3D ANALYSIS OF ROCK PORE MICROSTRUCTURE USING CONVOLUTIONAL NEURAL NETWORKS

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Introduction

In recent years, machine learning (ML) - especially convolutional neural networks (CNNs) - has become indispensable for predicting transport properties in porous media. Traditional methods of pore characterization can be both time-consuming and expensive, particularly for 3D datasets. Machine learning offers a data-driven approach that streamlines analysis, enabling more accurate segmentation and modelling of complex rock microstructures. This ML-driven method optimizes CO_2 sequestration (CCUS), improves geothermal reservoir predictions, and bolsters radioactive waste storage safety. This research, **supported by the EXCITE Network**, utilizes high-resolution 3D micro-CT scans of five rock mini-cores. By applying CNNs to these volumetric datasets, **we aim to quantify connected and unconnected porosity more efficiently**. These insights are directly relevant for carbon capture and underground storage (CCUS), geothermal energy exploration, and radioactive waste management—areas where understanding pore geometry and fluid flow is critical for safety, sustainability, and cost effectiveness.

Aims and Objectives

This project capitalizes on the 3D micro-CT data already acquired at the Centre for X-ray Tomography (UGCT) at Ghent University to measure both connected and isolated porosity and link these pore features to mineralogies and potential diagenetic histories. Our key objectives include:

- Train CNNs tailored to 3D data, accurately segmenting connected and isolated pores, while associating them with specific mineral phases.
- Gradually incorporate additional scanned volumes to enhance the diversity of the training set, improving the model's ability to detect subtle variations in pore structure and composition.
- Measure pore fractions, assess connectivity, and derive fractal metrics (e.g., lacunarity and succolarity) to gain insights into microstructure and reservoir quality.
- Apply the results to optimize processes such as CCUS, geothermal energy & radioactive waste storage by providing accurate, data-driven representations of subsurface rock systems.

Methodology

- **Proven 2D Pipeline** We have successfully trained a CNN model on 2D SEM images to distinguish connected and isolated pores, achieving reliable pore segmentation metrics.
- **3D Data Collection (EXCITE)** At Ghent University, we scanned five-rock mini-cores to acquire high-resolution 3D micro-CT datasets.
- **Transition to 3D** Our next step is to adapt the 2D CNN workflow for full volumetric analysis, preserving thin pore throats and accurately capturing connectivity.
- **Planned Implementation**

1. Compress the 3D dataset to reduce sample storage size,
2. Select and label one 3D sample for CNN training,
3. Reserve another sample for model validation,
4. Compare outputs against manual checks and fractal metrics.

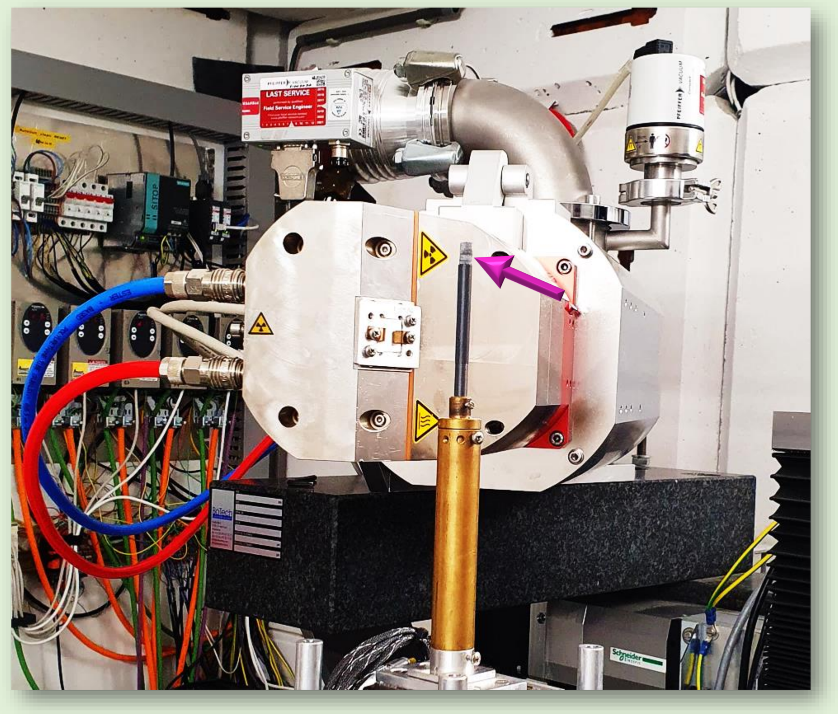

Fig. 2 Rock mini-core Positioned in front of HECTOR at UGCT. The arrow indicates the small sample used for high-resolution 3D imaging

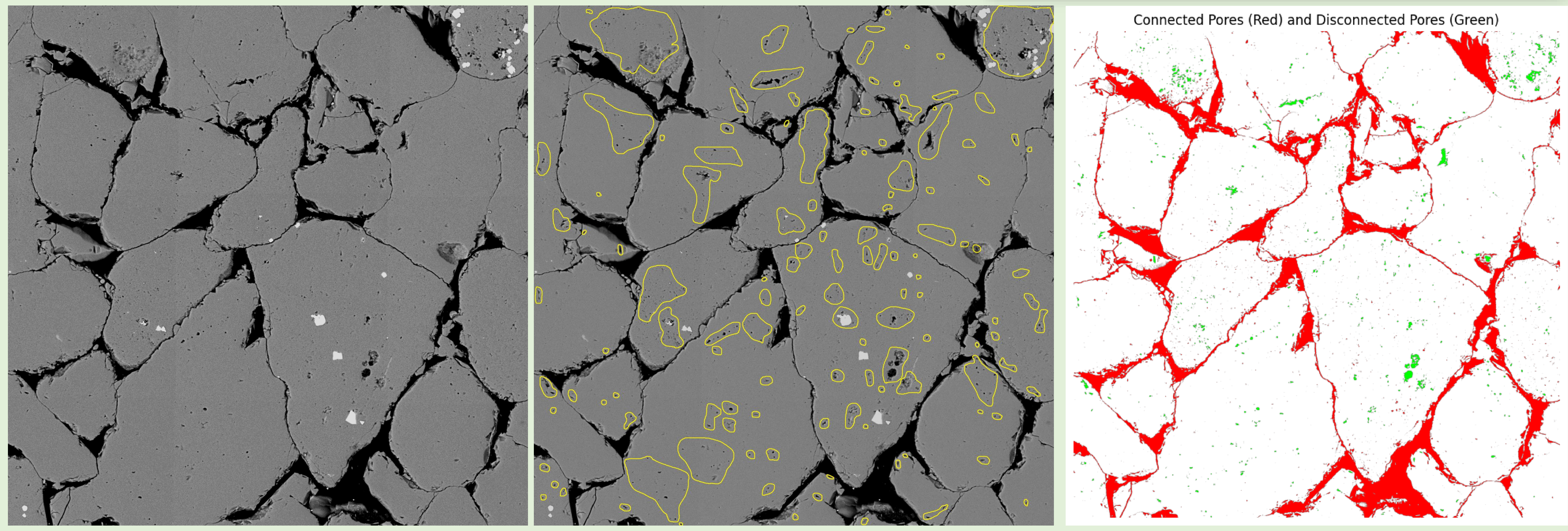

Fig. 1 Progressive 2D SEM segmentation: Left: Original cross-section of the rock. **Centre:** Manually outlined pore boundaries (yellow). **Right:** Final segmentation distinguishing connected pores (red) from dis-connected pores (green)

Conclusions

Building upon our proven 2D pore-segmentation approach, the next phase of this research focuses on transitioning to high-resolution 3D micro-CT datasets. Early findings suggest that machine learning is well-suited for analysing rock microstructures, thanks to both the extensive data generated and the availability of real-world images like SEM scans. Advancing multidisciplinary petrophysics, this AI-driven framework will facilitate automatic and accurate pore characterization, ultimately improving permeability predictions in various rock types. The broader impacts include:

- **Optimized Subsurface Operations:** Enhancing efficiency for CO_2 storage or hydrocarbon extraction.
- **Cost Reduction:** Reliable and robust automation of routine analyses.
- **Improved Reservoir Modelling:** Enabling more precise flow simulations to maximize resource recovery or storage.
- **Deeper Insights:** Linking porosity, mineralogy, and diagenesis for a more holistic understanding of rock evolution.

Dataset Generation

Five rock mini-cores were scanned Using the HECTOR scanner at **UGCT**, yielding high-resolution volumetric data. Each scan was acquired at **120 kV, 10 W**, using **1 mm Al** filter, collecting **3451 projections** over roughly **135 minutes** at a **0.003 mm voxel size**. These uniform parameters ensure consistent image quality across all samples. The visit to Ghent offered direct collaboration, enhancing both technical setup and overall scanning efficiency.

Parameter	PD01-13	PD02-17	PD02-9	PD03-5	PD08-1
Time taken	14:57 elapsed	05:25 elapsed	15:50 elapsed	14:56 elapsed	15:02 elapsed
Recon voxel size	3,000000	2,999998	–	3,000000	3,000000
Magnification	49,331584	49,331625	49,331625	49,331584	49,331584
Unique scan ID	HECTOR121107_11777	HECTOR121107_11774	HECTOR121107_11775	HECTOR121107_11778	HECTOR121107_11776
Sample size	0,000000 mm	10,000000 mm	0,000000 mm	0,000000 mm	0,000000 mm
Tube current	91,848854	92,254631	0,000000	91,853401	91,985268

Fig. 4 Scanning Parameters Among the Five Rock Mini-Cores

This cohesive dataset now serves as the cornerstone for transitioning our 2D CNN techniques into a 3D workflow, ultimately providing deeper insights into rock pore microstructures.

Next Steps

Having successfully demonstrated the CNN-based approach on 2D samples, the next major step involves fully implementing and validating this workflow on 3D micro-CT volumes, including:

Data Compression: CNNs are very slow on large images. The 3D samples are far too large to segment pores in a reasonable time. We intend to propose a lossless compression method for reducing the size of each sample while preserving important information.

Additional Annotation: Increasing the number of annotated 3D samples to improve the CNN's accuracy in capturing thin pore throats and subtle mineral differences.

Flow Analysis: Incorporating metrics such as lacunarity and succolarity for deeper insights into pore geometry and use these results to inform predictive flow models. This would extend the model beyond simply visual features and incorporate real-world context.

This multidisciplinary effort aims to produce a robust, AI-driven framework for pore-scale characterization—one that can ultimately guide more effective CO_2 sequestration, reservoir management, and other energy-related technologies.

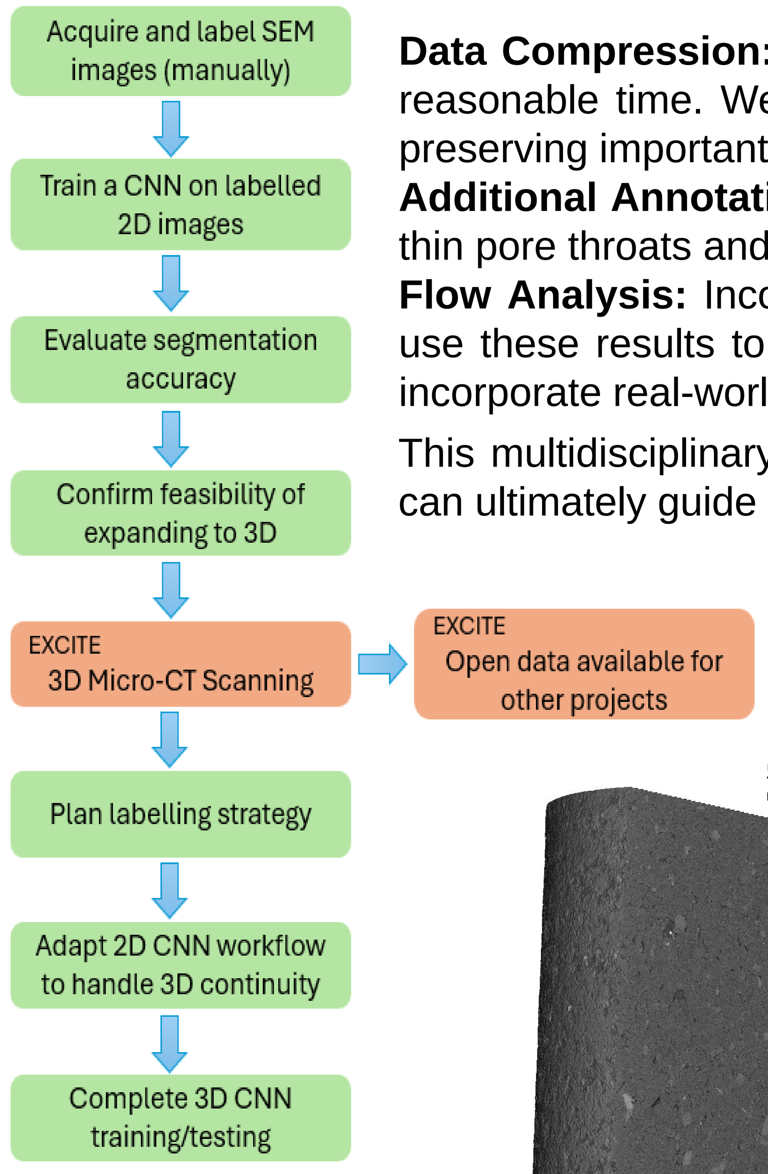

Fig. 5 Project Workflow EXCITE Items in Orange

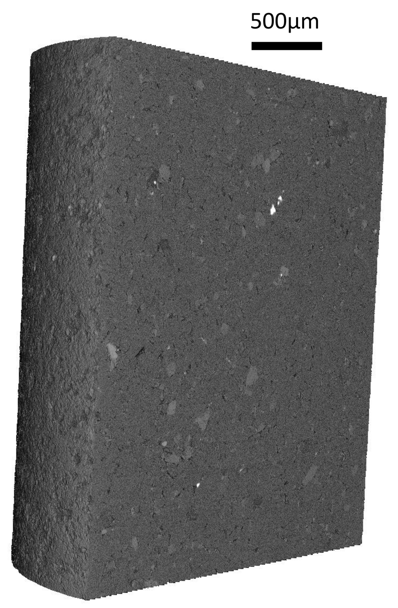

Fig. 6 Preliminary 3D rendering of the rock sample. The scale bar shown is approximate

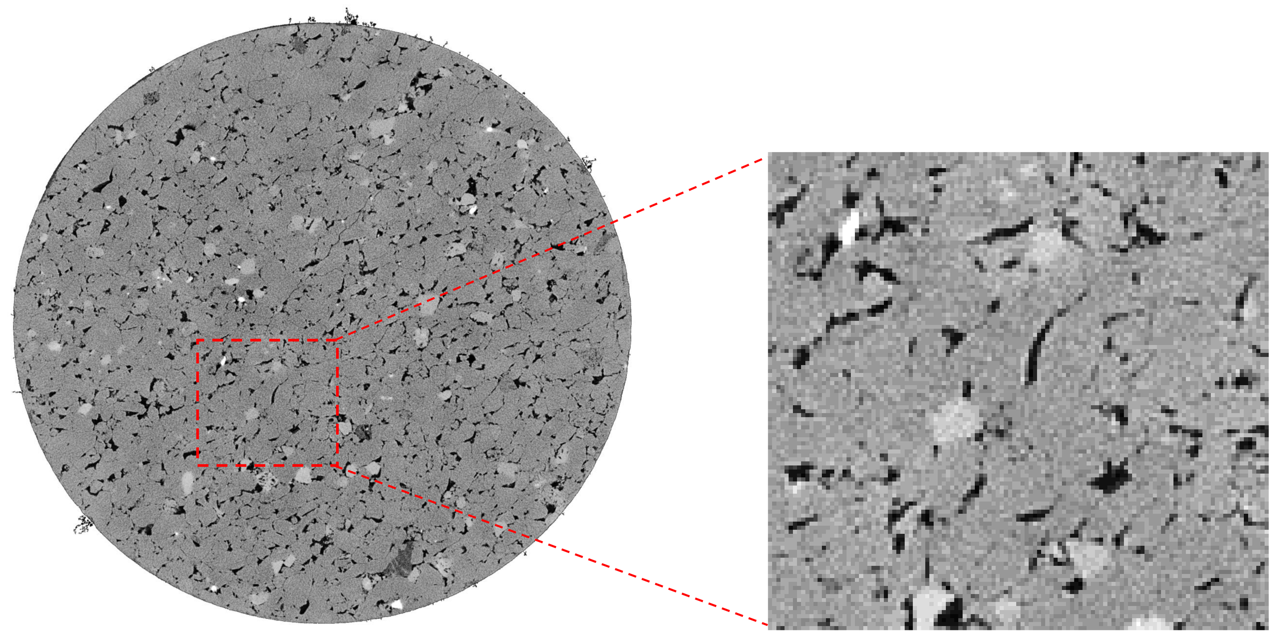

Fig. 7 Representative 2D slice from the 3D micro-CT dataset, showing pore spaces (dark) and surrounding rock matrix (light). The inset (right) is a magnified view of the same region, revealing finer details of the pore network

Acknowledgements

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