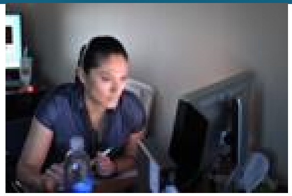
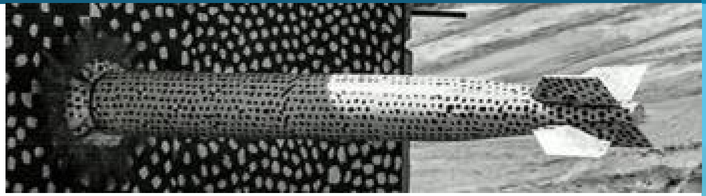
SAND2021-15313C

AGU2021 H12E-08

Deep Learning for Rock Semantic Segmentation





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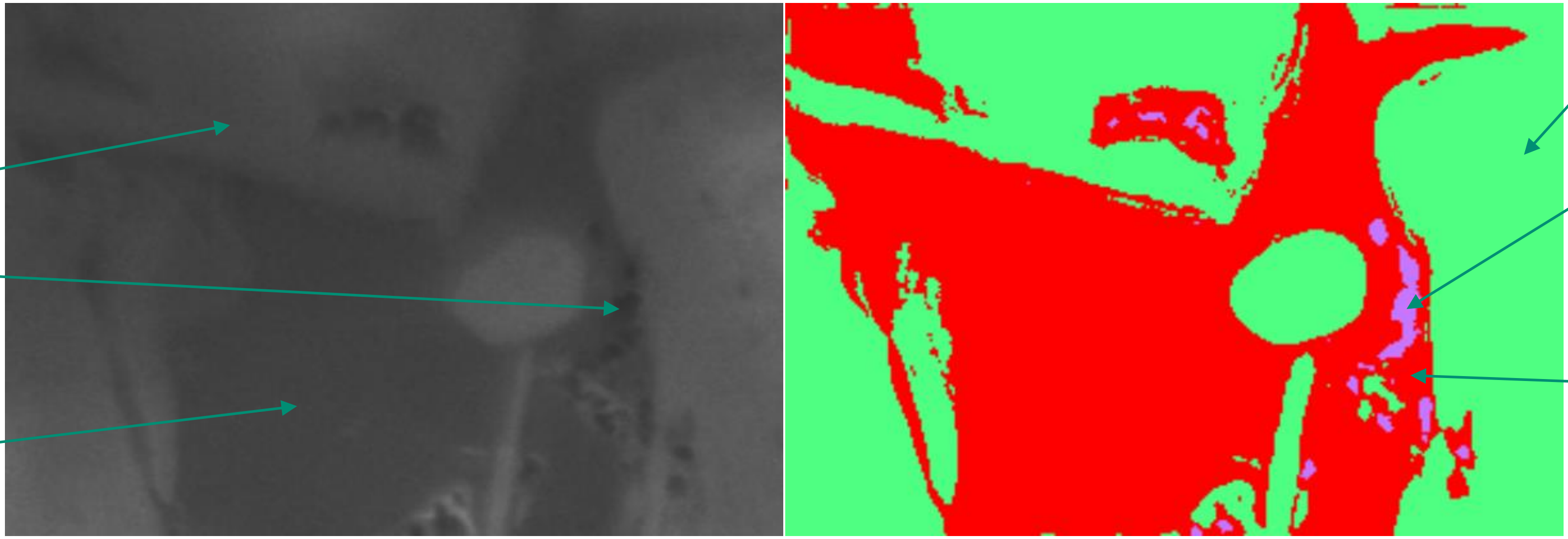
Background: What is Semantic Segmentation?

- Semantic segmentation aims to classify images at the pixel-level
- This is done by assigning a value to each pixel based upon its class



Focused Ion Beam-Scanning Electron Microscopy image of Marcellus Sandstone (left) and manually segmented image (right)

- Generating accurate segmentations of rock images is critical to geomaterial characterizations
- Challenges: Complexity in geometry, size, scale, and compositions

Motivations: Why use Deep Learning Methods?

- Manual or traditional image segmentation tends to be ***labor-intensive, often subject to user-bias, not easy to adapt to other class of images, and/or manual correction***
- ***U-Net based approaches*** have been successfully applied for image classification, segmentation, object detection of various types of images including medical, rocks, satellites, cracks, etc.
- Many open-source packages are available for easy adoption

Objectives and DL Methods

- U-Net and hybrid version of other well-known architectures*: U-Net (Ronneberger et al., 2015), U-VGG16 (Simonyan and Zisserman 2014), U-ResNet (He et al. 2016), MultiResU-net (Ibtehaz & Rahman 2020), 3D U-Net
- Investigation of improvements through transfer learning and ensemble approaches

*Base code is available from Keras Segmentation
https://github.com/divamgupta/image-segmentation-keras
*MultiResU-Net from github repository

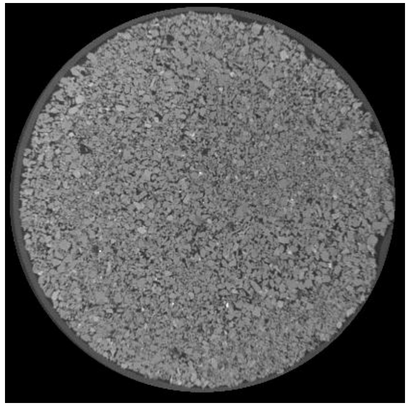
Image Data

- Original datasets include 3D microCT and FIB-SEM images
- Original images have been segmented with various traditional methods (e.g., Yoon and Dewers, 2013 GRL for S-Chalk)
- 128x128 and 128x128xD images are used for 2D and 3D models
- Dataset is split randomly into training (70%), validation (15%), and testing (15%)

Dataset	Num. of Training Images	Num. of Validation Images	Num. of Testing Images
Sandstone	27173	5869	5870
Carbonate Chalk	4812	1050	1050
Shale*	1593	231	231
Liege Chalk	11827	2534	2535

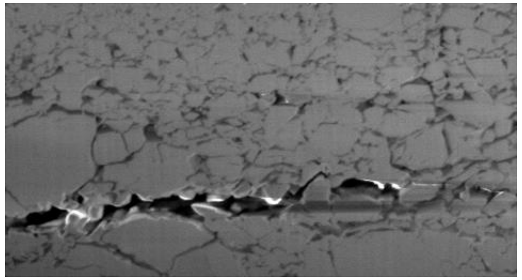
*Shale training data was augmented to increase # of pore samples

Boise Sandstone



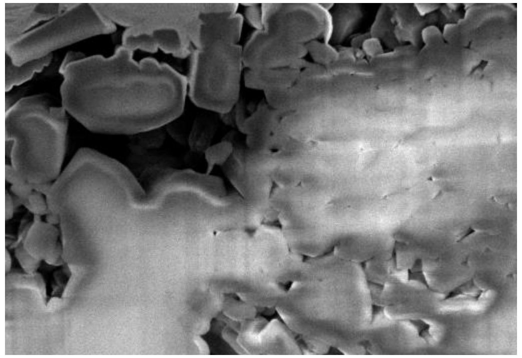
MicroCT images at 30 micron resolution (1500x1500x1800)

Carbonate Chalk (S-Chalk)



FIB-SEM images at 15 nm resolution (932x620x930)

Carbonate Chalk (L-Chalk)



FIB-SEM images at 10 nm resolution (900x700x900)

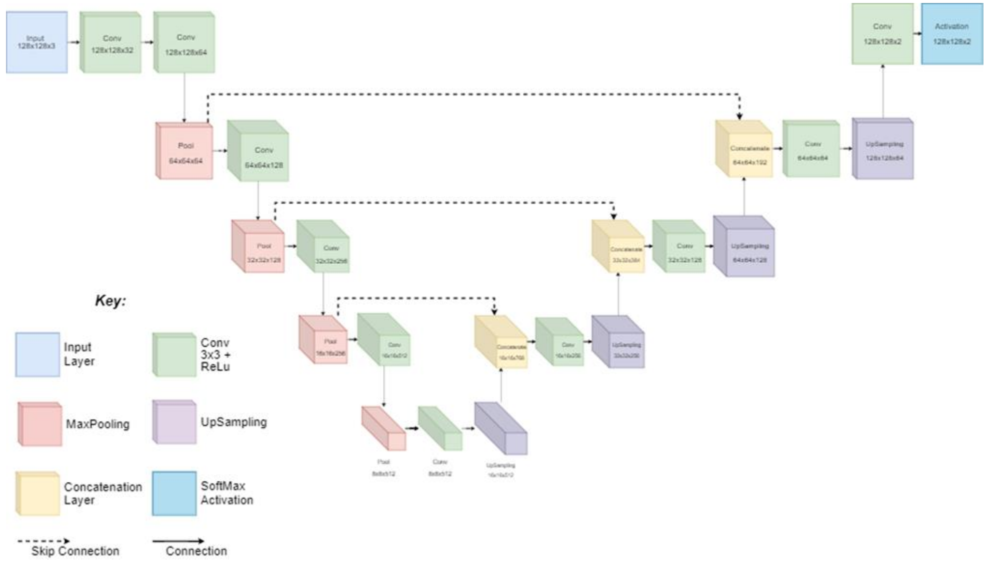
Marcellus Shale

FIB-SEM images at 10 nm resolution (900x700x900)

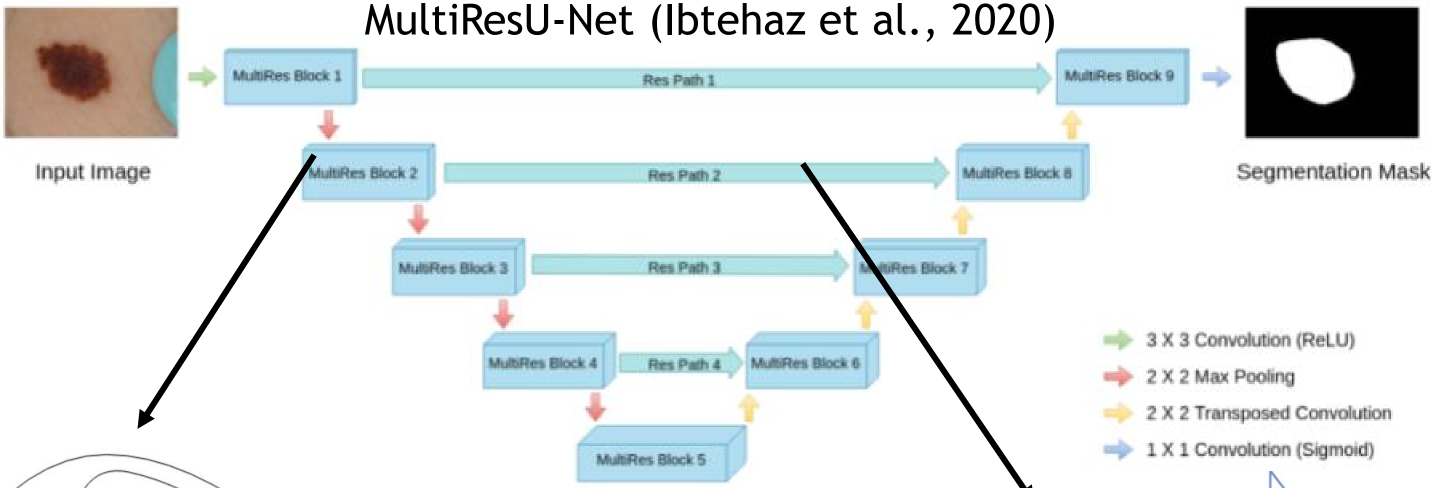
Methods: Model Architectures

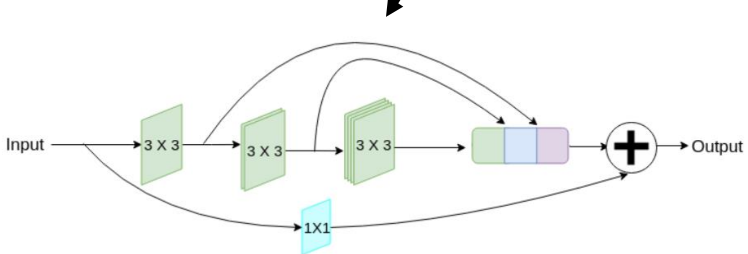
- Models are U-Net based architectures (U-Net 2D/3D, U-VGG16, U-ResNet, MultiResUnet)
- U-Net follows “U” shape of convolutional neural network architecture with a feature of skip connection
- All models follow an encoder-decoder architecture
  - Encoder extracts feature maps from input image
  - Decoder transforms these feature maps into a pre

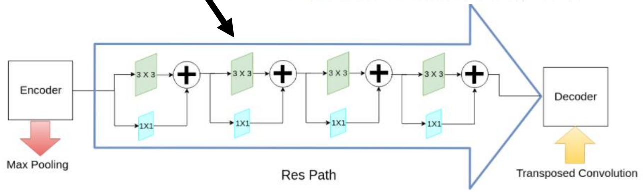
U-Net (Ronneberger et al., 2015)



MultiResU-Net (Ibtehaz et al., 2020)





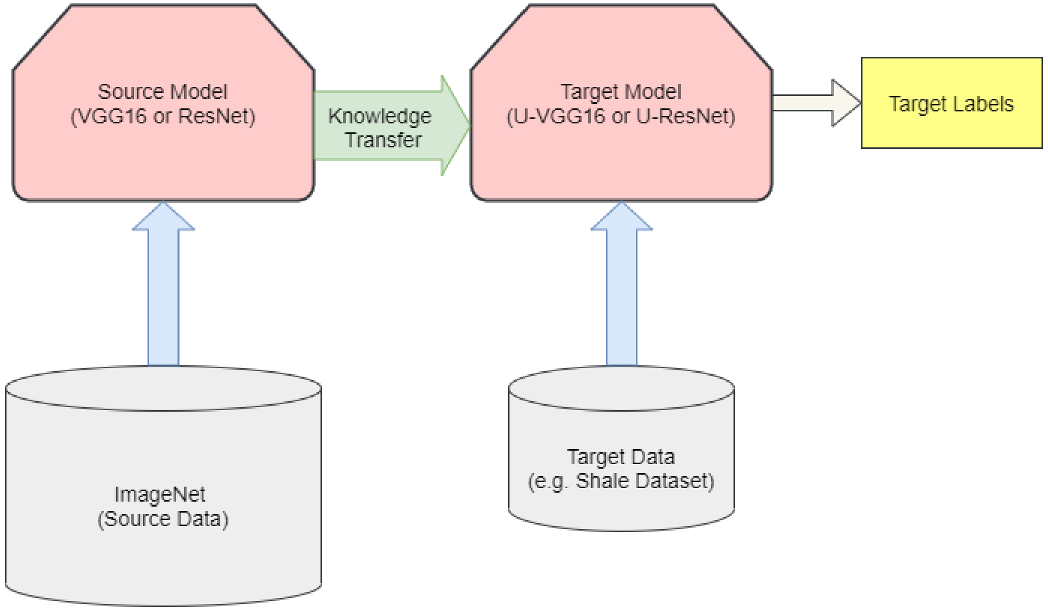


Methods: Hyperparameters & Transfer Learning

- Adam optimizer with a learning rate of 0.001
- Loss: categorical focal loss
- Batch size: 196 for U-Net and U-VGG16, 128 for U-Resnet, 64 for MultiResUnet
- Early stopping: 100 epochs

Transfer Learning Approach

- Method where model originally trained on one task leveraged for another
- Useful because it can allow for training to converge at a faster rate and lead to more robust models
- Investigated by initializing VGG16 and ResNet models with weights from ImageNet



Evaluation Metrics

- Testing data are used for evaluation
- Frequency Intersection Over Union (F-IoU)
- Pixel-wise accuracy (Pixel-Acc)

$$IoU = \frac{TP}{TP + FP + FN}$$

$$Freq\ IoU = \frac{1}{\sum_{i=0}^{k}\sum_{j=0}^{k} pij} \sum_{i=0}^{k} \frac{\sum_{j=0}^{k} pij * pii}{\sum_{j=0}^{k} pij + \sum_{j=0}^{k} pji - pii}$$

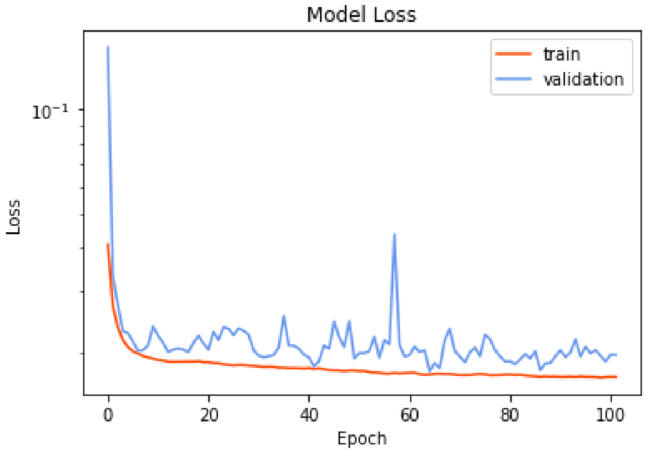
$$PA = \frac{TP + TN}{TP + TN + FP + FN}$$

Key:

- TP = true positives
- TN = true negatives
- FP = false positives
- FN = false negatives
- pij = pixels of class i predicted to belong to class j
- Assuming $k - 1$ classes

Base Results

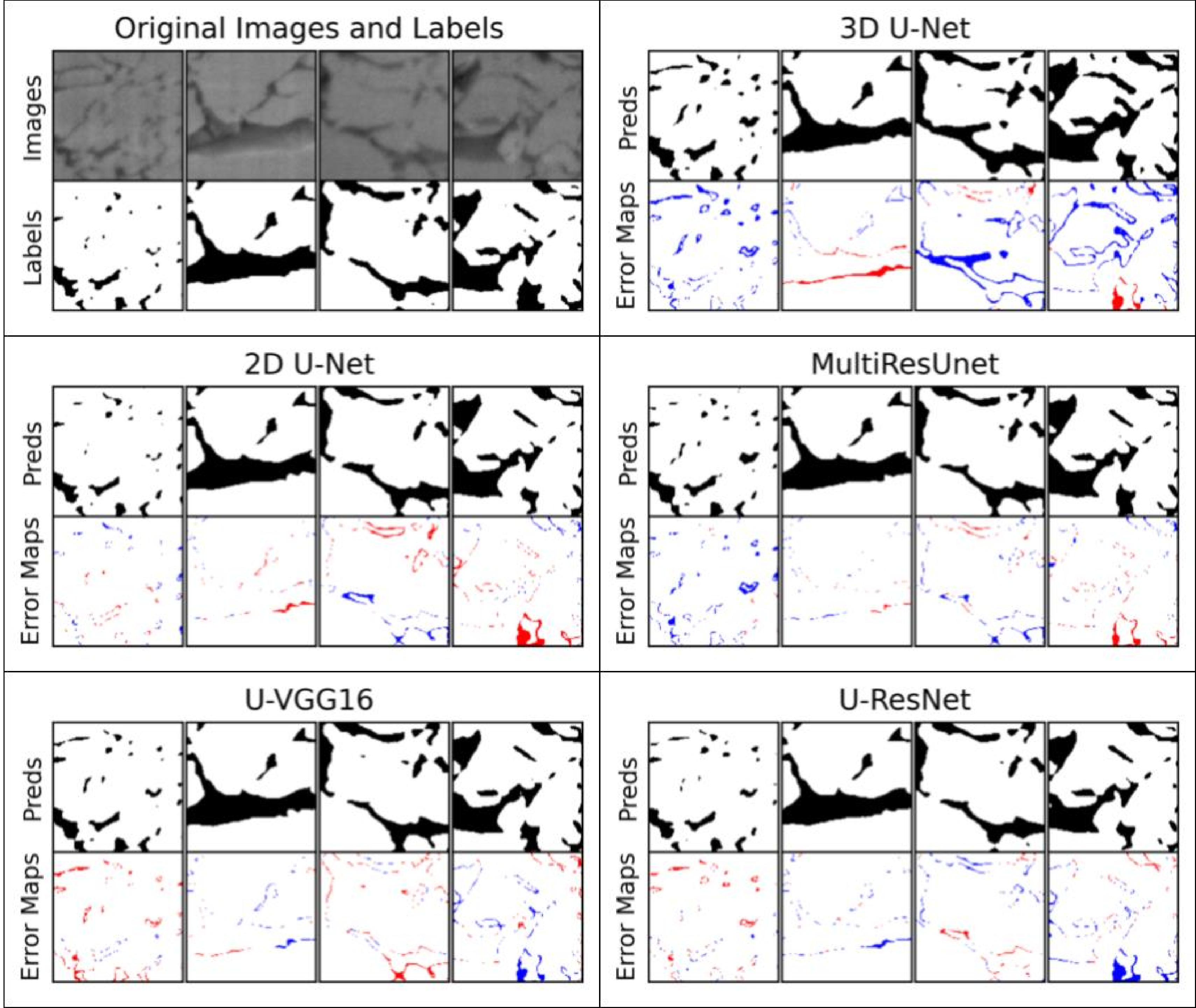
- "F-IoU" refers to frequency IoU
- "Pixel Acc" refers to the pixelwise accur



Example training plot showing validation and training loss as MultiResUnet is trained on Sandstone data

	Sandstone		S-chalk		L-chalk		Shale	
	F-IoU	*Pixel Acc*	*F-IoU*	*Pixel Acc*	*F-IoU*	*Pixel Acc*	*F-IoU*	*Pixel Acc*
U-Net	0.9522	0.9753	0.9514	0.9748	0.9219	0.9573	0.9332	0.9653
U-Net-3D	0.9270	0.9623	0.9006	0.9457	0.8752	0.9243	0.5989	0.7480
U-VGG16	0.9687	0.9840	0.9519	0.9749	0.9250	0.9572	0.7966	0.8863
U-ResNet	**0.9829**	**0.9913**	0.9397	0.9687	**0.9476**	**0.9719**	0.8948	0.9444
MultiResUnet	**0.9826**	**0.9912**	**0.9601**	**0.9794**	**0.9492**	**0.9730**	**0.9444**	**0.9713**

Predictions for Selma Chalk Data (Only Base Models Shown)



Sample images, predictions, and error maps from the testing split of the Selma chalk dataset. On the error maps, white indicates label and prediction agree, blue indicates pore was predicted but expected solid, red indicates solid was predicted but expected pore.

Transfer Learning Results

- "Fine-tune" refers to the revision of weights from ImageNet as training progresses.
- Numbers below given values indicate a comparison to the base case (e.g., (+0.1) indicates the metric improved by 0.1)

	Sandstone		S-chalk		L-chalk		Shale	
	F-IoU	*Pixel Acc*	*F-IoU*	*Pixel Acc*	*F-IoU*	*Pixel Acc*	*F-IoU*	*Pixel Acc*
U-VGG16-fine tune	0.9617 (-0.0070)	0.9805 (-0.0035)	0.9580 (+0.0061)	0.9784 (+0.0036)	0.9347 (+0.0097)	0.9655 (+0.0083)	0.6839 (-0.1127)	0.8121 (-0.0742)
U-Resnet-fine tune	0.9732 (-0.0097)	0.9863 (-0.0050)	0.9525 (+0.0128)	0.9751 (+0.0064)	0.9459 (-0.0017)	0.9709 (-0.0017)	0.9363 (+0.0415)	0.9671 (+0.0227)
MultiResUnet	**0.9826**	**0.9912**	**0.9601**	**0.9794**	**0.9492**	**0.9730**	**0.9444**	**0.9713**

Methods: Ensemble Approach

- Rather than generating predictions from a single model, multiple models are trained and then their predictions are combined
- In theory can reduce the variance of models and lead to better predictions
- In our implementation:
  - Model trained for 200 epochs, saving weights every 5 epochs
  - Best 3 models (based on validation sets) from 200 epochs are used to make ensemble predictions (i.e., average prediction)
  - Also tested special cases where models are drawn from a certain period of epochs in training (e.g. 3 models only taken from epochs 100-150)

Ensemble Results

- Note that for the U-ResNet base case is the fine-tuned model
- Numbers in parenthesis indicate a comparison to the base case (e.g., (+0.1) indicates the metric improved by 0.1)

	Sandstone		S-chalk		L-chalk		Shale	
	F-IoU	*Pixel Acc.*	*F-IoU*	*Pixel Acc.*	*F-IoU*	*Pixel Acc.*	*F-IoU*	*Pixel Acc.*
U-Net Ensemble	0.9633 (+0.0111)	0.9813 (+0.0060)	0.9521 (+0.0007)	0.9752 (+0.0004)	0.9458 (+0.0244)	0.9715 (+0.0142)	0.9346 (+0.0024)	0.9661 (+0.0008)
U-Resnet fine-tune ensemble	0.9781 (+0.0049)	0.9889 (+0.0026)	0.9532 (+0.0007)	0.9756 (+0.0005)	0.9587 (+0.0128)	0.9782 (+0.0073)	0.9428 (+0.0065)	0.9706 (+0.0055)
MultiResU-Net ensemble	0.9850 (+0.0024)	0.9828 (-0.0084)	0.9590 (-0.0011)	0.9787 (-0.0007)	0.9557 (+0.0085)	0.9766 (+0.0036)	0.9471 (+0.0027)	0.9728 (+0.0015)

Ensemble Results (Special Cases)

- Models were trained for 300 epochs
- Each respective case comes from a different epoch range:
  - C1: [100-300], C2: [100-200], C3: [250-300]
- In table case which achieved highest F-IoU is shown (indicated by C1, C2, or C3 below values)

	Sandstone		S-chalk		L-chalk		Shale	
	F-IoU	*Pixel Acc.*	*F-IoU*	*Pixel Acc.*	*F-IoU*	*Pixel Acc.*	*F-IoU*	*Pixel Acc.*
U-Net ensemble	0.9768 (C1)	0.9882	0.9569 (C1)	0.9775	0.9512 (C2)	0.9741	0.9497 (C3)	0.9741
U-Resnet ensemble	0.9878 (C2)	0.9938	0.9621 (C1)	0.9804	0.9568 (C1)	0.9773	0.9522 (C3)	0.9754
MultiResU-Net ensemble	0.9840 (C3)	0.9920	0.9646 (C1)	0.9818	0.9575 (C1)	0.9776	0.9503 (C1)	0.9745

Conclusions

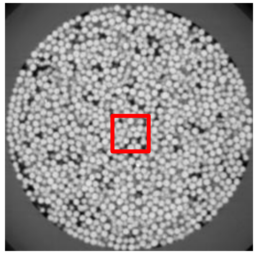
- Deep learning architectures can successfully be applied to the task of semantic segmentation for rock images and can perform better than manual segmentation to recover natural morphology of original images
- Ensemble approach consistently improved performance
- Use of transfer learning led to mixed results
- 3D model underperformed
  - May be due to lack of training data and enough training (a small # of epochs in this work)
  - Complications can arise when using depth data, such as unpredictable variations in illumination between images
- Ensemble approach with hyperparameter tuned (results not shown) tend to improve performance in all cases
- Data labeling and curation will be explored to improve supervise learning process

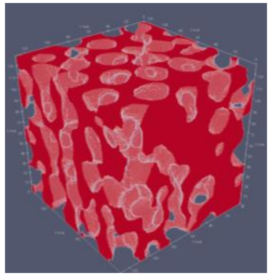
Thank You!!!

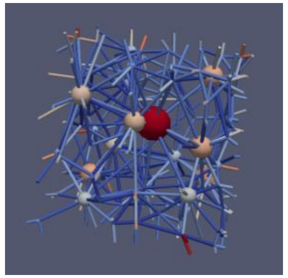
Porous Media and Pore Network (PN) Systems

- Generating accurate segmentations of rock images is critical to geomaterial characterizations
- Challenges: Complexity in geometry, size, scale, and compositions

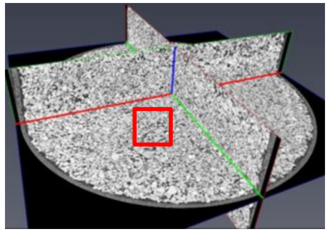
Glass bead pack (100 μm-1mm)

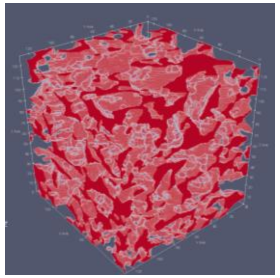


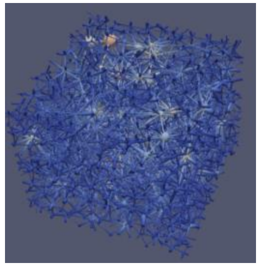




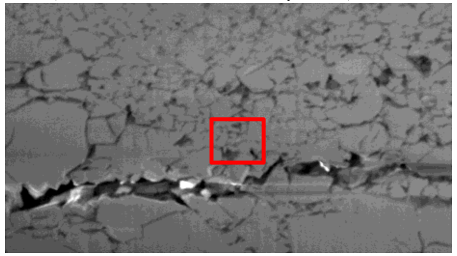
Sandstone (10’s-100’s μm)

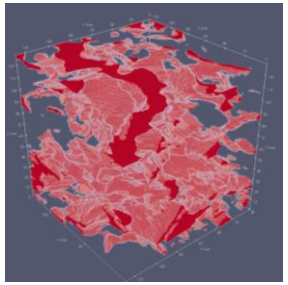




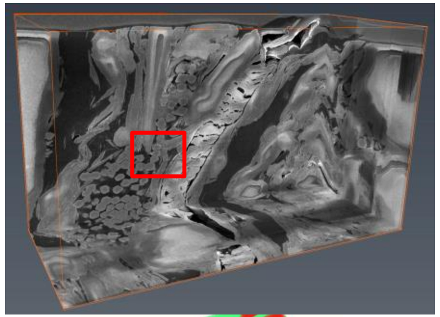


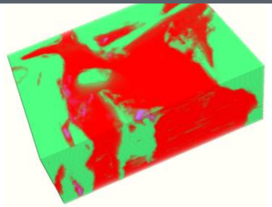
Chalk (10 nm - 100μm)

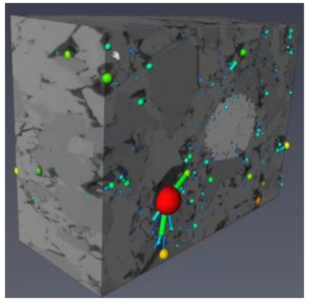




Shale (1 nm - microns)





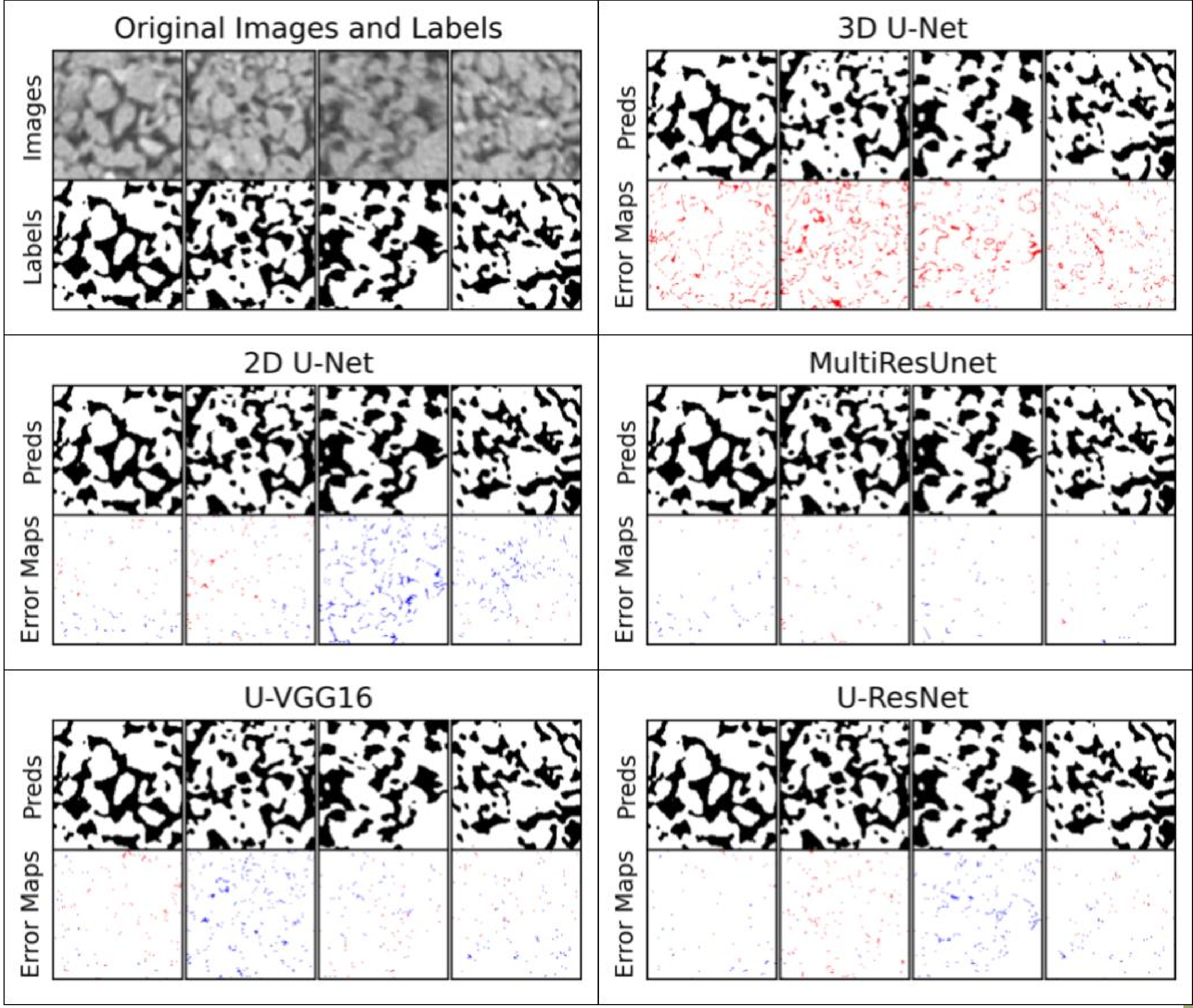


Binary 3D images

PN from microCT image

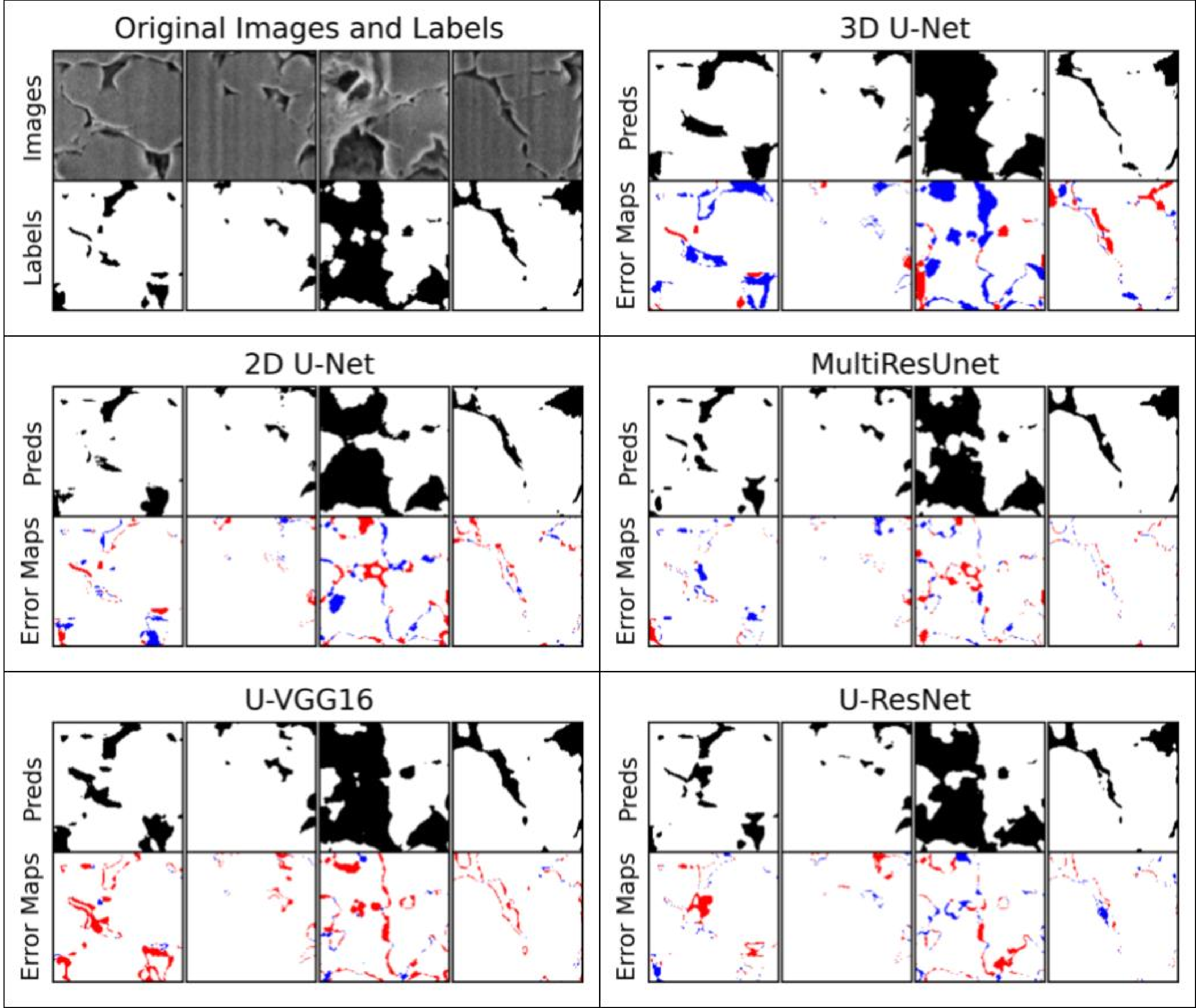
Xtlas.pergeos.com PN from FIB-SEM image

Predictions for Sandstone Data (Only Base Models Shown)



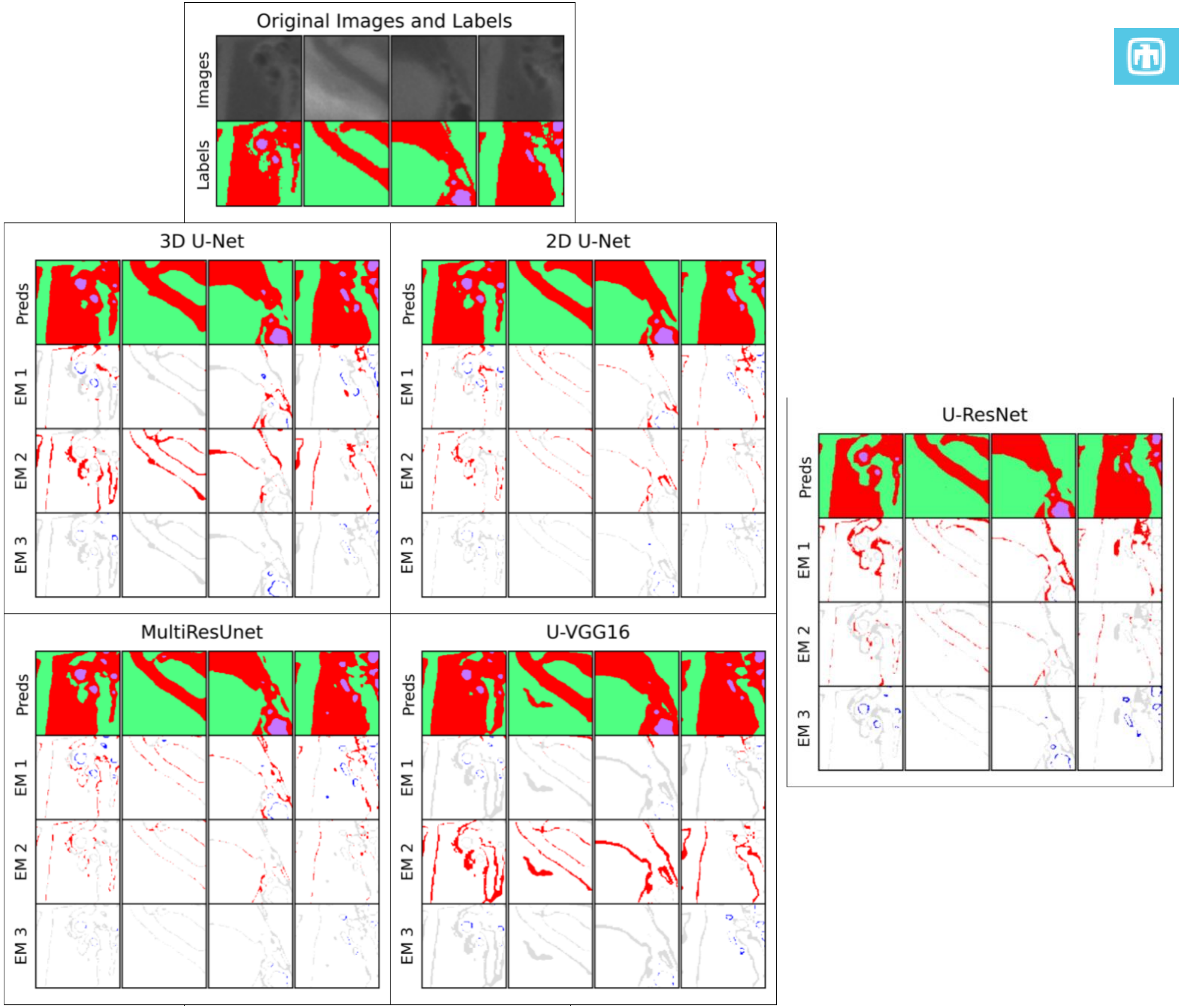
Sample images, predictions, and error maps from the testing split of the sandstone dataset. On the error maps, white indicates label and prediction agree, blue indicates pore was predicted but expected solid, red indicates solid was predicted but expected pore.

Predictions for Liege Chalk Data (Only Base Models Shown)



Sample images, labels, predictions, and corresponding error maps from liege chalk dataset. For the error maps, white indicates label and prediction agree, blue indicates pore was predicted but expected solid, red indicates solid was predicted but expected pore.

Predictions for Shale Data (Only Base Models Shown)



Sample Images, Labels, Predictions, and Corresponding Error Maps* from the Shale dataset.

* Error maps key:

Error Map 1 (EM 1):

- White: Label and prediction agree
- Blue: Pore predicted, expected organic
- Red: Solid predicted, expected organic
- Light-grey: Other error

Error Map 2 (EM 2):

- White: Label and prediction agree
- Blue: Pore predicted, expected solid
- Red: Organic predicted, expected solid
- Light-grey: Other error

Error Map 3 (EM 3):

- White: Label and prediction agree
- Blue: Organic predicted, expected pore
- Red: Solid predicted, expected pore
- Light-grey: Other error