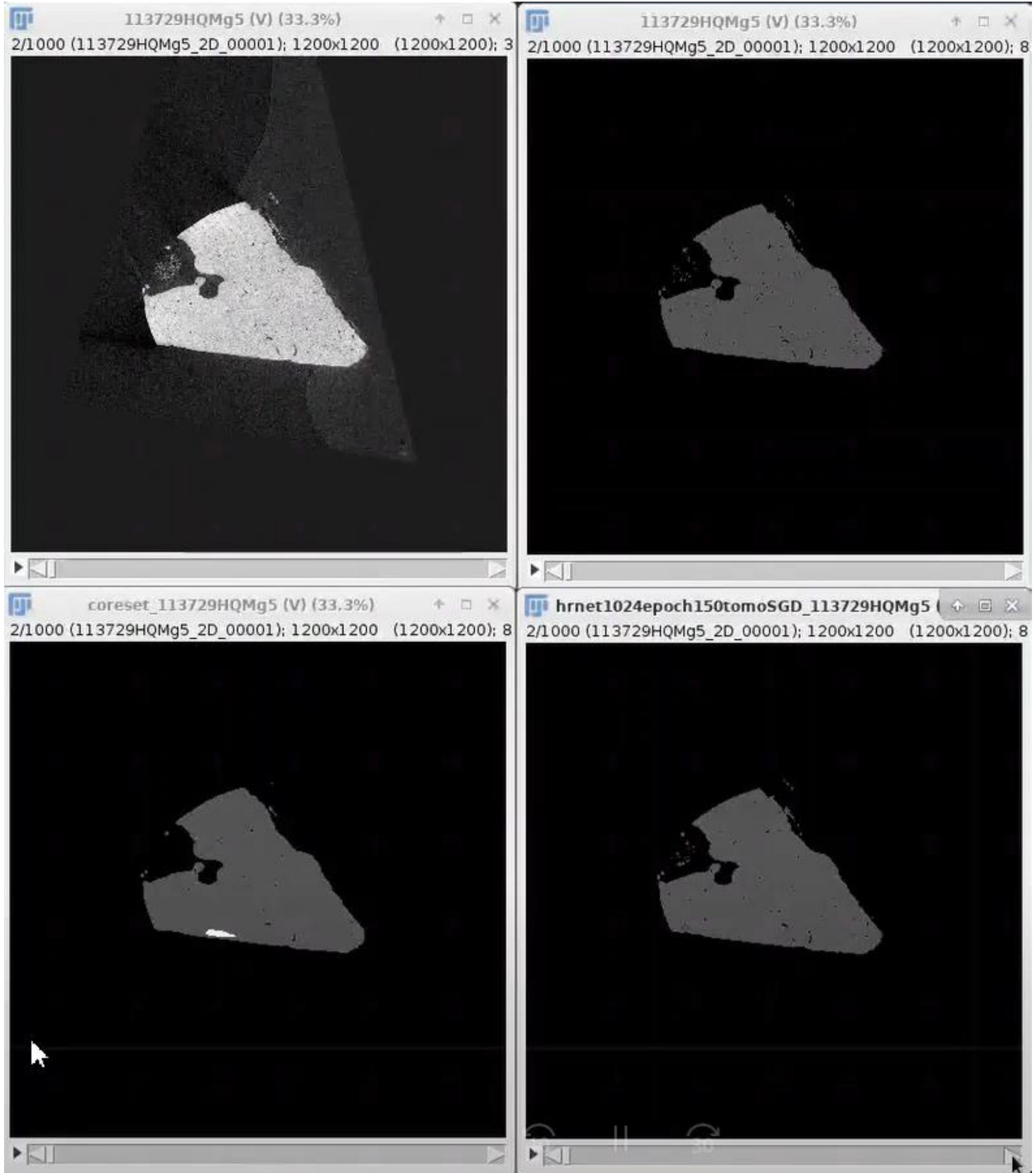
Results: Video

Image

Segmentation Mask



Background

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Screw

Active Learning (Coreset)

Full Supervised Learning

Conclusion

- Deep active learning for segmentation of biodegradable bone implants
- Very few annotated images
  - 80 annotated images in the 10^{th} round of active learning
  - ~ 7000 annotated images for fully supervised learning
- 80.51 % mIoU score by active learning
- 82.91 % mIoU score by fully supervised learning
- **➔ 97 percent of performance using only 1.16 percent of annotations!!!**
- A web-service is ready
- Next steps:
  - Incorporate the active learning system in the web-service
  - Work on denoising/super-resolution

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Feedback/Questions?

- Thank you ☺

Appendix: Acquisition Functions

- **Softmax Entropy:**
  - Sum of entropy for all pixels is calculated

$$S_I^{\mathrm{ENT}} = -\sum_{i}^{I} \sum_{c=1}^{C} p(y_{i,c}|x_i;\theta_{\mathrm{SEG}}) \log p(y_{i,c}|x_i;\theta_{\mathrm{SEG}})$$

  - K images with maximum entropy are selected to be annotated

Appendix: Acquisition Functions

- **Softmax Margin:**
  - **Sum of difference of softmax probabilities of the top most and 2nd most probable label for each pixel is calculated**

$$S_I^{\mathrm{MAR}} = \sum_{i}^{I} \max{}_1 p(y_{i,C} | x_i; \theta_{\mathrm{SEG}}) - \max{}_2 p(y_{i,C} | x_i; \theta_{\mathrm{SEG}})$$

  - **K samples with the least difference are selected for annotation**

Appendix: Acquisition Functions

- **Cost Effective Active Learning (CEAL)**
  - Use softmax entropy, softmax confidence and softmax margin to select K samples for annotation
  - Use the same acquisition function again to select another K samples and then pseudo-label them using the trained model

Appendix: Acquisition Functions

- **Monte Carlo Dropout**
  - Run trained model on unlabeled data for *N* iterations using dropout
  - Calculate entropy and sum them

$$S_I^{\mathrm{MCDR}} = -\sum_{i}^{I}\sum_{c=1}^{C} p_{\mathrm{MCDR}}(y_{i,c}|x_i;\theta_{\mathrm{SEG}}) \log p_{\mathrm{MCDR}}(y_{i,c}|x_i;\theta_{\mathrm{SEG}})$$

$$p_{\mathrm{MCDR}}(y_{i,c}|x_i;\theta_{\mathrm{SEG}}) = \frac{1}{N}\sum_{n=1}^{N} p(y_{i,c}|x_i;\theta_{\mathrm{SEG}})$$

  - K samples with the most entropy scores are selected for annotation

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Appendix: Acquisition Functions

- **Maximum Representation**
  - Use MC Dropout to select 2*K most uncertain samples
  - Use similarity measures (e.g., Euclidean norm) to select K most representative samples
  - K samples most distant to each other are selected for annotation

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