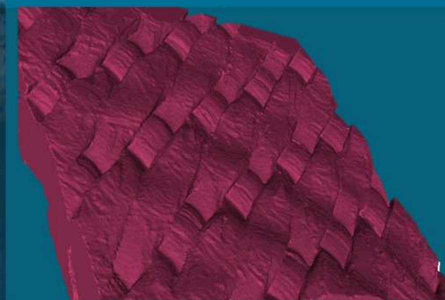
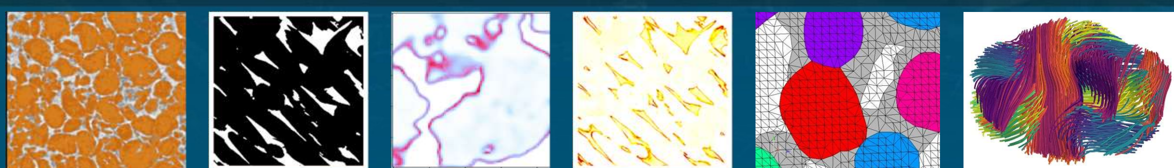
SAND2020-13150C

Sandia National Laboratories



CT segmentation of woven composite materials over shifted domains via deep learning



Carianne Martinez, Brendan Donohoe, Matthew D. Smith, Scott A. Roberts

LDRD LABORATORY DIRECTED RESEARCH & DEVELOPMENT

U.S. DEPARTMENT OF ENERGY NNSA

Sandia National Laboratories is a multimission laboratory managed and operated by National Technology & Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.

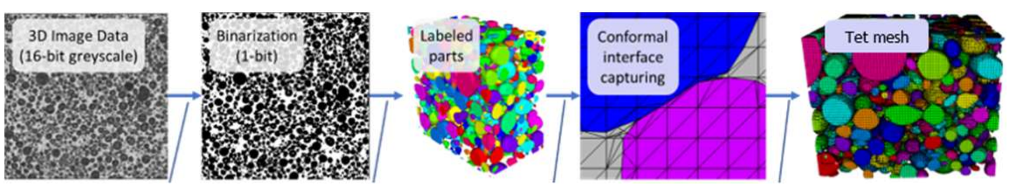
Can we predict the behavior of as-built parts with error bars?

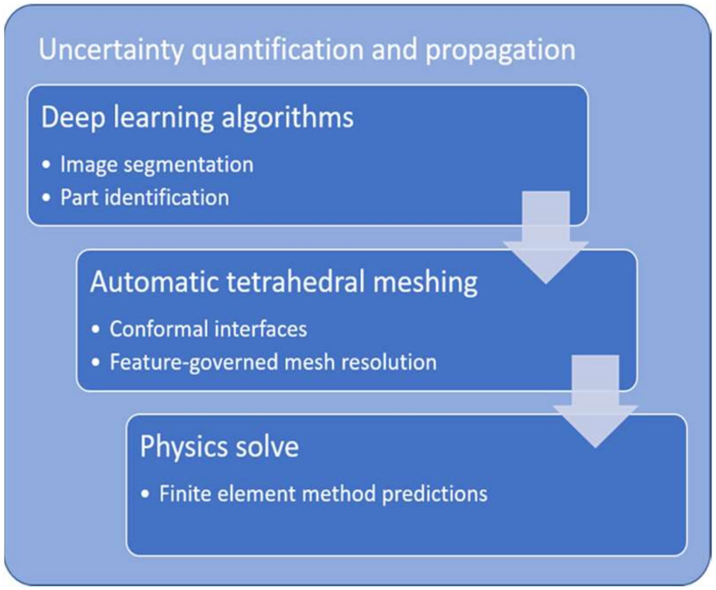
Hypothesis: We can develop an automated and credible image-to-mesh technology that can demonstrate the physics impact of per-unit variability on material, component, or system performance

Objective: We seek to develop a methodology for **automatically**, **efficiently**, and **reproducibly** creating **conformal** finite element meshes from **3D tomography** with **quantified uncertainty**.

Research thrusts – primary science questions:

1. Automatic CT segmentation via Deep Learning (DL)
2. Automatic conformal tetrahedral mesh creation (ATM)
3. Uncertainty quantification and propagation (UQ)





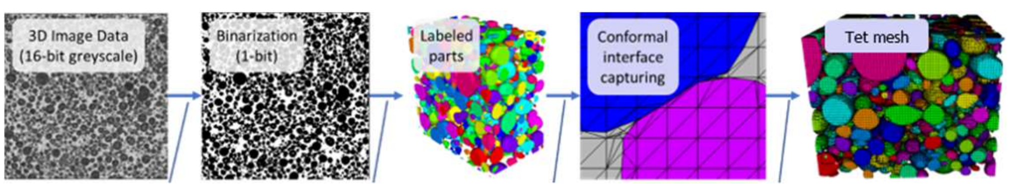
Can we predict the behavior of as-built parts with error bars?

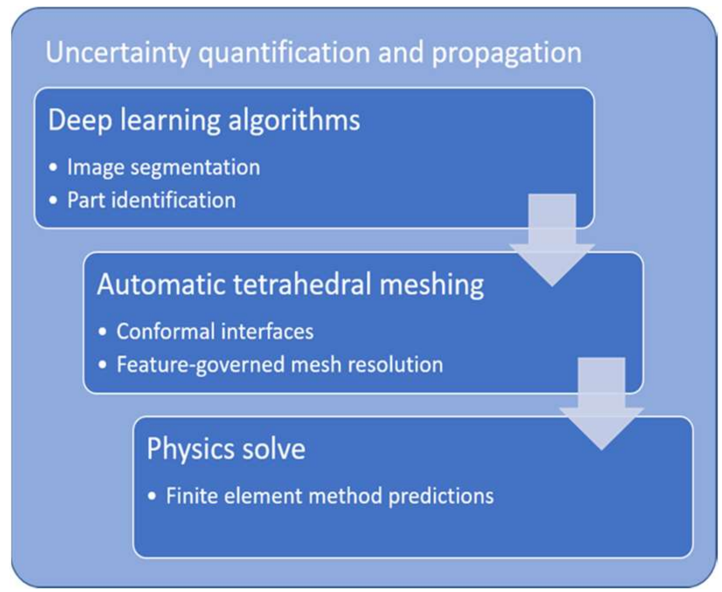
Hypothesis: We can develop an automated and credible image-to-mesh technology that can demonstrate the physics impact of per-unit variability on material, component, or system performance

Objective: We seek to develop a methodology for **automatically**, **efficiently**, and **reproducibly** creating **conformal** finite element meshes from **3D tomography** with **quantified uncertainty**.

Research thrusts – primary science questions:

1. Automatic CT segmentation via Deep Learning (DL)
2. Automatic conformal tetrahedral mesh creation (ATM)
3. Uncertainty quantification and propagation (UQ)





Segmentation is a classic computer vision problem

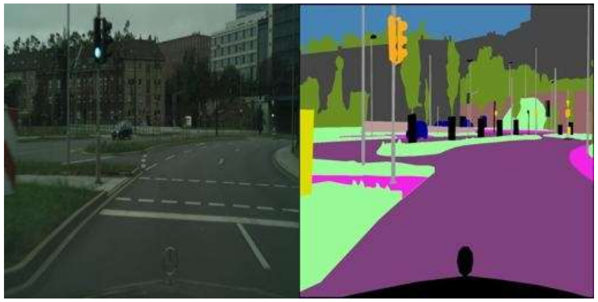
Image segmentation is well studied

- Small files
- Large training sets

CT segmentation is different

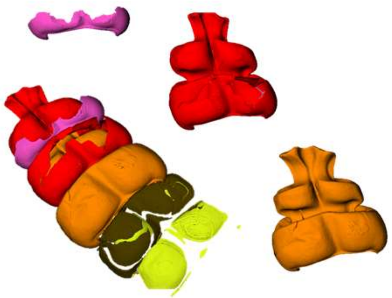
- Volumetric; larger files
- Class imbalance (lots of background)
- Noise/artifacts in scans
- Small training sets with “bad” human labels
- Inconsistent scan quality (domain shift)

Medical researchers are leading this work toward Deep Learning solutions.



https://www.cityscapes-dataset.com/

Cityscape
(~1e5 pixels)



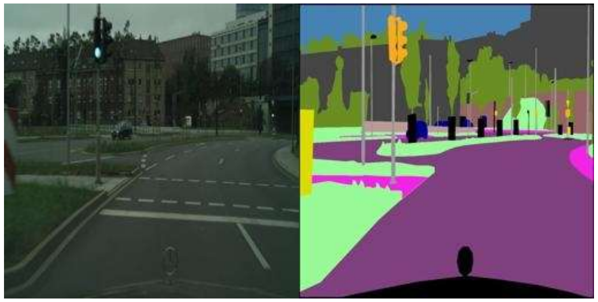
Rattlesnake Tail
(~1e9 voxels)

Segmentation is a classic computer vision problem

Image segmentation is well studied
- Small files
- Large training sets

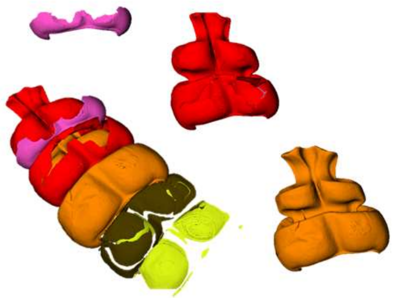
CT segmentation is different
- Volumetric; larger files
- Class imbalance (lots of background)
- Noise/artifacts in scans
- Small training sets with "bad" human labels
- Inconsistent scan quality (domain shift)

Medical researchers are leading this work toward Deep Learning solutions.



https://www.cityscapes-dataset.com/

Cityscape
(~1e5 pixels)



Rattlesnake Tail
(~1e9 voxels)

Encoder-decoder network with skip connections

Encoder learns features at different resolutions.

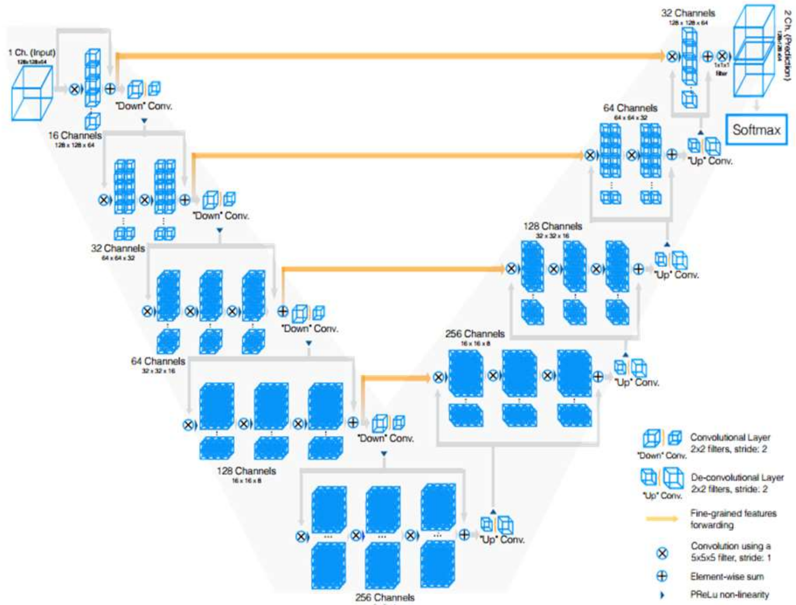
Decoder uses encoded features passed via skip connections for segmentation.

U-net: significant advance for biomedical segmentation

- Olaf Ronneberger, Philipp Fischer, Thomas Brox , “U-Net: Convolutional Networks for Biomedical Image Segmentation”, in Medical Image Computing and Computer-Assisted Intervention (MICCAI), Springer, LNCS, Vol.9351: 234--241, 2015

V-net follows as a natural extension to handle 3D images.

- F. Milletari, N. Navab, and S. A. Ahmadi, “V-net: Fully convolutional neural networks for volumetric medical image segmentation,” in 2016 Fourth International Conference on 3D Vision (3DV), Oct 2016, pp.565–571



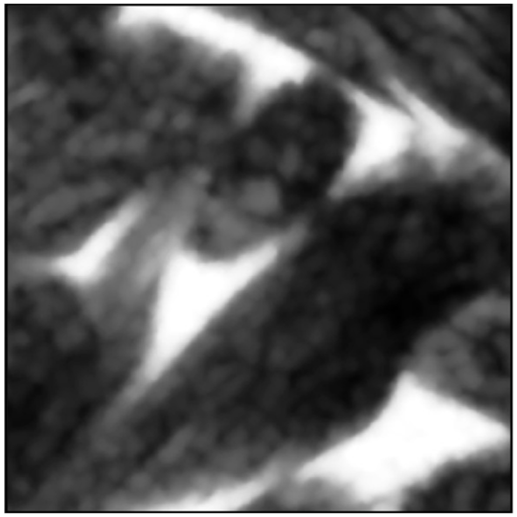
V-Net architecture for segmenting volumetric data
(Image from Milletari, et al. 2016)

Geometric uncertainty is characterized with dropout layers

Dropout layers can be used to add stochasticity in DL model predictions.
- Typically used for regularization during training
- Gal, et al. [1] introduced active dropout layers during inference

Variance over several DL binary segmentation predictions is an indication of uncertainty.

CT scan slice



[1] Y. Gal and Z. Ghahramani, Dropout as a bayesian approximation: Representing model uncertainty in deep learning, in Proceedings of the 33rd International Conference on Machine Learning, 2016.

Geometric uncertainty is characterized with dropout layers

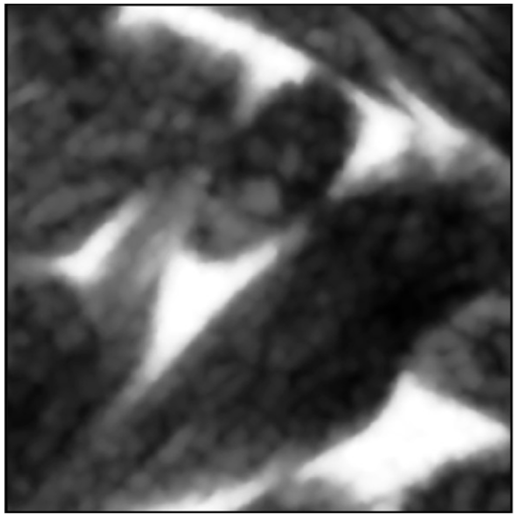
Dropout layers can be used to add stochasticity in DL model predictions.

- Typically used for regularization during training
- Gal, et al. [1] introduced active dropout layers during inference

Variance over several DL binary segmentation predictions is an indication of uncertainty.

[1] Y. Gal and Z. Ghahramani, Dropout as a bayesian approximation: Representing model uncertainty in deep learning, in Proceedings of the 33rd International Conference on Machine Learning, 2016.

CT scan slice



Expert label

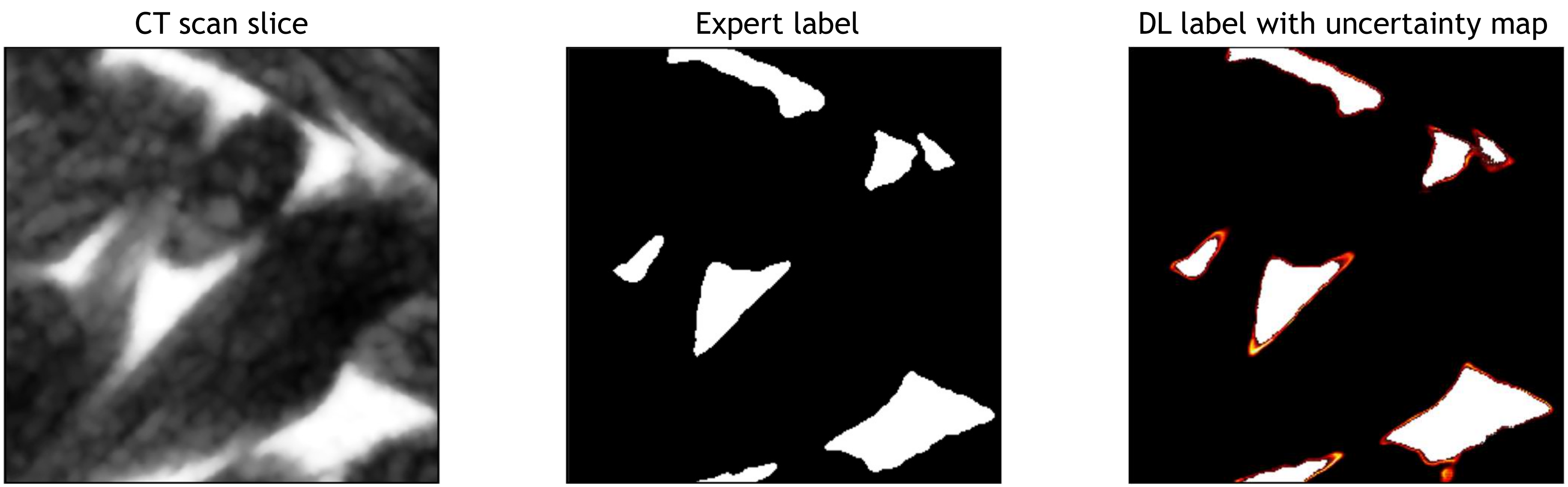
Geometric uncertainty is characterized with dropout layers

Dropout layers can be used to add stochasticity in DL model predictions.

- Typically used for regularization during training
- Gal, et al. [1] introduced active dropout layers during inference

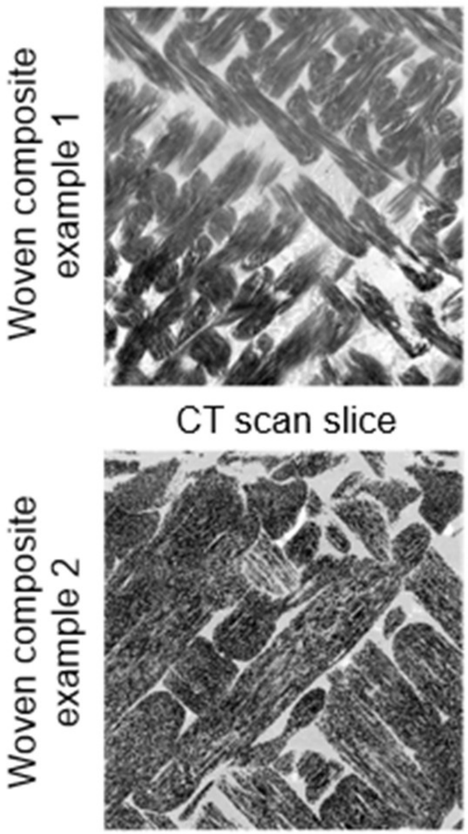
Variance over several DL binary segmentation predictions is an indication of uncertainty.

[1] Y. Gal and Z. Ghahramani, Dropout as a bayesian approximation: Representing model uncertainty in deep learning, in Proceedings of the 33rd International Conference on Machine Learning, 2016.



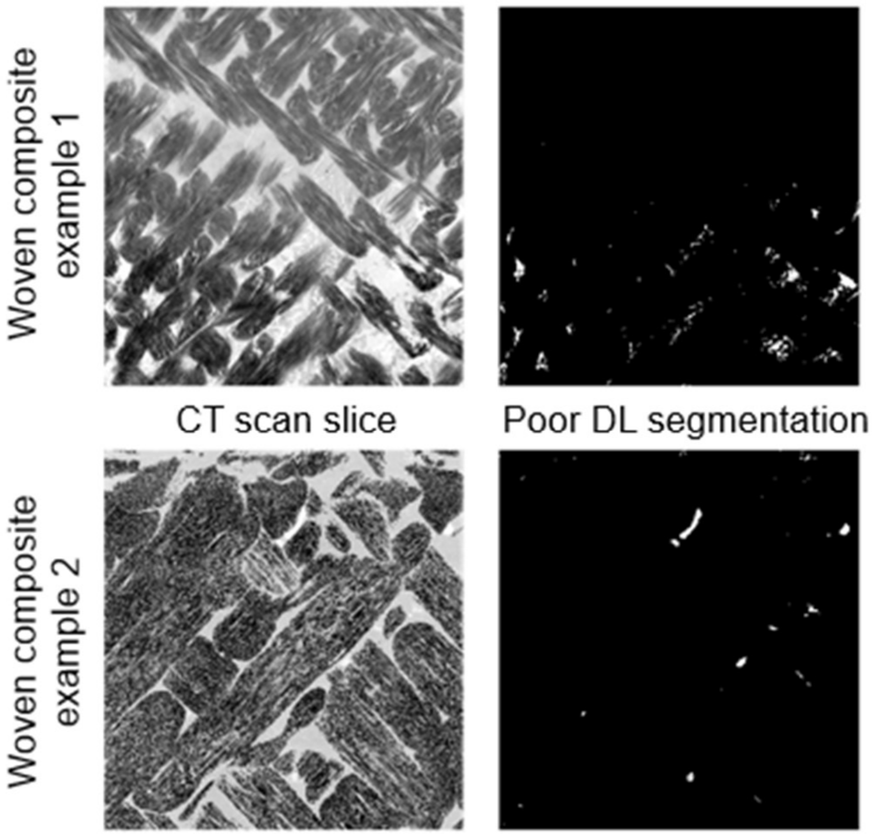
In the training domain, the DL model is accurate and exhibits little uncertainty about predictions.

DL model trained and ready for deployment

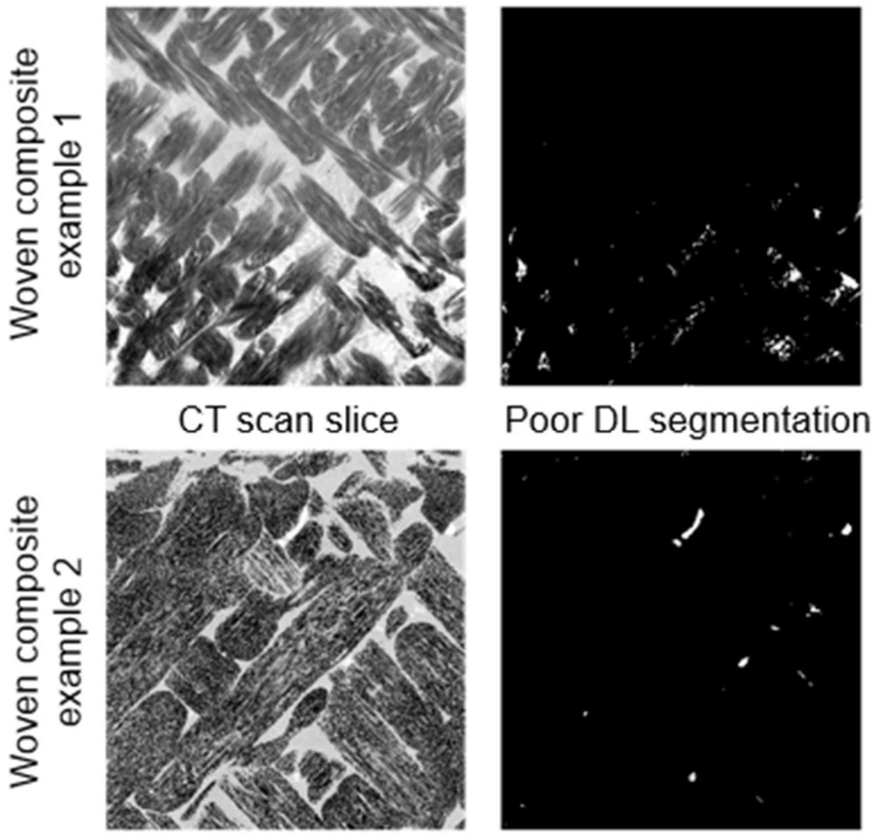


Once the model is trained using an expert label, we use the model to predict segmentations for new CT scans.

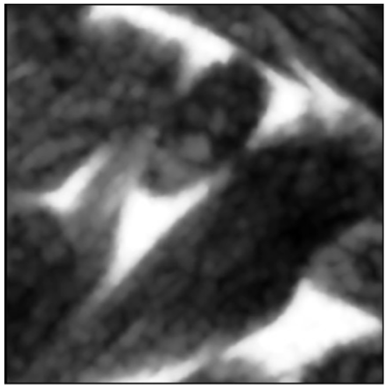
DL model trained and ready for deployment: the bad news



DL model trained and ready for deployment: the bad news



Recall our training example:

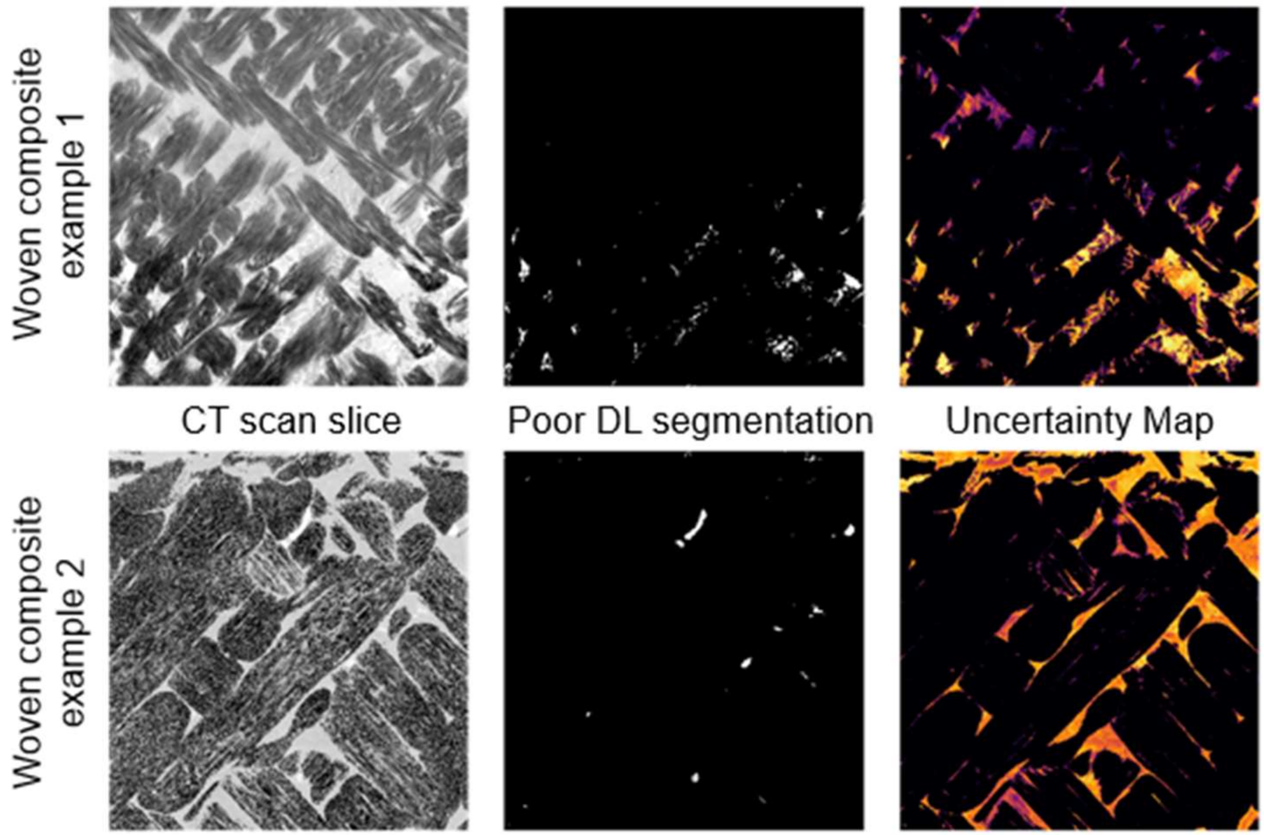


The new examples are different:

- Scanning equipment
- Resolution
- Material composition

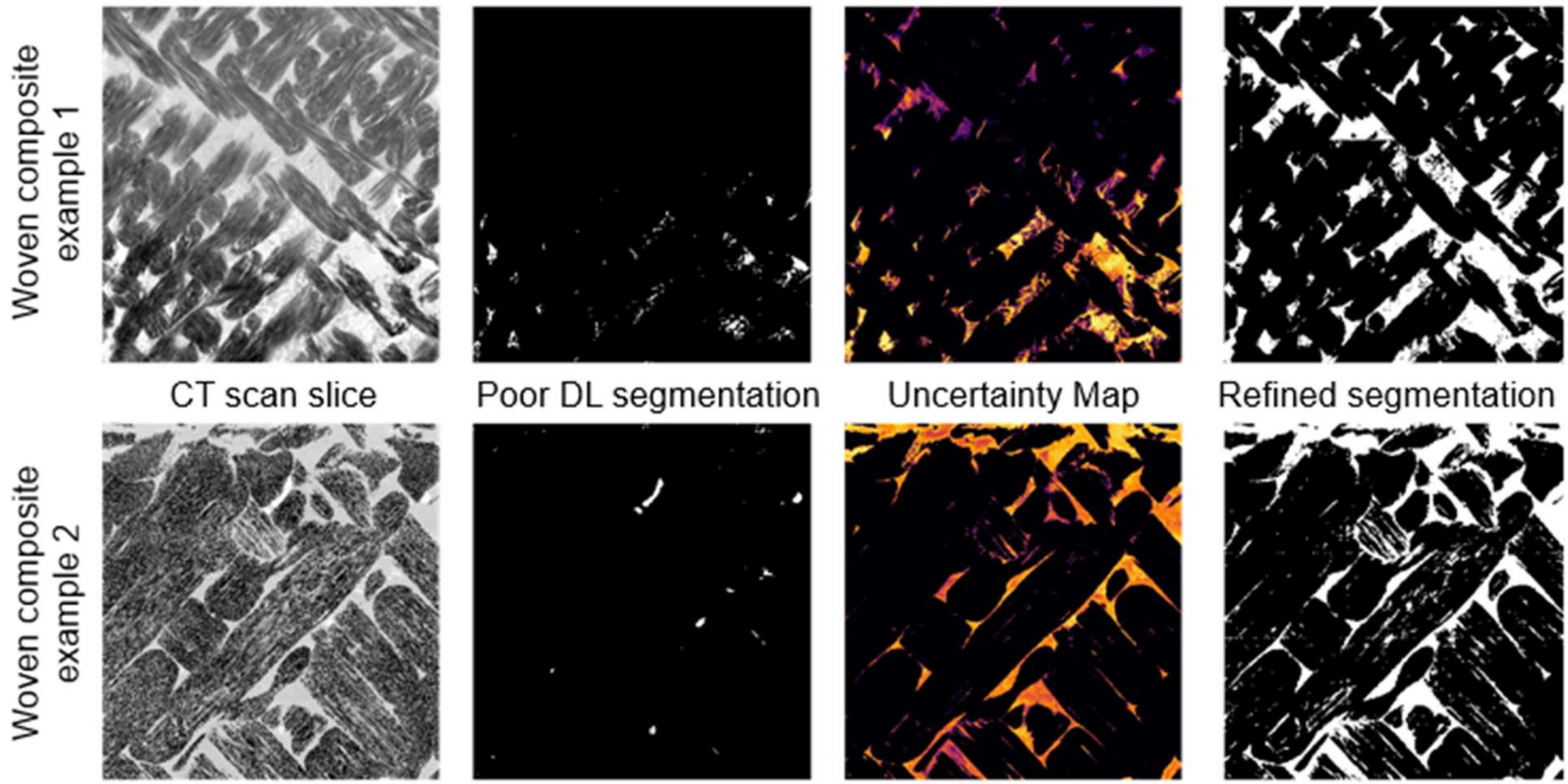
DL notoriously fails to generalize under domain shift.

DL model trained and ready for deployment: the good news



DL prediction is incorrect, but with high uncertainty compared with the training domain:

DL model trained and ready for deployment: the good news

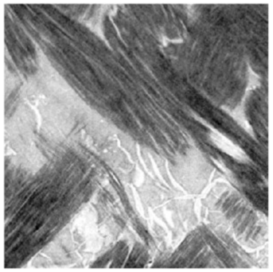


We can refine our predictions using uncertainty maps.

Uncertainty can be used to inform segmentation

We leverage uncertainty maps to enable generalization of a trained model to shifted domains

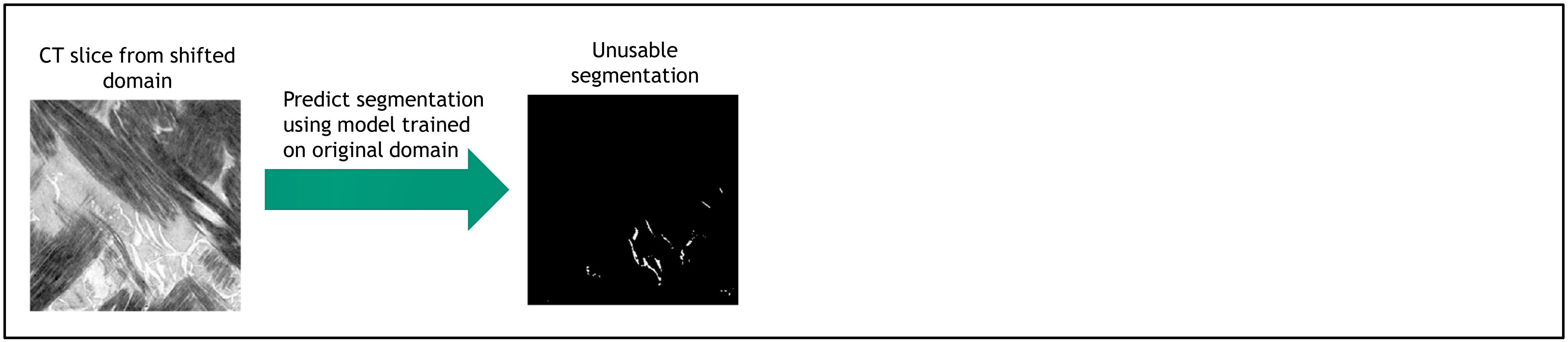
CT slice from shifted domain



C. Martinez, K. M. Potter, M. D. Smith, E. A. Donahue, L. Collins, J. P. Korbin, and S. A. Roberts, Segmentation certainty through uncertainty: Uncertainty-refined binary volumetric segmentation under multifactor domain shift, in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, 2019.

Uncertainty can be used to inform segmentation

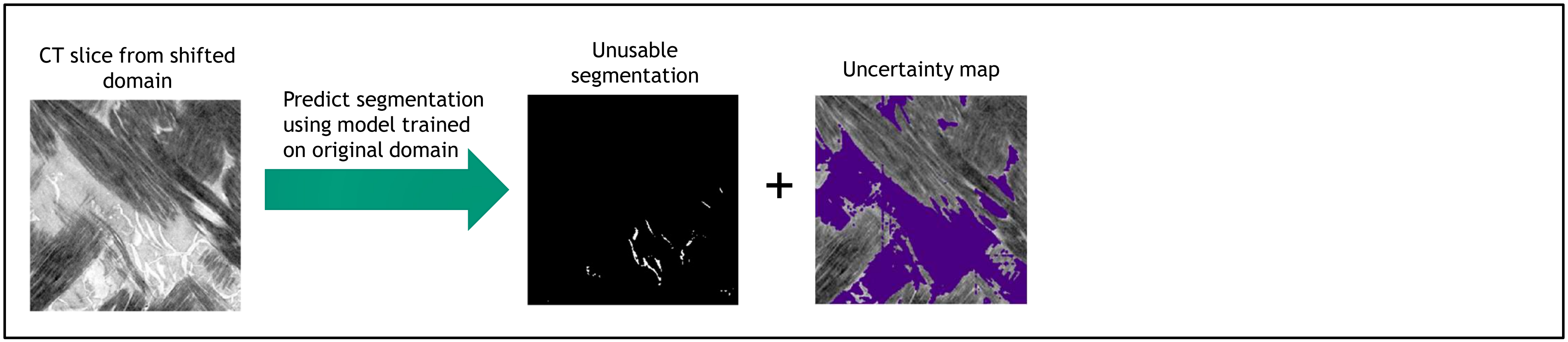
We leverage uncertainty maps to enable generalization of a trained model to shifted domains



C. Martinez, K. M. Potter, M. D. Smith, E. A. Donahue, L. Collins, J. P. Korbin, and S. A. Roberts, Segmentation certainty through uncertainty: Uncertainty-refined binary volumetric segmentation under multifactor domain shift, in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, 2019.

Uncertainty can be used to inform segmentation

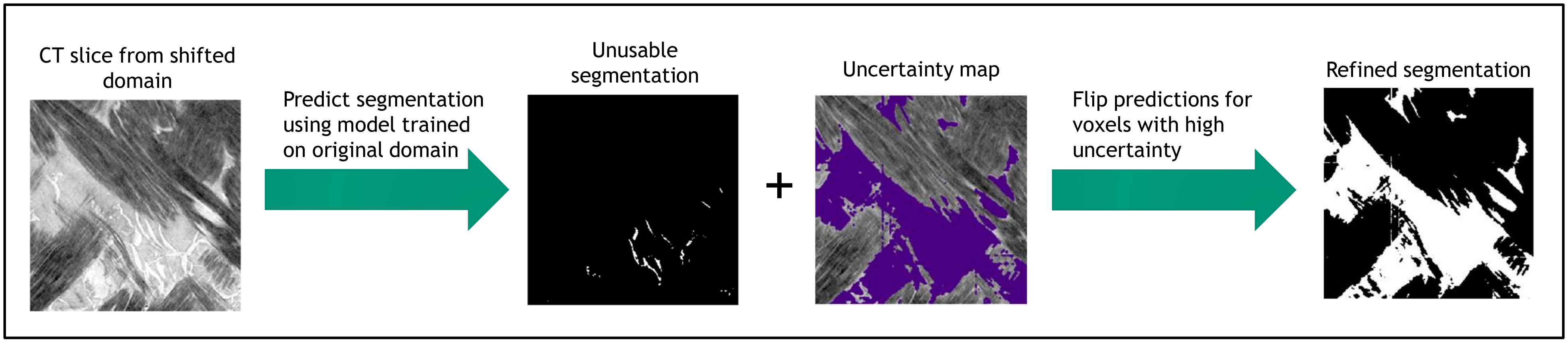
We leverage uncertainty maps to enable generalization of a trained model to shifted domains



C. Martinez, K. M. Potter, M. D. Smith, E. A. Donahue, L. Collins, J. P. Korbin, and S. A. Roberts, Segmentation certainty through uncertainty: Uncertainty-refined binary volumetric segmentation under multifactor domain shift, in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, 2019.

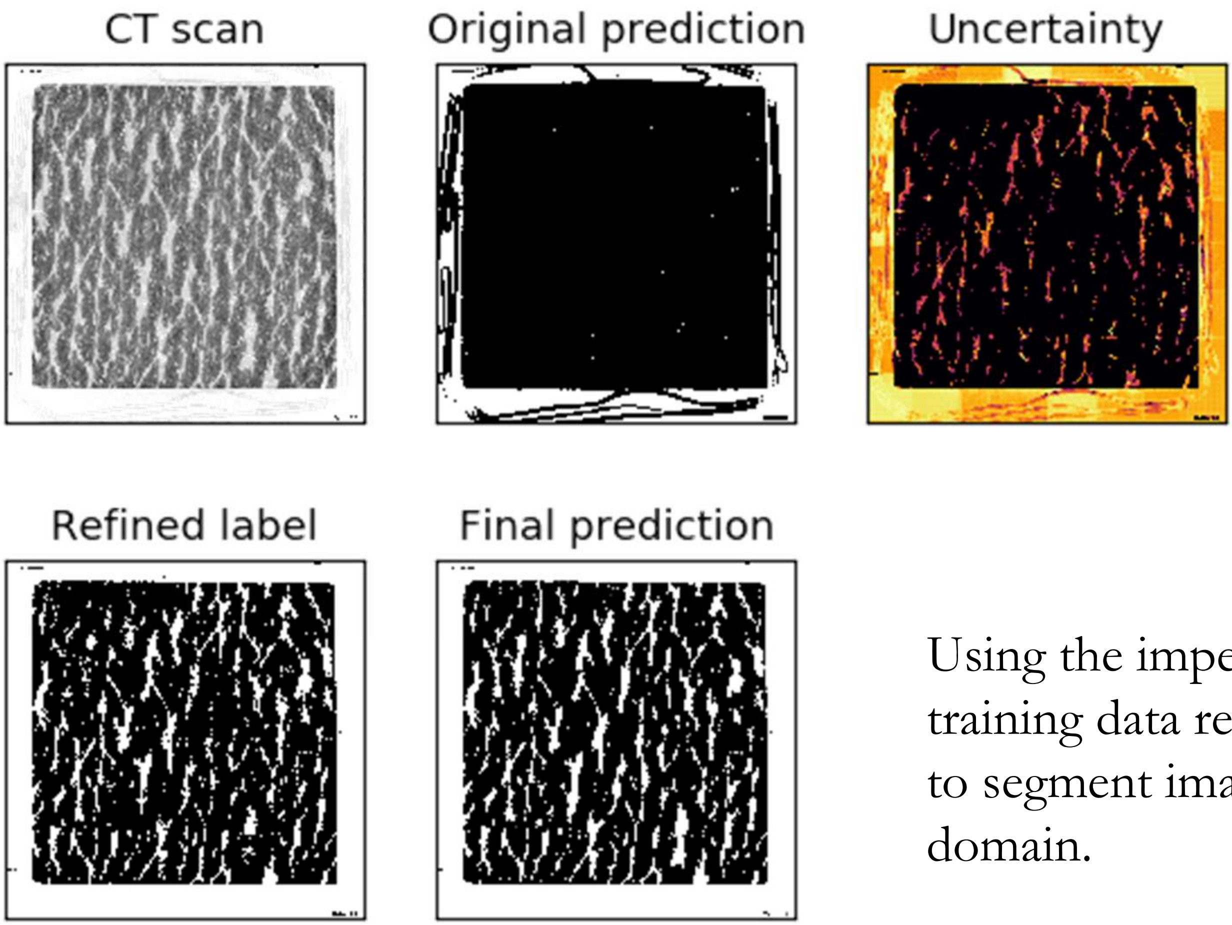
Uncertainty can be used to inform segmentation

We leverage uncertainty maps to enable generalization of a trained model to shifted domains



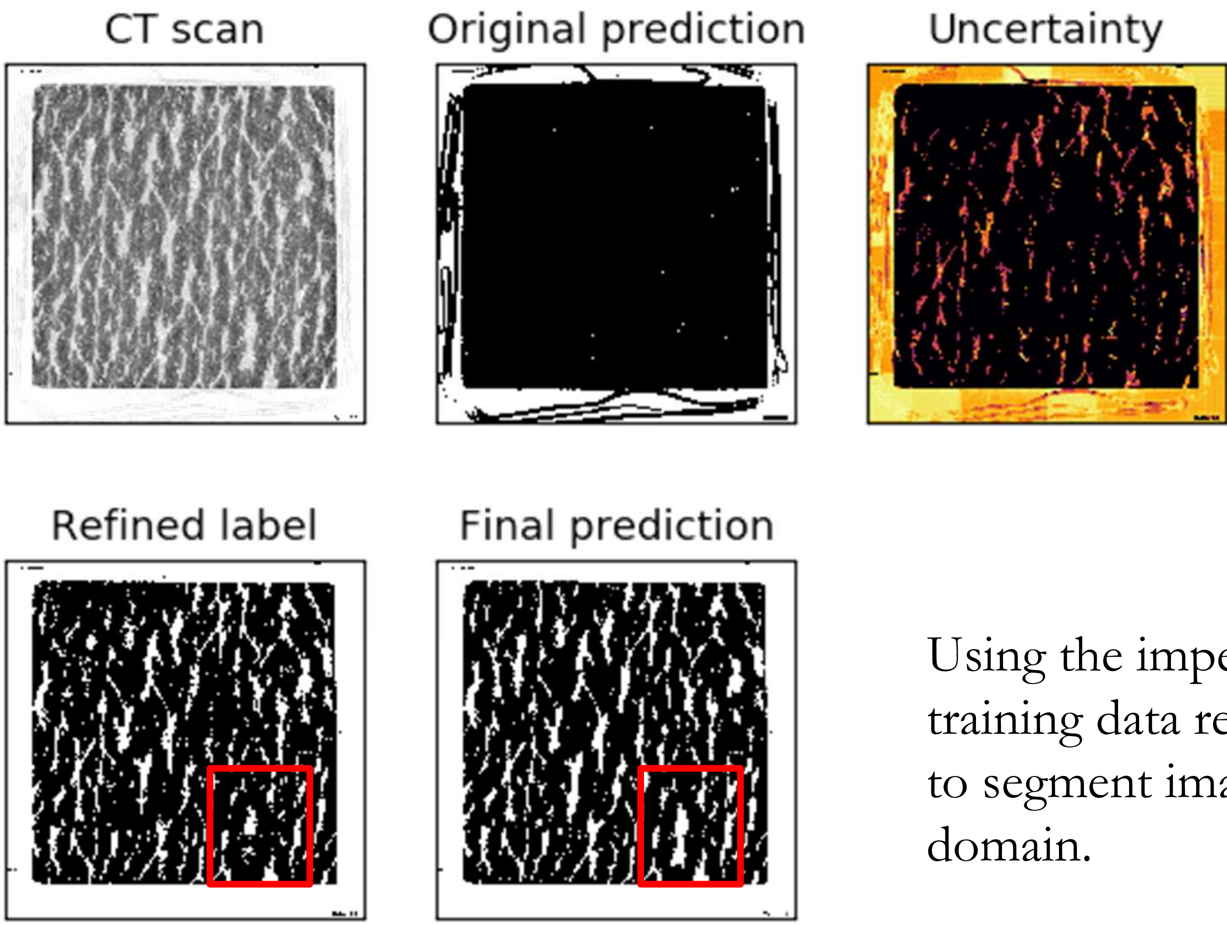
C. Martinez, K. M. Potter, M. D. Smith, E. A. Donahue, L. Collins, J. P. Korbin, and S. A. Roberts, Segmentation certainty through uncertainty: Uncertainty-refined binary volumetric segmentation under multifactor domain shift, in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, 2019.

Key idea: Use imperfect refined results as training data



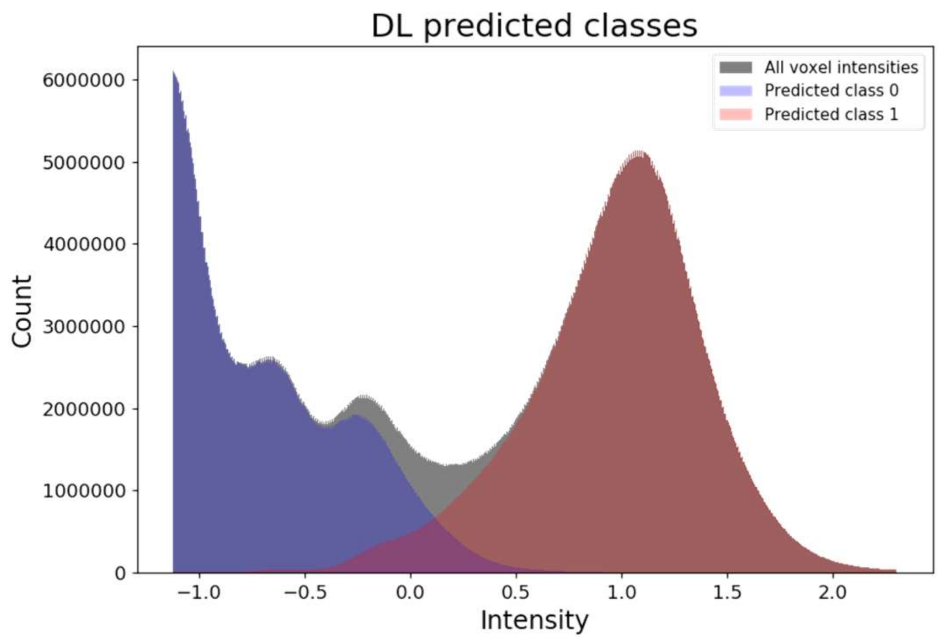
Using the imperfect refined label as training data results in a model able to segment images from the shifted domain.

Key idea: Use imperfect refined results as training data



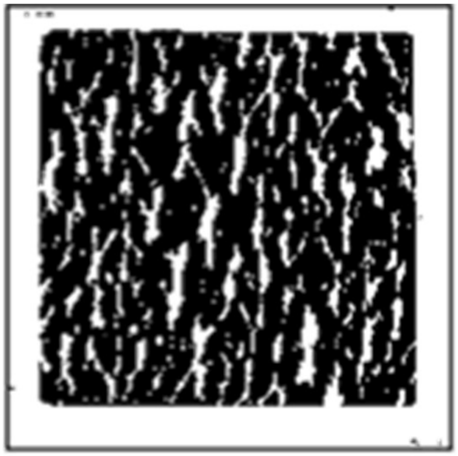
Using the imperfect refined label as training data results in a model able to segment images from the shifted domain.

Deep learning is not thresholding.



CT scan slice

Final prediction



The coarseness of the prediction is at the level of the expert label from the original training domain and does not separate individual fibers.

Conclusion

- CT segmentation can be automated with DL.
- Supervised learning with expert labels is best.
- Limitations in training data availability can be overcome by leveraging uncertainty maps to refine predictions.
- Qualitative results indicate that imperfect labels can be used as training data to produce a new DL model that overcomes domain shift.

Thank you!