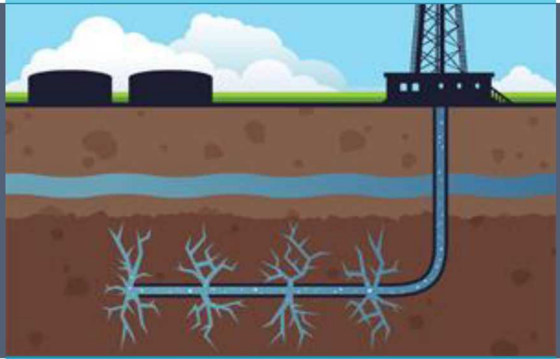
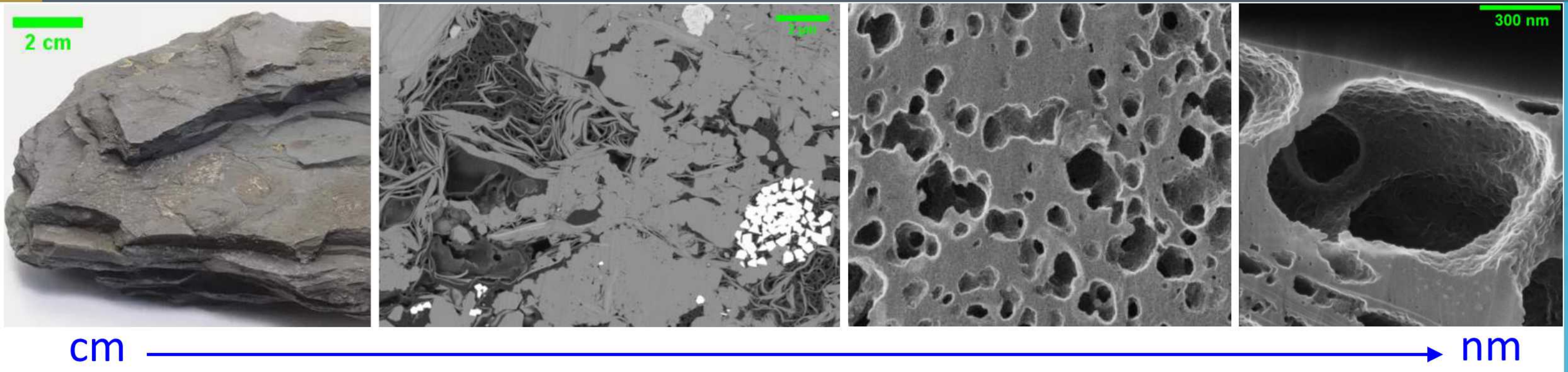
SAND2019-3128C

Neural Networks for microscopic image analysis



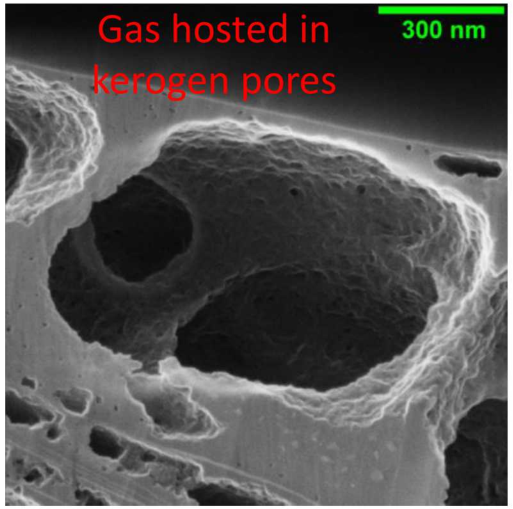


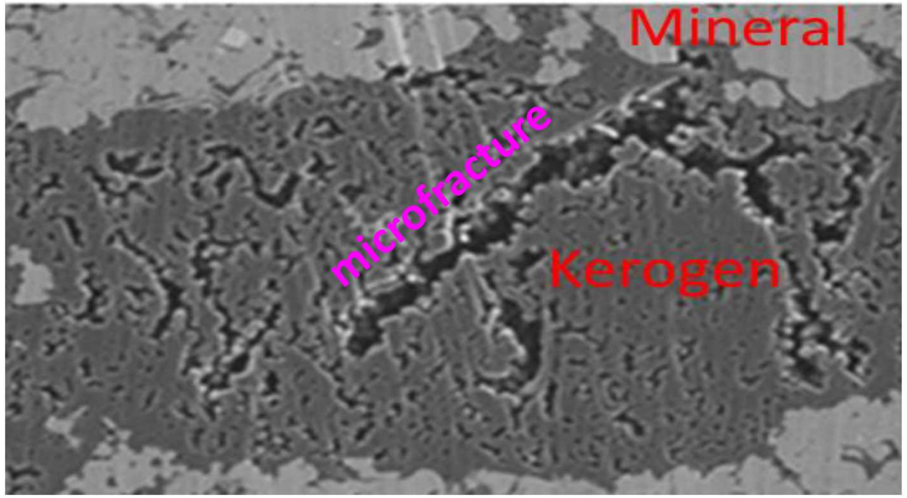
PRESENTED BY

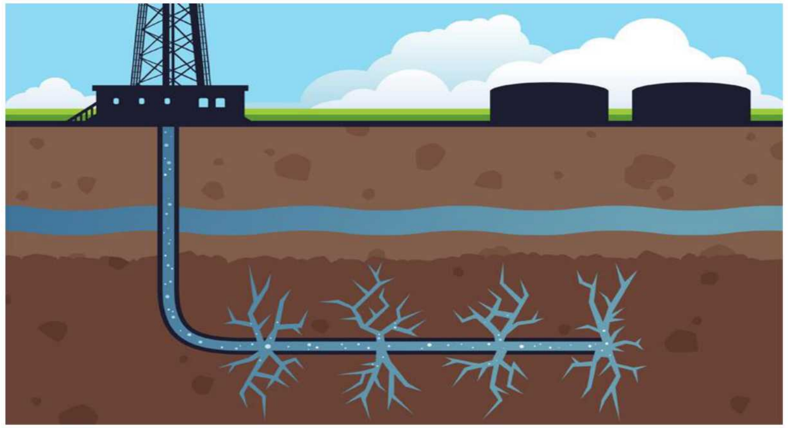
Guangping Xu, Yifeng Wang and Stephen J Verzi

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.

Shale Gas Extraction Process







Gas release from kerogen pores (size: nanometer scale) → Fluids "flow" from kerogen via nano- or micro-fractures (Channel size: nanometer to micrometer scale) → Fluids flow into hydraulic fractures then to production well (Channel size: millimeters to decimeters)

Limiting steps

↓

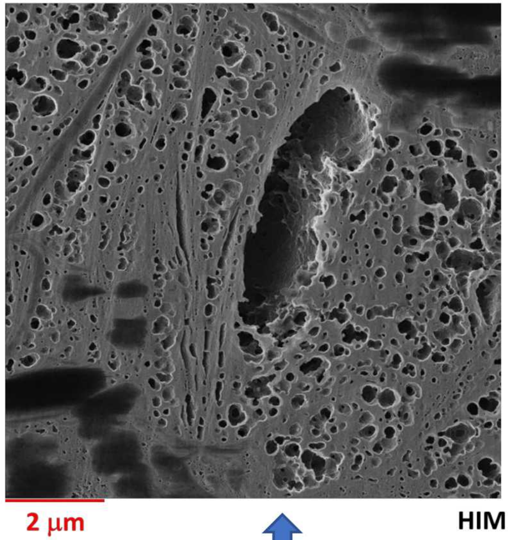
Need to quantify the spatial distribution network for Kerogen – Pore – Micro-channels

Thinking of an escape plan in case of fire:

(1) Space between rows (micro-channels) only allows people to leave one by one – "diffusion process"
(2) The width of the door – "pore network tortuosity"
(3) Once hallway is reached – hydraulic fractures, then highway

Shale Imaging

Nano-meter resolution images can be acquired by FE-SEM, FIB-SEM, Helium Ion Microscope under different modes



Secondary electron mode (SE1)

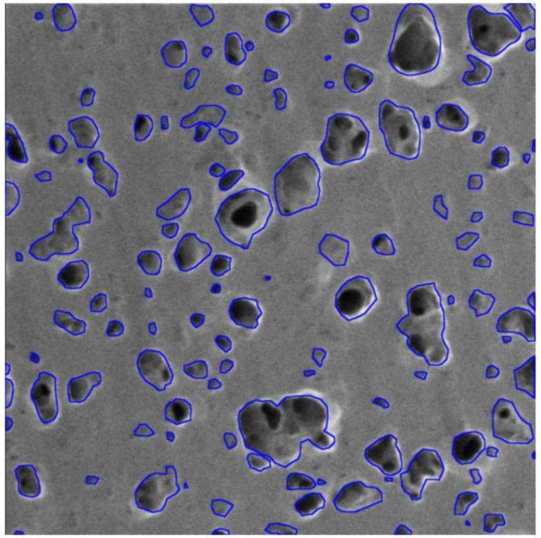
He ion mode

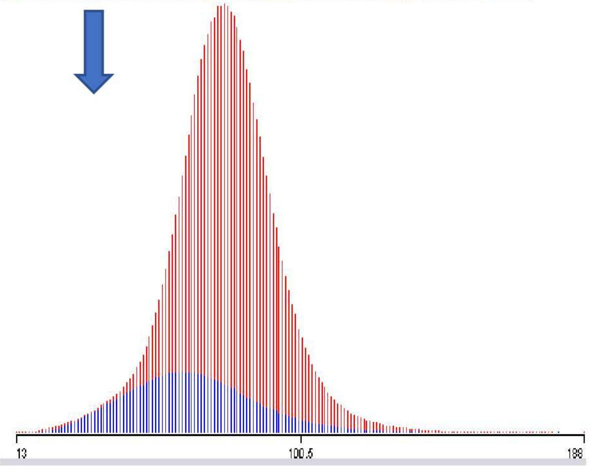
Secondary electron (SE2) plus SE3

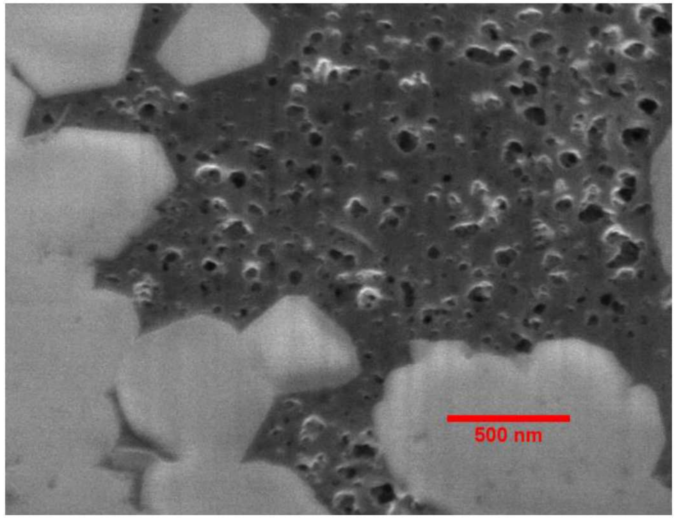
Shale is NOT a black box. Gas shale has three main constituents: framework minerals, kerogen, and pore space

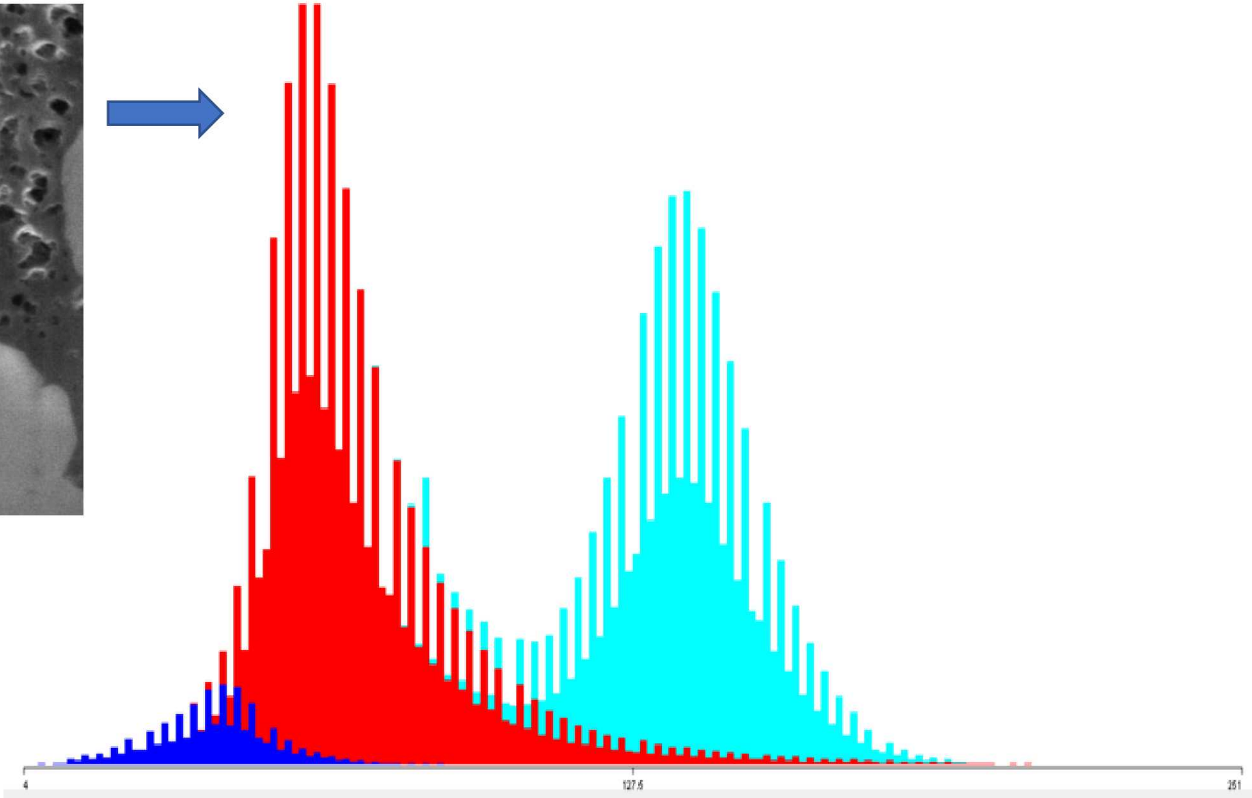
Image Segmentation

Traditionally, intensity is used for segmentation (only one dimension)









Blue – pore; Red – kerogen; light blue - mineral

Special challenges:
(1) Edge effect
(2) Depth of field view
(3) Large dimension of images

There are overlaps in intensities

Machine Learning based Image Segmentation

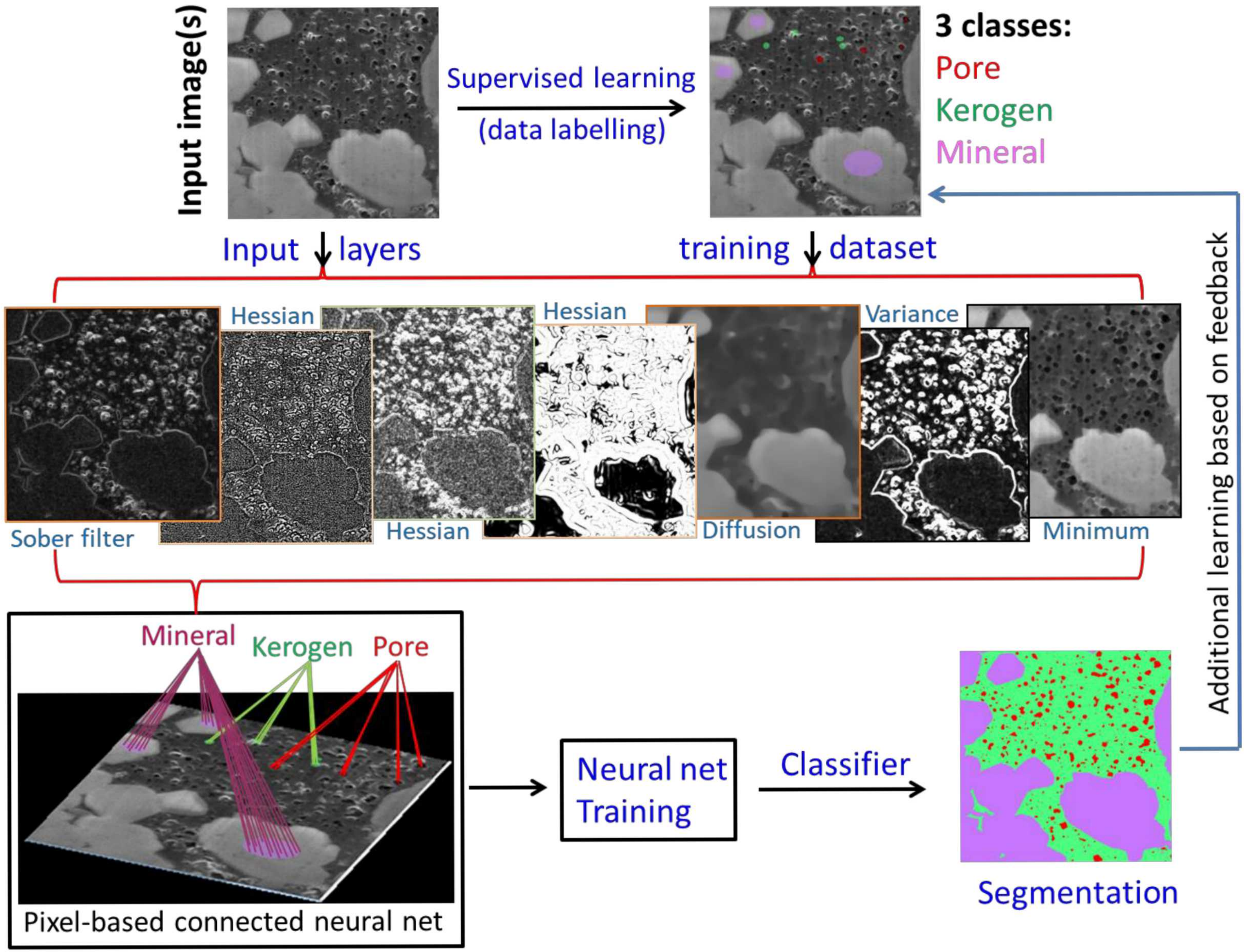
Step 1. image normalization

Step 2. data labelling

Step 3. feature extraction

Step 4. train dataset

Step 5. Use classifier to segment images

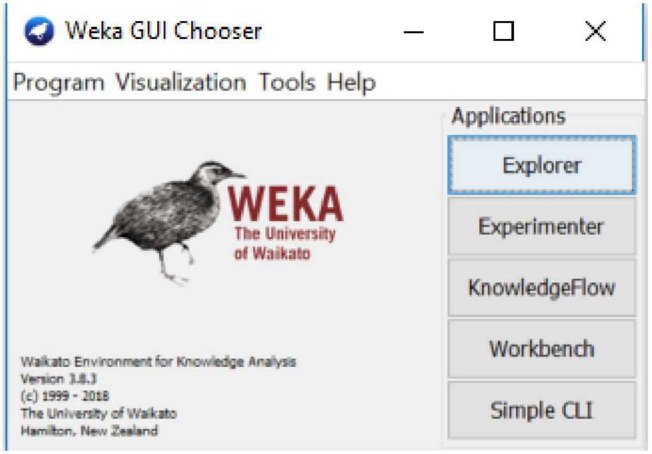


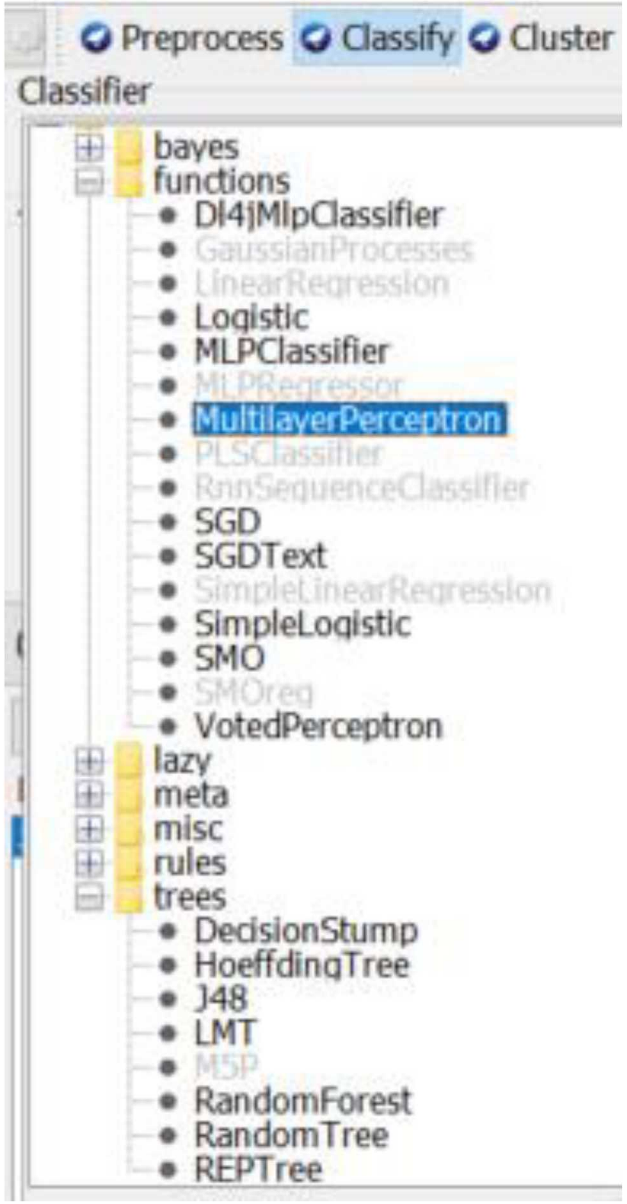
Filters for extracting features
- Edge detectors (Laplacian and Sobel filters …)
- Texture filters (min, max, variance, entropy …)
- Noise reduction filters (Gaussian blur …)
- Structure /morphology filters …

Neural Network Training

The dataset can be trained on Weka GUI interface (or ImageJ) using existing machine learning / deep learning algorithms:

(1) MultilayerPerceptron
(2) Random Forest
(3) Deeplearning4j



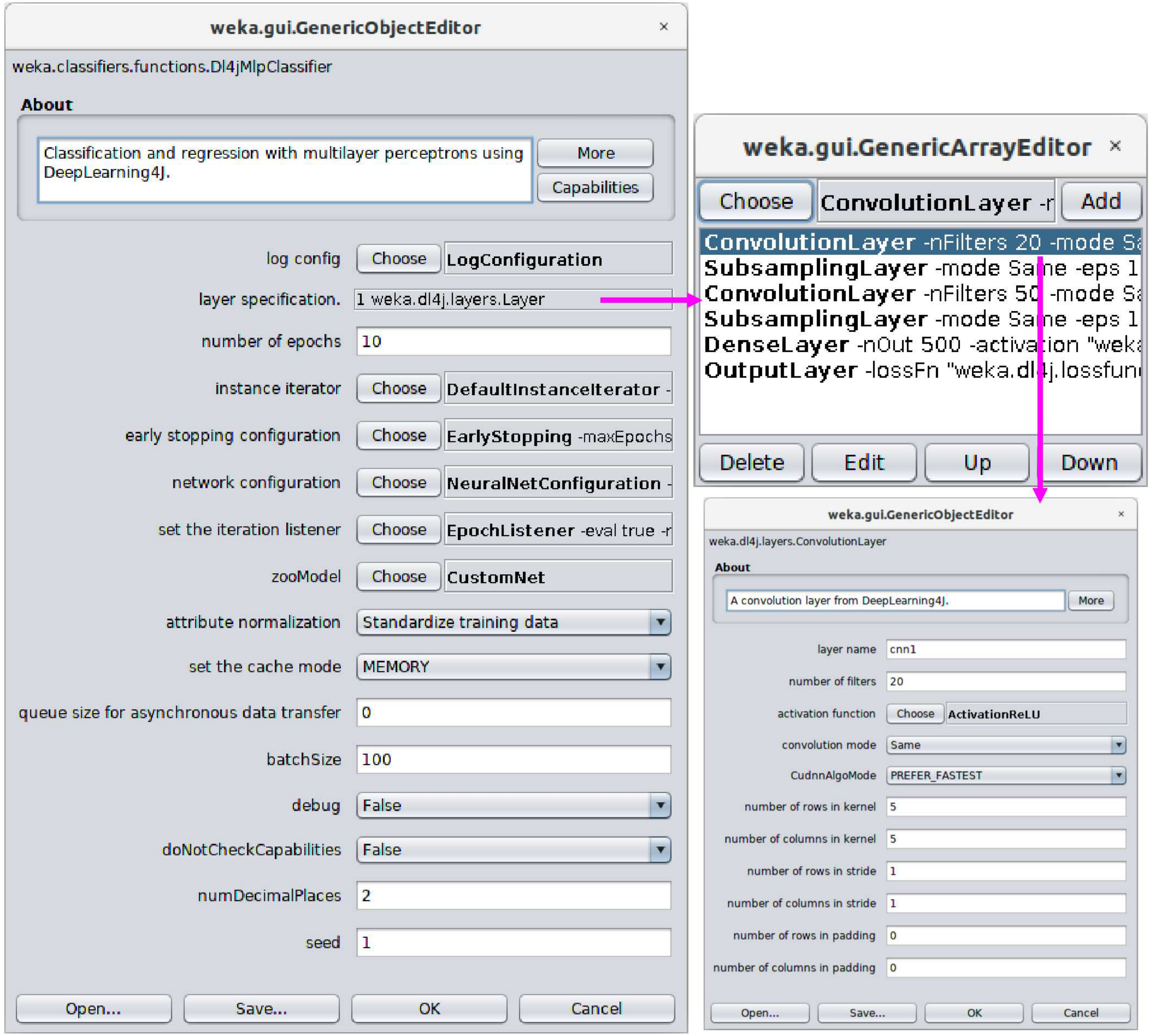


Neural Network Training - implementation

The dataset can be trained on Weka GUI interface (or ImageJ) using existing machine learning / deep learning algorithms:

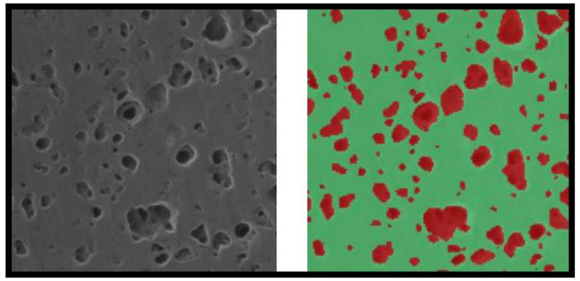
(1) MultilayerPerceptron
(2) Random Forest
(3) Deeplearning4j

It can also be easily implemented using personal computer without GPU. It does not need large training dataset. No Programming skills needed!



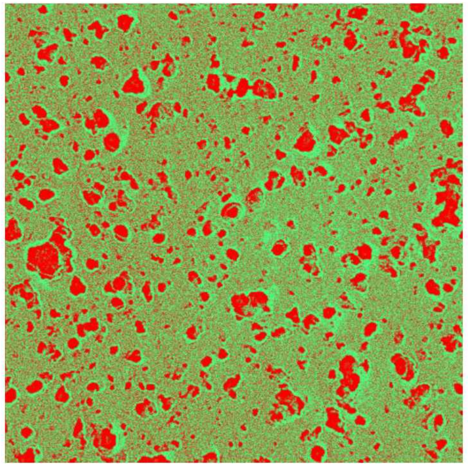
Knowledge Transfer Challenges

Classifier based on trained image (200 x 200, downsized from 2048 x 2048)

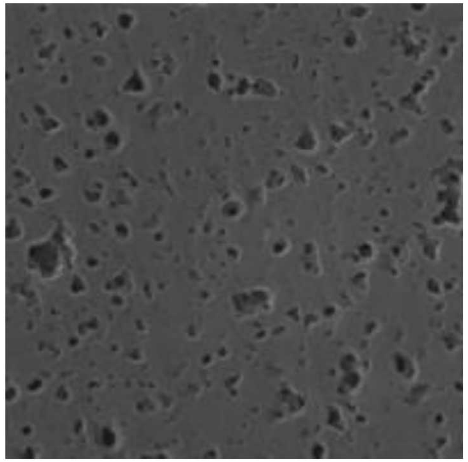


Because intensity gradient is an important parameter that separates pore from kerogen, changing resolution changes the gradient and thus produces noise

Segmented image (2048 x 2048)

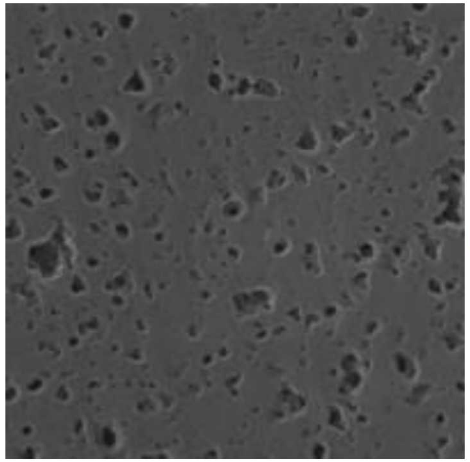


Tested image (2048 x 2048)

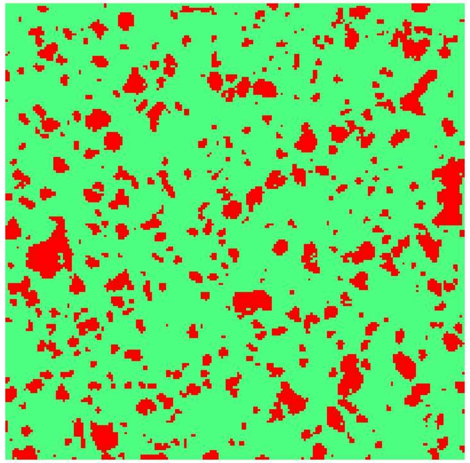


Downsize to 200 x 200

Tested image (200 x 200)



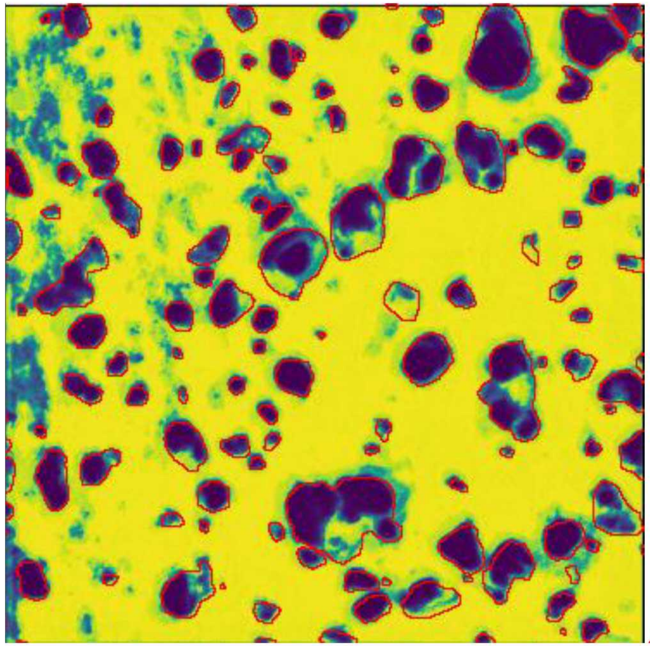
Segmented image (200 x 200)



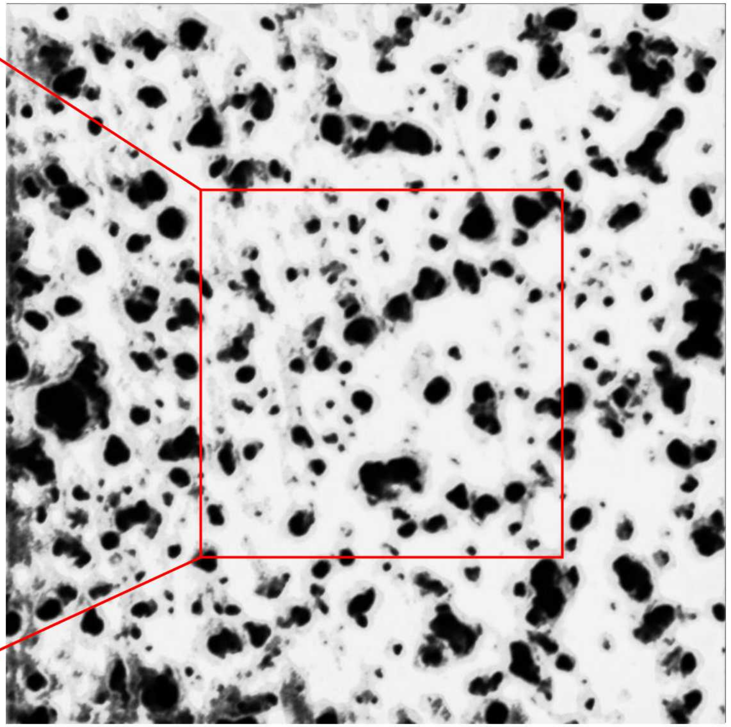
Convolutional Neural Network (CNN) Training

A 2048 U-Net (CNN) is built to accommodate 2048x2048 training image:

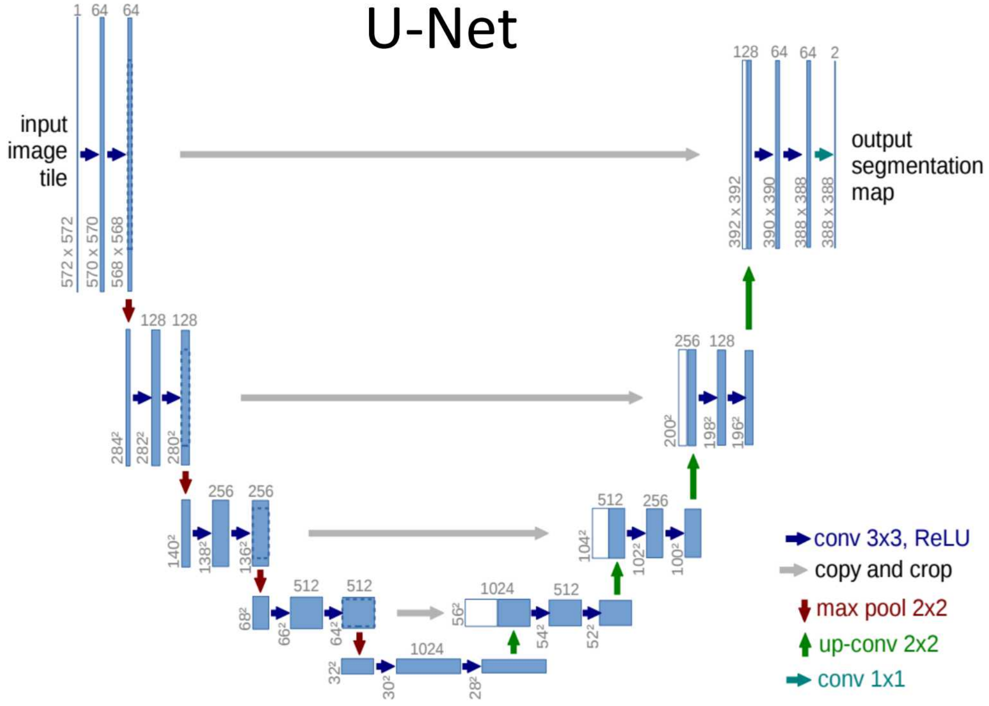
- Total 83 convolution layers; 138,453,465 trainable parameters;
- Regular neural network training is based on artificial extraction of limited image features; CNN can extract large amount of image features automatically
- Trained for 50 epochs using **one** training image plus the 7 rotation & flip transformations
- 91.7% accuracy on a pixel-by-pixel basis on training image



Training image (2048x2048)



Test image (2048x2048)



Ronneberger et al. 2015
arXiv:1505.04597

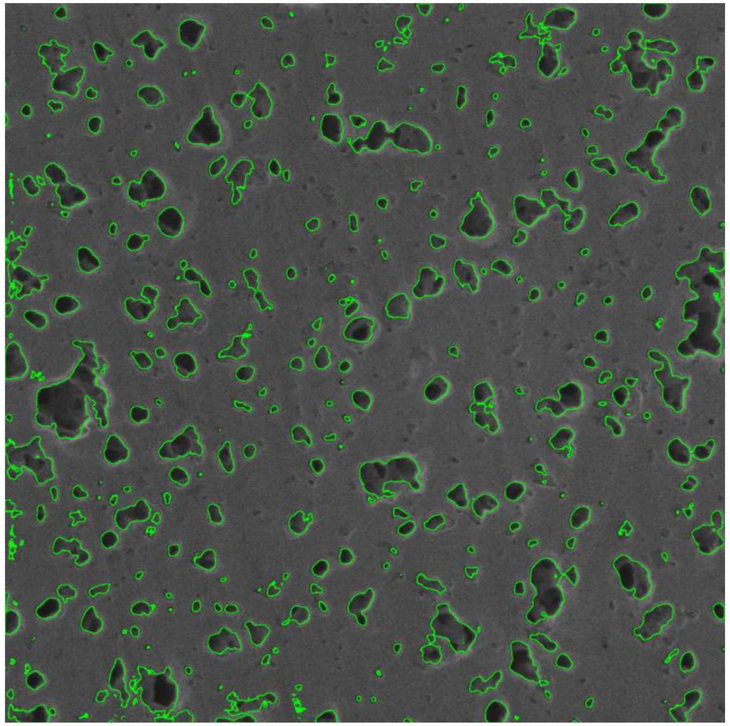
Convolutional Neural Network (CNN) Training

A 2048 U-Net (CNN) is built to accommodate 2048x2048 training image:

- Total 83 convolution layers; 138,453,465 trainable parameters;
- Regular neural network training is based on artificial extraction of limited image features; CNN can extract large amount of image features automatically
- Trained for 50 epochs using **one** training image plus the 7 rotation & flip transformations
- 85% accuracy on a pixel-by-pixel basis based on test image

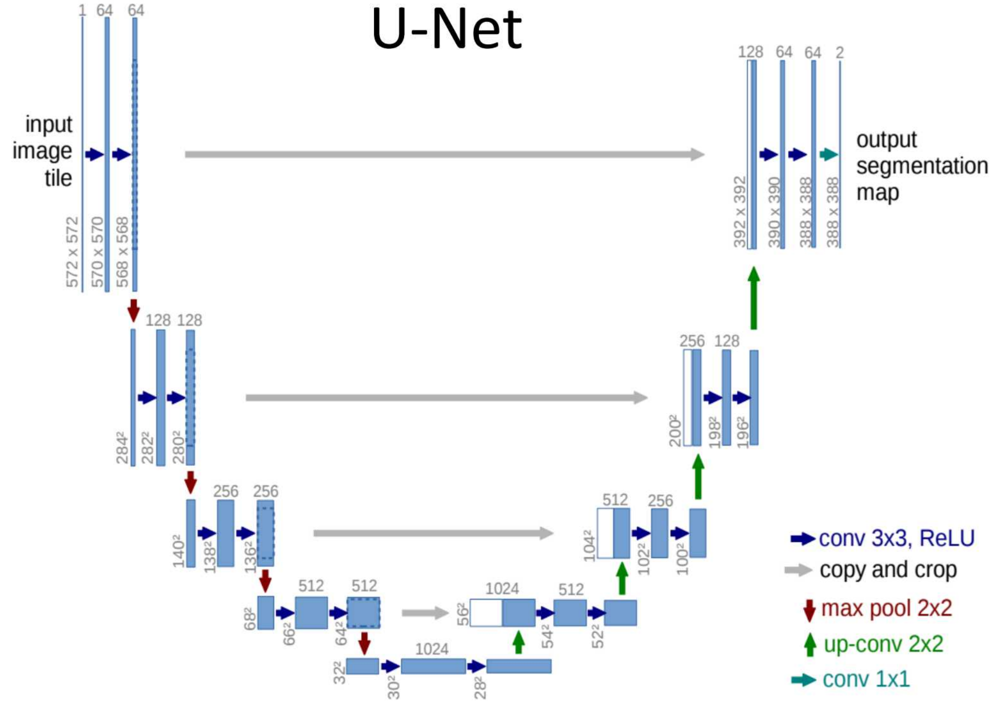
Confusion Matrix:

	Predicted Non-Pore	Predicted Pore
True Non-Pore	**69.7%**	5.6%
True Pore	9.6%	**15.1%**



Test image (2048x2048)

U-Net

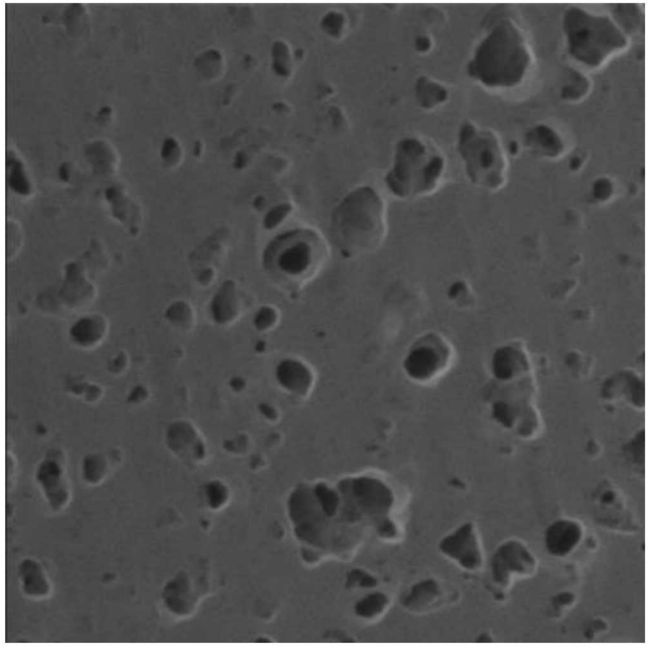


Ronneberger et al. 2015
arXiv:1505.04597

CNN Knowledge Transfer

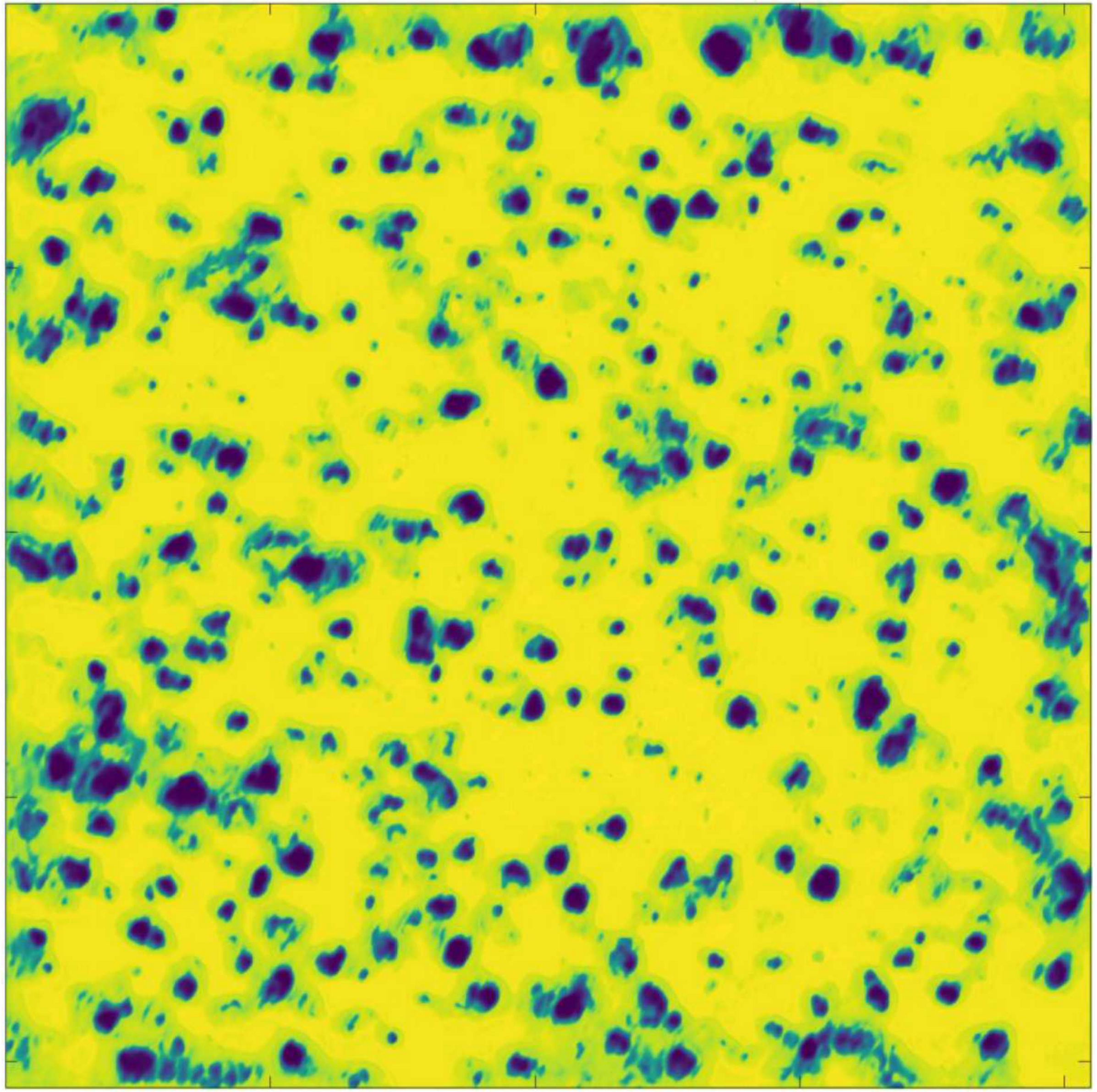
A 2048 U-Net (CNN) is used to accommodate 2048x2048 training image:

- Total 83 convolution layers;
- 138,453,465 trainable parameters;
- Trained for 50 epochs using **one** training image plus the 7 rotation & flip transformations
- 91.7% accuracy on a pixel-by-pixel basis



Trained image (HIM)

Test image from SEM which CNN has never seen!



CNN Knowledge Transfer

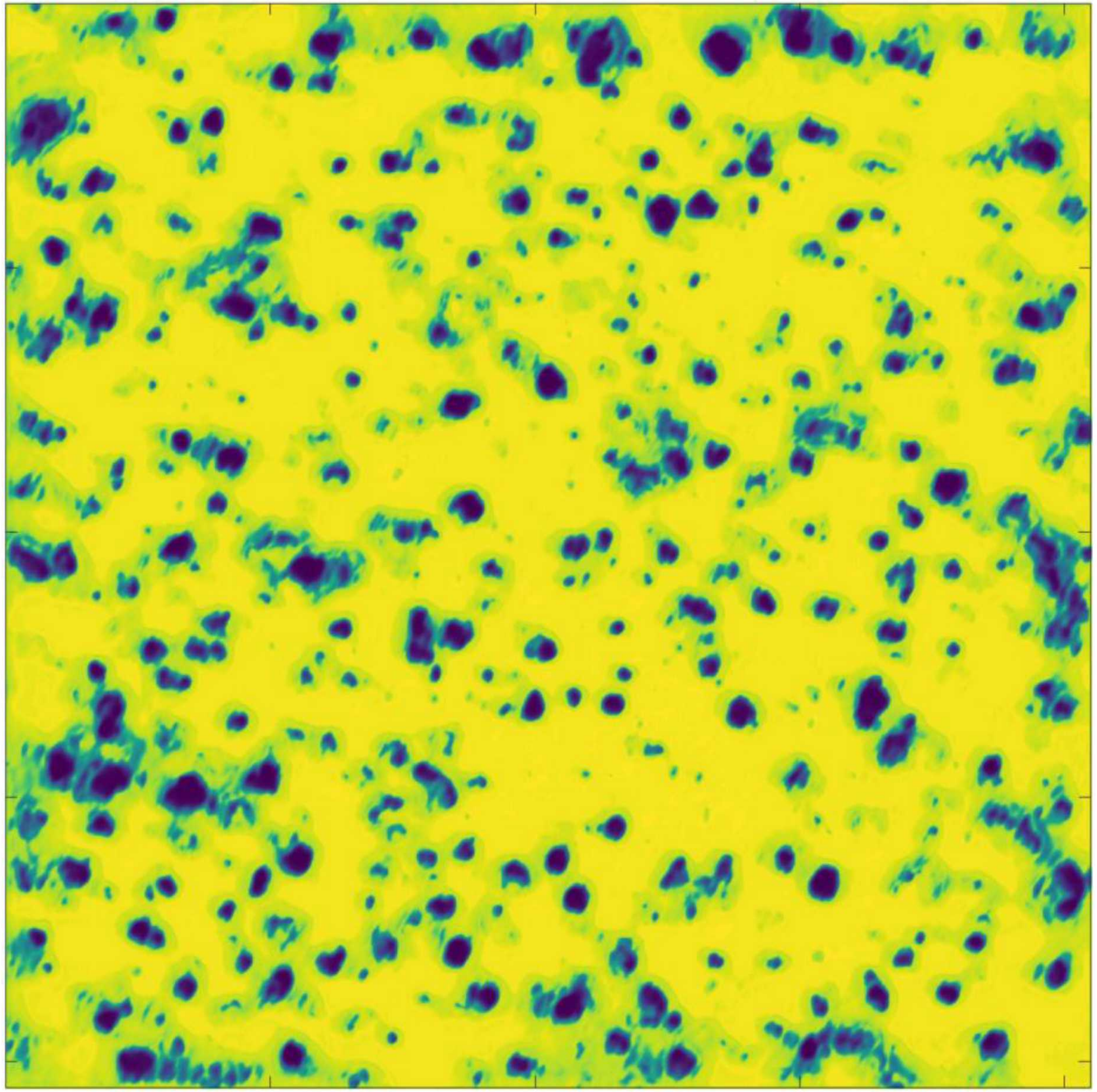
A 2048 U-Net (CNN) is used to accommodate 2048x2048 training image:

- Total 83 convolution layers;
- 138,453,465 trainable parameters;
- Trained for 50 epochs using **one** training image plus the 7 rotation & flip transformations
- 82% accuracy on a pixel-by-pixel basis

Confusion Matrix:

	Predicted Non-Pore	Predicted Pore
True Non-Pore	**72.4%**	1.7%
True Pore	16.3%	**9.65%**

Test image from **SEM** which CNN has never seen!



CNN in Grain Boundary Detection (Preliminary)

Mineral granularity and aspect ratios are directly related to reservoir properties such as porosity, permeability and dialectic constant

- A 2048 U-Net (CNN) is used to accommodate 2048x2048 training image
- Three classes: mineral – boundary – non-mineral

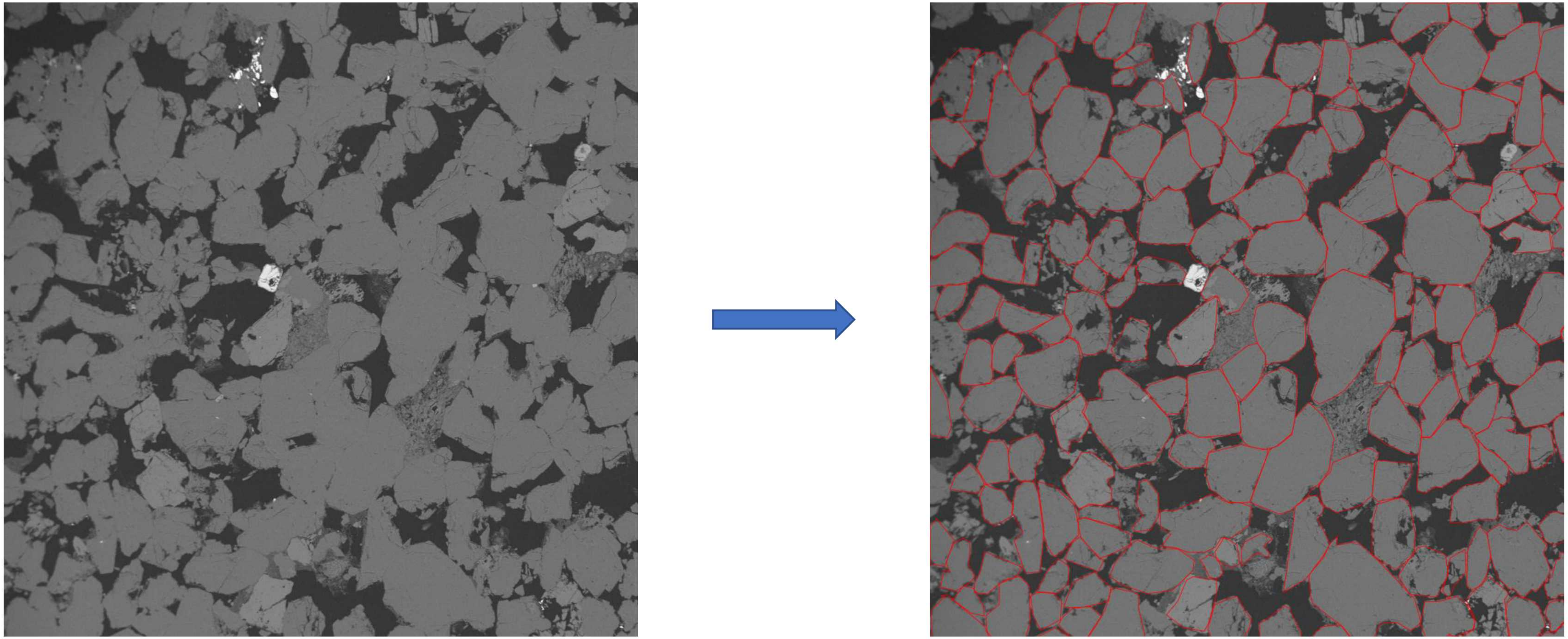
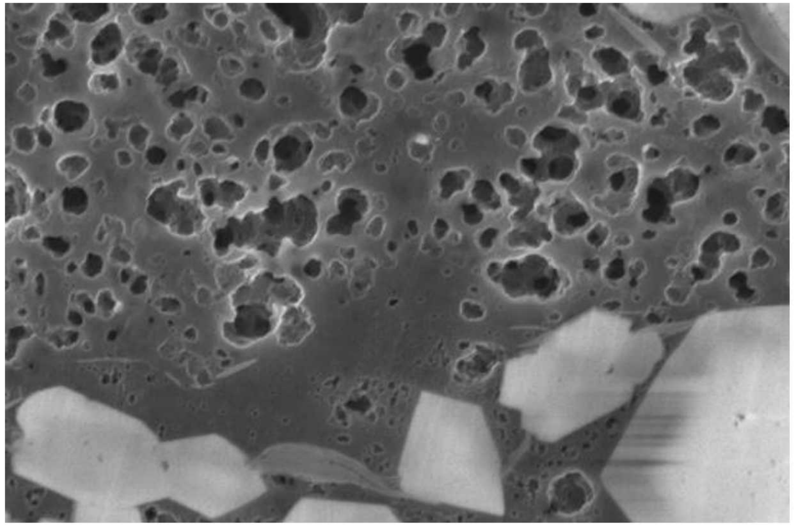


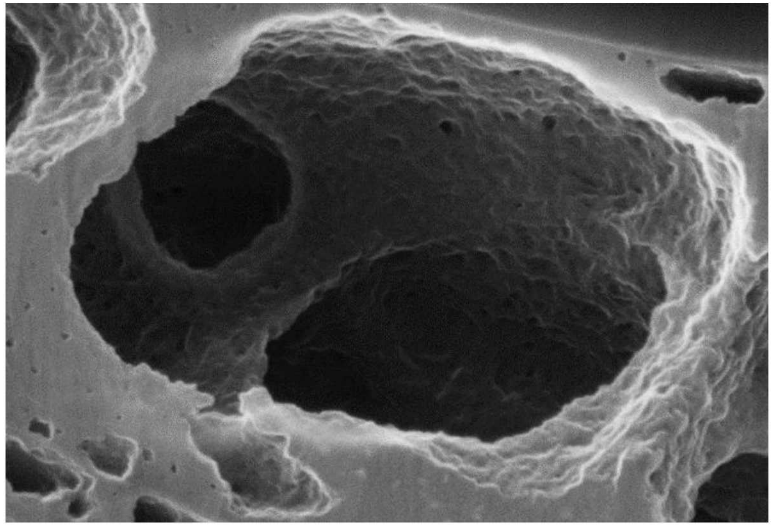
Image Segmentation Results

- Kerogen and mineral spatial distribution
- 3D pore network (connectivity, tortuosity…)
- Pore size distribution
- Pore morphology / stereology

Pore morphology

Kerogen hosted pores: rounded





Mineral hosted pores: angular

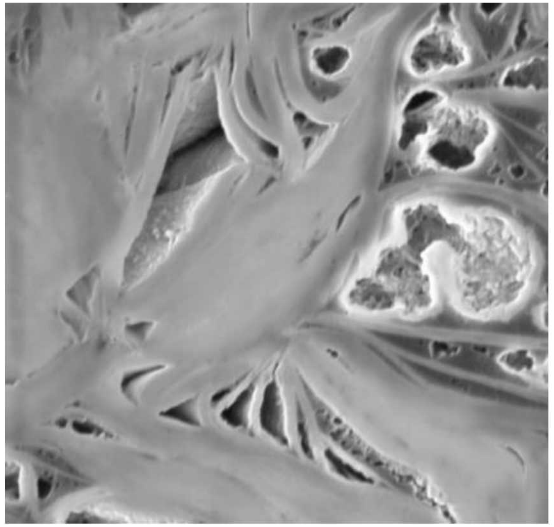
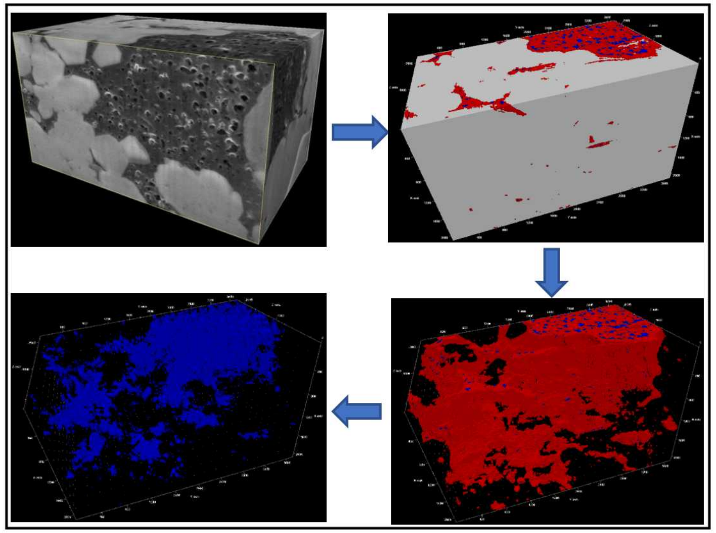
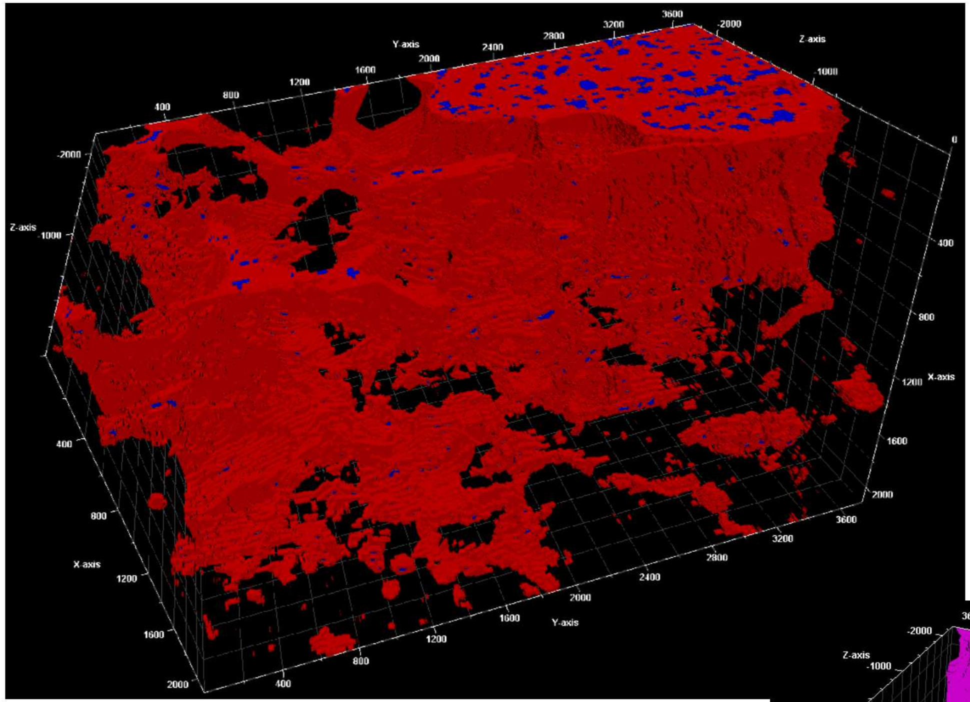
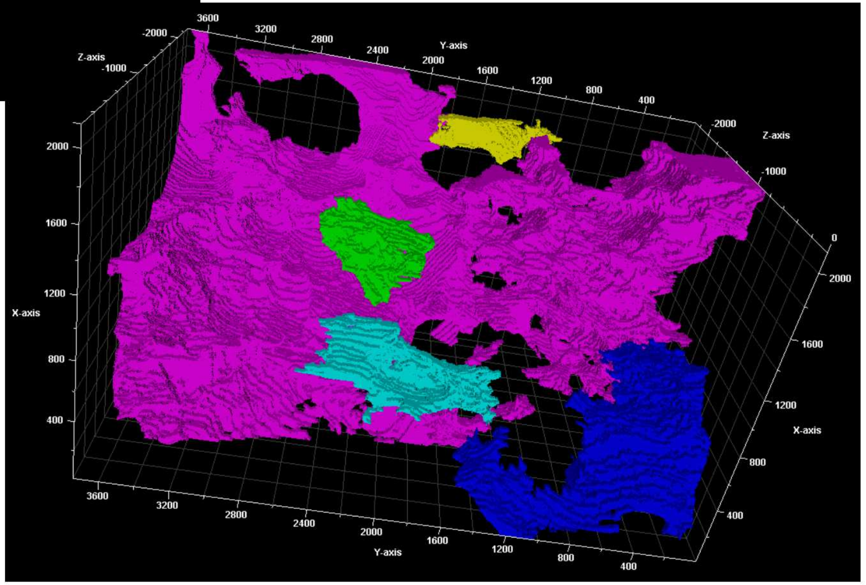


Image Segmentation Results



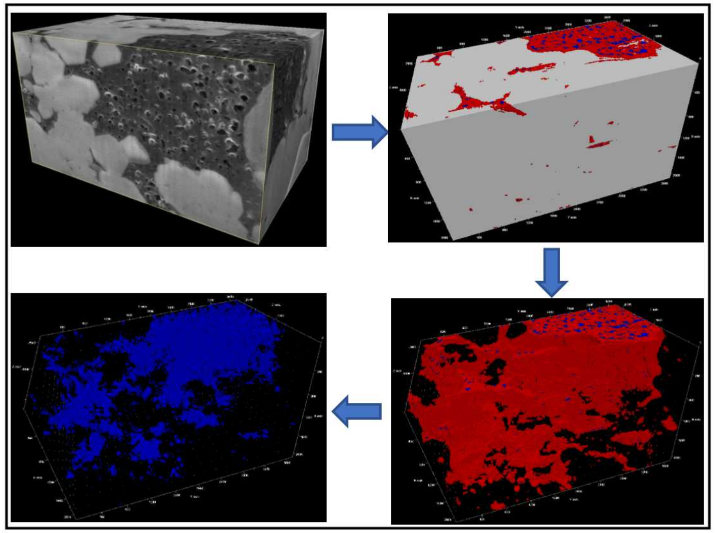
blue – pore; red – kerogen;
white - mineral



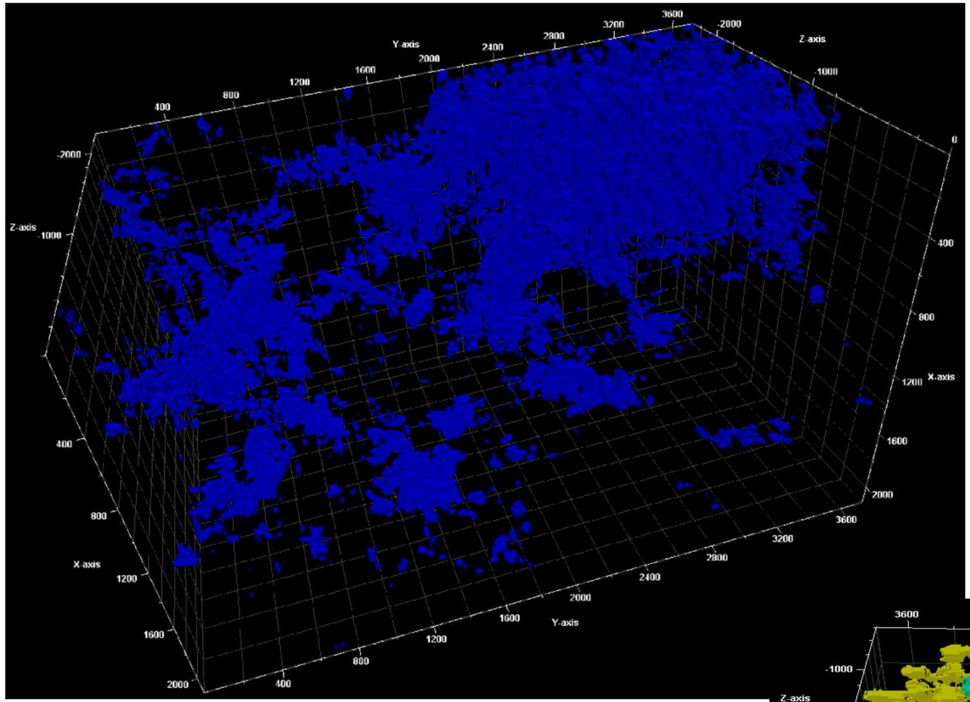


The largest connected kerogen body accounts for 91.5% of total kerogen volume

Image Segmentation Results



blue – pore; red – kerogen;
white - mineral



The largest connected pore body accounts for 21.3% of total pore volume

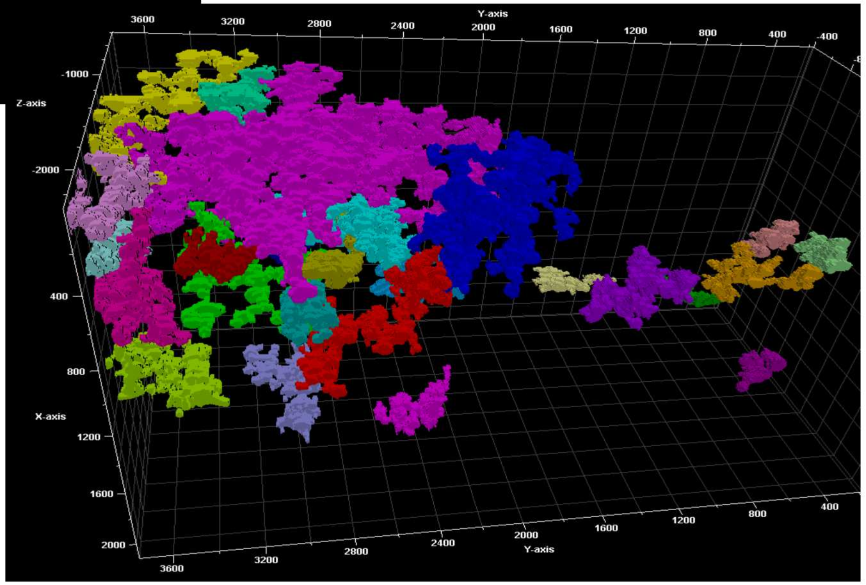
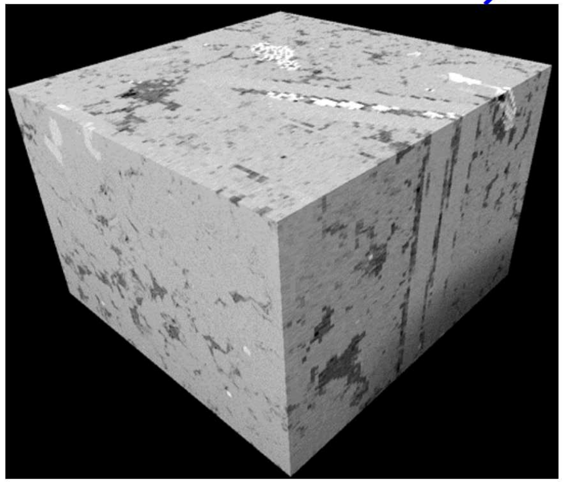
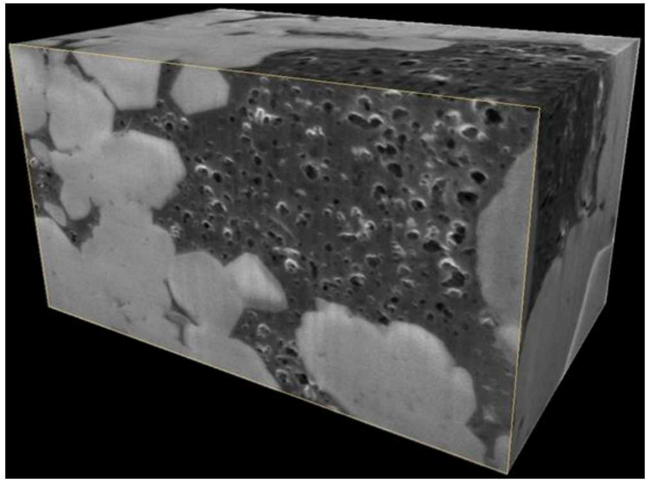
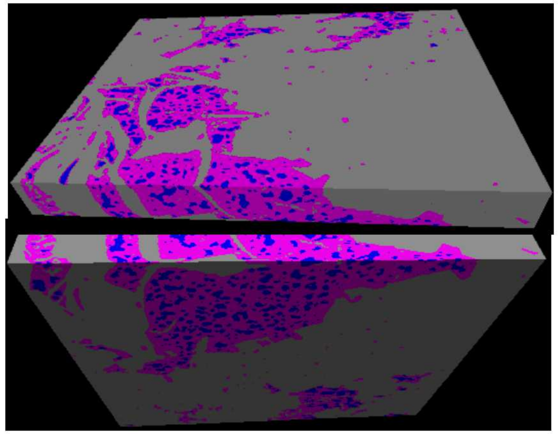


Image Segmentation Results

	Coarse Grid	Intermediate Grid	Fine Grid
Dimension	20.4 x 14.0 x 20.8 μm	3.74 x 2.12 x 2.31 μm	4.61 x 3.55 x 0.44 μm
Slices	83	77	88
Resolution	26.98 x 26.98 x 250 nm	2.7 x 2.7 x 30 nm	3.47 x 3.47 x 5 nm
Porosity	0.92%	2.55%	3.41%
Kerogen %	16.70%	17.77%	19.31%
Kerogen porosity	5.22%	12.55%	17.66%
Largest connected Kerogen body	94.20%	91.50%	62.7%, 20.34%
Largest connected pore body	3.9%, 2.6%	21.30%	24.9%, 15.12%







Summary

- Machine learning assisted segmentation can build Kerogen – Pore –Mineral network from microscopic images, overcoming the complexities caused by edge effect, depth of field of view issue…

- CNN has great potential when large training dataset are avaialable

- These results reveal the connectivity for kerogen and its hosted pores in 3D are much better than in 2D

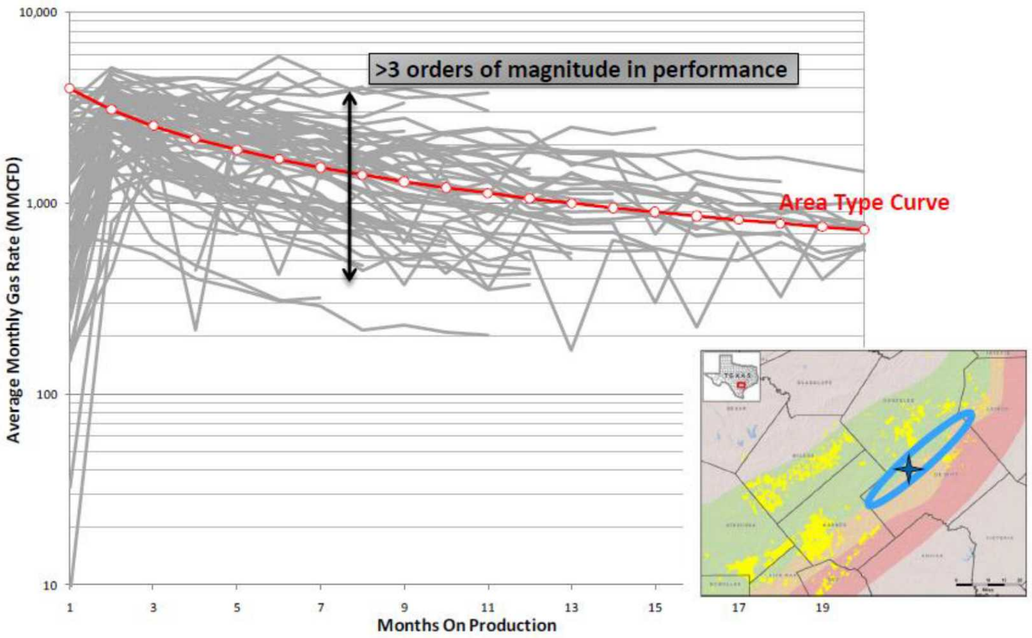
- This information can facilitate shale gas/oil production prediction utilizing “big data” analyses

Future work

(1) Build a transferrable trained model for images acquired across different imaging platforms, such as SEM, HIM, CT, XPS
(2) Using deep learning for upscaling from micron scale to mm scale

(3) Implement multiple levels of characterization for understanding decline curves:

- Kerogen pore network
- Kerogen distribution
- Mineral hosted pore network
- Natural fracture network
- Hydraulic fracture network



Robertson (2013)