Geological Survey of Canada
Scientific Presentation 96

APPLICATIONS OF MACHINE LEARNING TO GEOSCIENCE: NANOPOROSITY AND FLUID FLOW IN TIGHT FORMATIONS

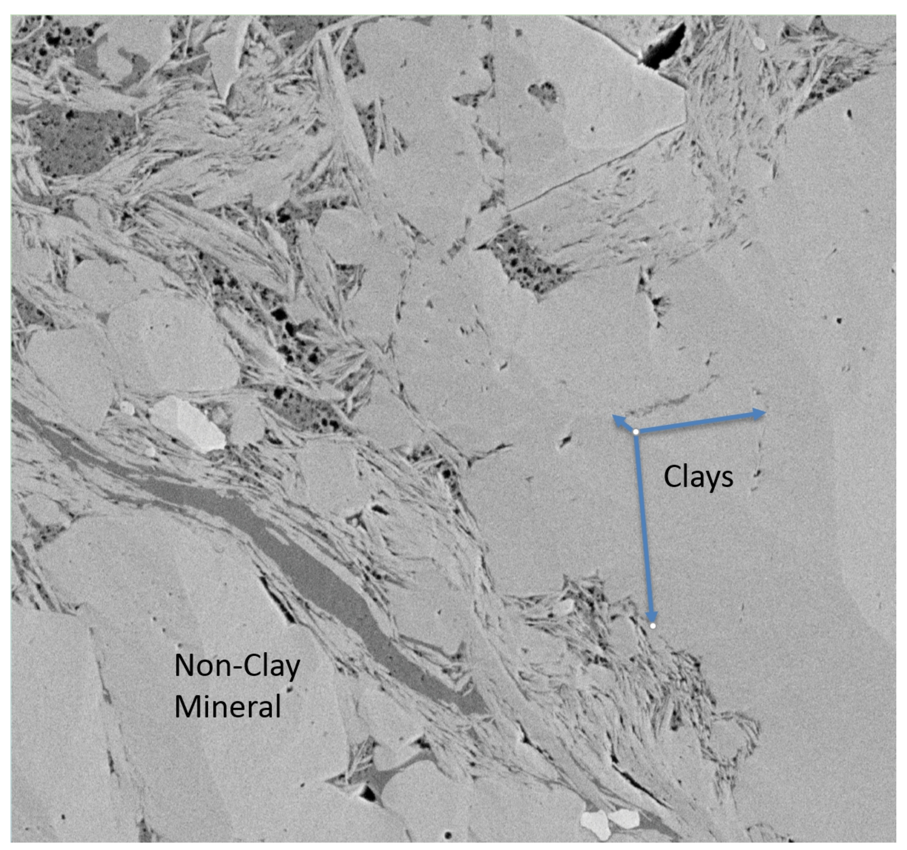
Z. Chen[1], S.R. Stoyanov[2], X. Liu[1], J. Mane[2], and E. Little[1]

Introduction

- Collaborative engagement to develop an artificial intelligence (AI) tool for hydrocarbon (HC) recovery from tight formations
- Applications of machine learning (ML) in feature extraction using scanning electron microscopy (SEM) images for nanopore characterization
- Physico-chemical modeling of HC distribution in nanopores
- Use ML for mineral classification to benefit our improved resource assessment and optimized production performance efforts
- Develop AI decision-making tool to enhance resource recovery beyond the current single-digit percent performance and address environmental challenges

Nanopore Feature Extraction and Characterization

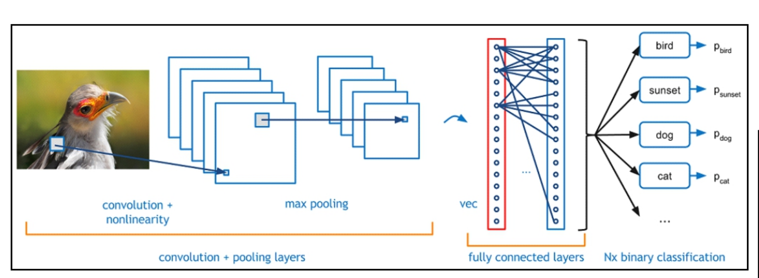
- **Feature extraction**: extract features from SEM images (shape, orientation, grain size, location of organic pores, pore types, structure and pore size distribution) with increasing thermal maturity
- **Feature characterization**: Treating features as objects, statistics of the objects and their spatial associations used to describe nanopore structures and their evolution with thermal maturity



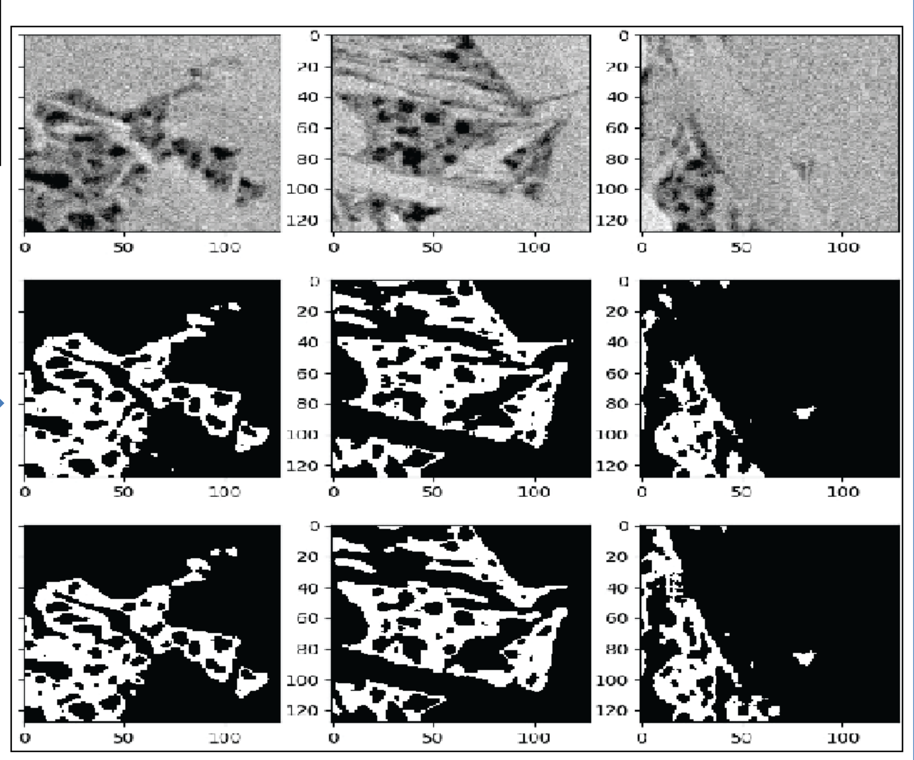
Challenges

- Large amount of data to handle
- Features with similar grey-level; Conventional processing algorithms do not work (left)
- A few training datasets are available; Convolutional Neural Network (CNN) deep learning requires a large number of training datasets

Left: Example SEM image showing the occurrences and general characteristics of a nanopore and its association with organic matter and other rock matrices in a typical marine source rock sample.



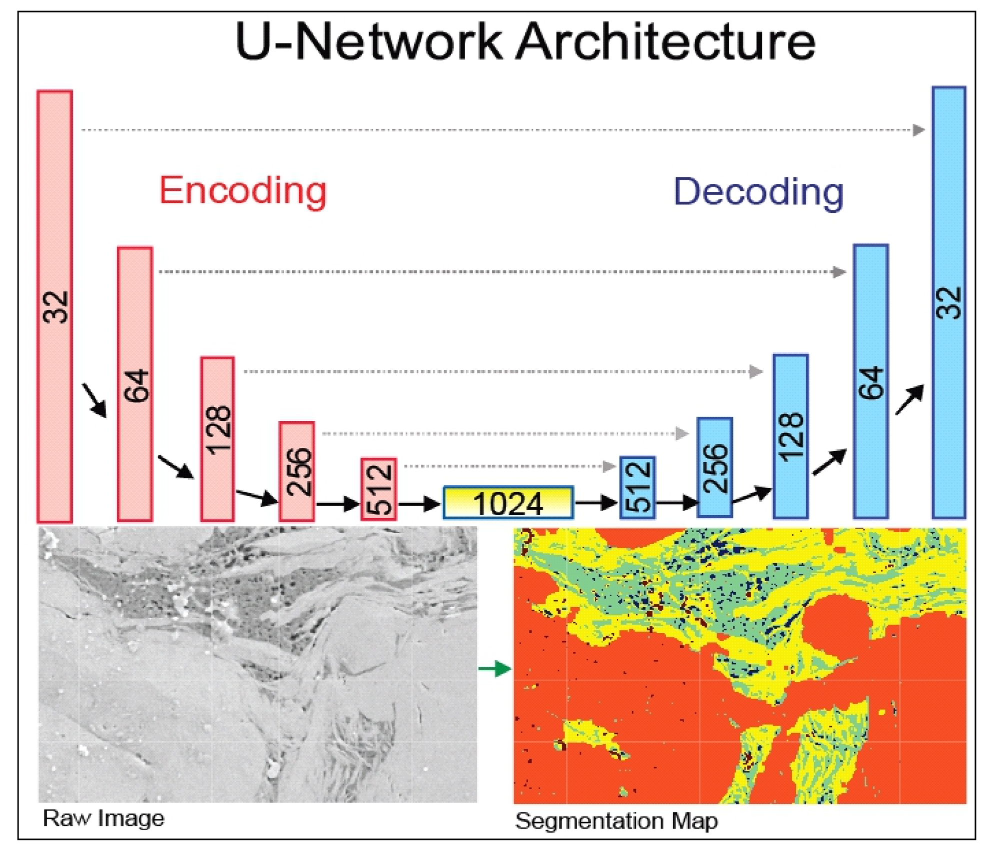
A schematic diagram showing a typical CNN for image classification.
https://adeshpande3.github.io/adeshpande3.github.io/ABeginner's-Guide-To-Understanding-Convolutional-Neural-Networks/



Right-Top: *Original SEM images: kerogen (dark grey), Organic pores (black) & clay-matrix (grey).*
Right-Middle: *Training masks*
Right-Bottom: *Results from deep learning; reproducibility >95%.*

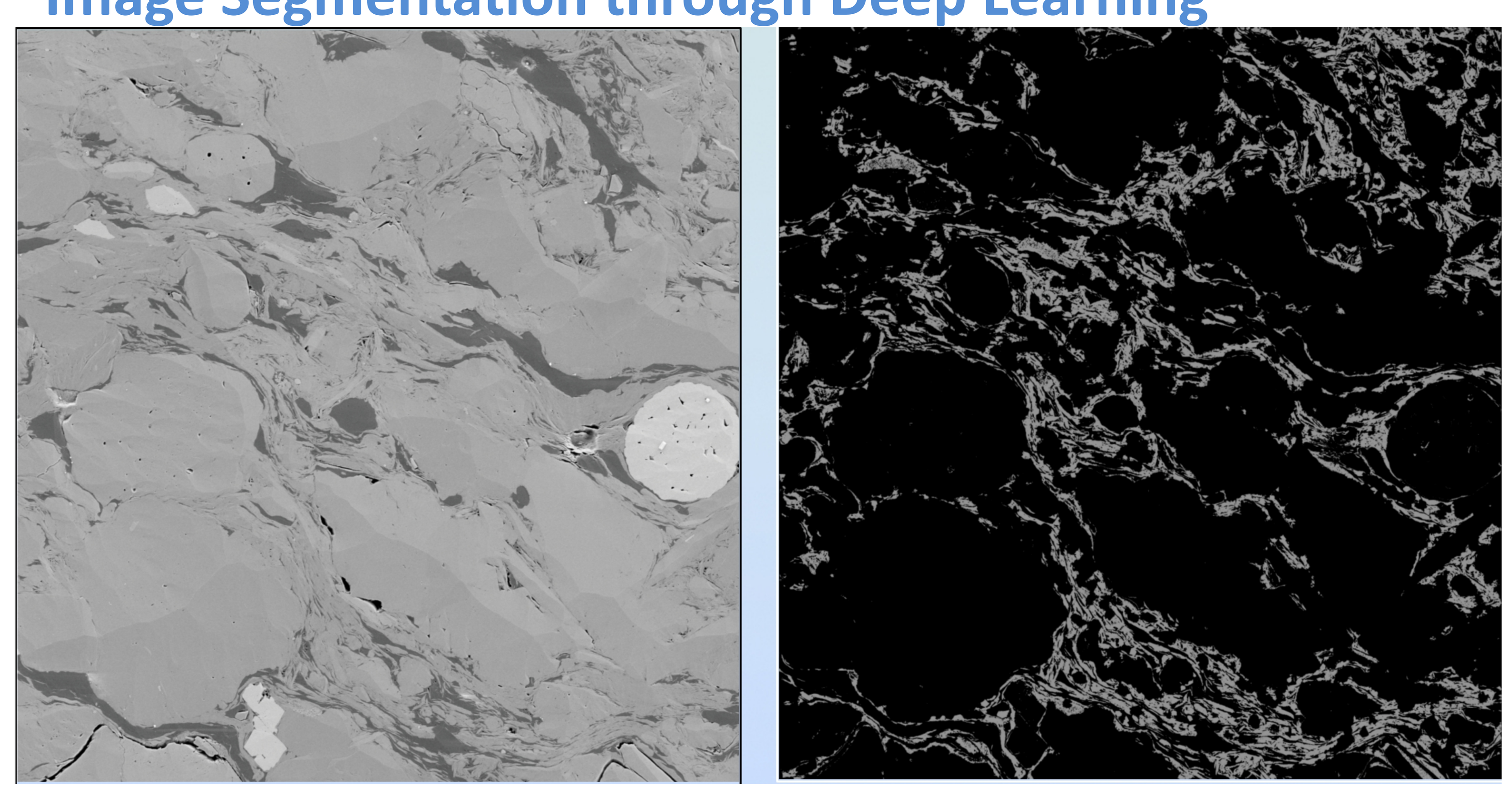
Feature Extraction from Deep Learning Algorithms

- A modified and extended CNN to work with fewer training images and yield more precise segmentation (Ronneberger, et al. 2015)
- Each repeated convolution was followed by a rectified linear unit (ReLU) and a max-pooling operation in the encoding path to reduce spatial information and enhance feature information
- Feature and spatial information combined in the contracting path through a sequence of up-convolutions and concatenations with high-resolution features in decoding path



Upper: *A schematic of U-network architecture for image segmentation;*
Lower: *Original image (left) showing rock matrix (grey, lacking texture), clay mineral (grey narrow, linear clusters), organic matter (dark grey) and pores within organic matter (black). Classification and segmentation results (right) illustrating rock matrix (red), clay mineral clusters (yellow), organic matter (blue) and pore spaces (black).*

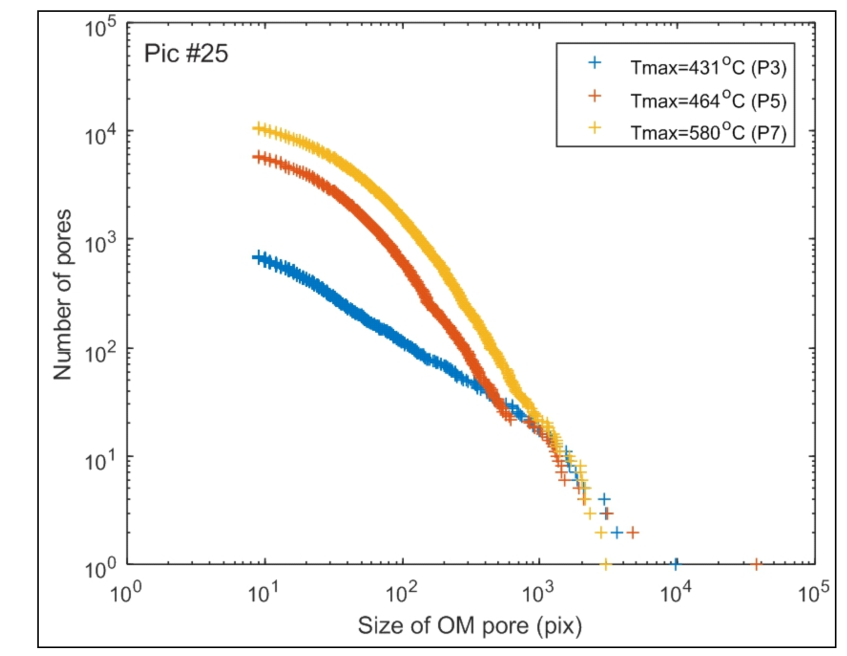
Image Segmentation through Deep Learning



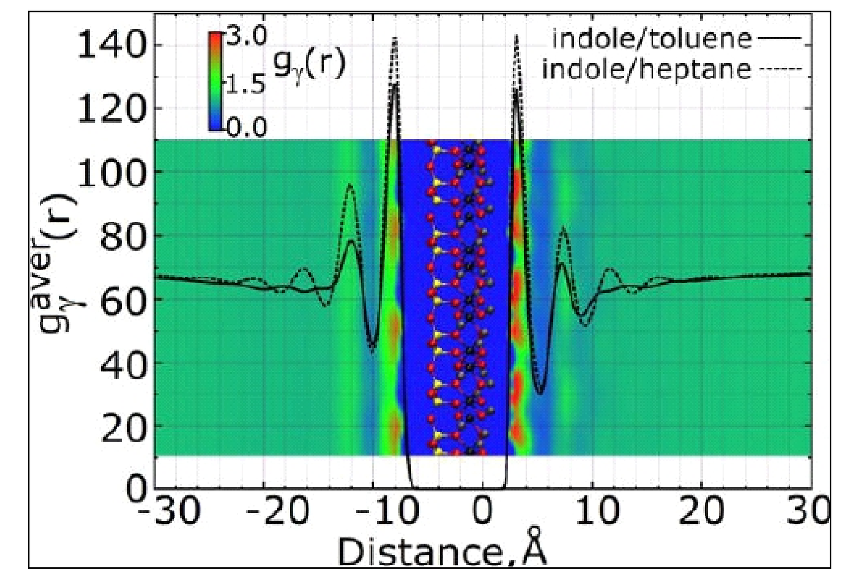
Left: *Original secondary electron SEM image of early mature source rock sample in Duvernay Shale (Tmax=431°C).*
Right: *Clay mineral networks segmented from the original SEM image through deep learning.*

Organic Pore-Size Characteristics from Deep Learning

- Each pore size distribution was derived from one single image of one of three maturity samples (P3 early oil window, P5 end of oil window, and P7 dry gas window)
- Pore size is measured by pixels
- For over 500 images and multiple objects, feature extraction and analysis take about two weeks by computer time using machine learning



Statistical distributions of extracted pore objects for samples of different thermal maturity.



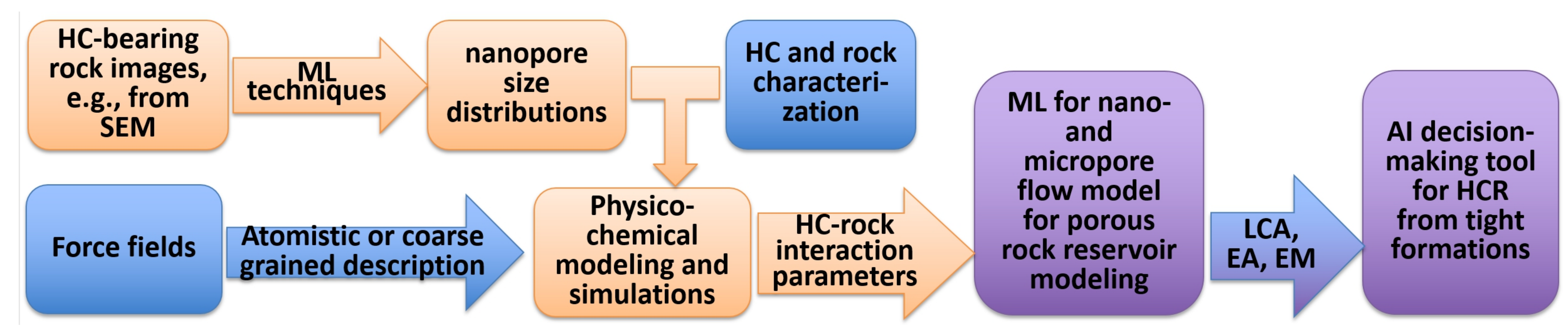
Multilayer adsorption of a heavy oil moiety on kaolinite in solution (Fafard et al. 2013; Stoyanov, et al. 2018).

Physico-Chemical Modeling

- Predict the distribution and interactions of HC within tight rock nanopores
- Account for oil and host rock chemistry
- Produce sorption, diffusion, and slip parameters to enable nanopore modeling at non-Darcy flow regime

ML Model Development and AI Decision Making

- Organic pore size characteristics based on deep learning analyses of rock images
- Physico-chemical model based on HC and rock characterization data
- AI decision-making tool for HC recovery which accounts for life cycle analysis (LCA), economic analysis (EA) and engineering modeling (EM)



Scheme I. Collaborative engagement to develop an AI decision making tool.

References

Ronneberger, O.; Fischer, P.; Brox, T. N. *Medical Image Computing and Computer-Assisted Intervention (MICCAI) 2015, Part III, LNCS 9351*, Navab, et al. (Eds.), 234–241.
Fafard, J.; Lyubimova, O.; Stoyanov, S. R.; Dedzo, G. K.; Gusarov, S.; Kovalenko, A.; Detellier, C. *J. Phys. Chem. C* 2013, *117* (36), 18556–18566.
Stoyanov, S. R.; Lin, F.; Xu, Y. *Clays Clay Miner.* 2018, *66* (3), 286-296.

COLLABORATORS & ENGAGEMENTS

[1]Geological Survey of Canada, 3303-33rd Street NW, Calgary, Alberta T2L 2A7
[2]CanmetENERGY Devon, 1 Oil Patch Drive, Devon, Alberta T9G 0A2

For further information, please contact Z. Chen (Zhuoheng.Chen@canada.ca)

2019

Publications in this series have not been edited; they are released as submitted by the author.

Permanent link: https://doi.org/10.4095/313629

This publication is available for free download through GEOSCAN (http://geoscan.nrcan.gc.ca/).

Presented at CanmetEnergy Devon Artificial Intelligence Symposium, Devon, Alberta
Date presented: October 30, 2018

Recommended citation
Chen, Z. Stoyanov, S.R., Liu, X., Mane, J., and Little, E., 2019. Applications of machine learning to geoscience: nanoporosity and fluid flow in tight formations; Geological Survey of Canada, Scientific Presentation 96, 1 poster. https://doi.org/10.4095/313629

Natural Resources Canada / Ressources naturelles Canada

Canada