Using machine learning to discriminate between mineral phases and pore morphologies in carbonate systems

Leeds University Petrophysics

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Outstanding Student & PhD candidate Presentation contest

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Introduction

In recent years, machine learning (ML), including Convolutional Neural Networks (CNNs) and Deep Neural Networks (DNNs), has become crucial for predicting transport properties in porous media. Traditional methods face limitations due to the complex structures of porous media and the labor-intensive nature of experiments, but ML offers a data-driven approach to overcome these challenges. ML finds extensive application in Carbon Capture and Underground Storage (CCUS) for optimizing operations and reducing greenhouse gas emissions. Additionally, ML aids in geothermal energy exploration by predicting reservoir characteristics, enabling sustainable resource extraction. Moreover, ML techniques are instrumental in ensuring the safety of radioactive waste storage by modeling fluid flow and contaminant transport, mitigating environmental risks. Overall, the integration of ML enhances our understanding of transport phenomena and addresses critical challenges in CCUS, geothermal energy, and radioactive waste storage, contributing to sustainable practices and innovative solutions.

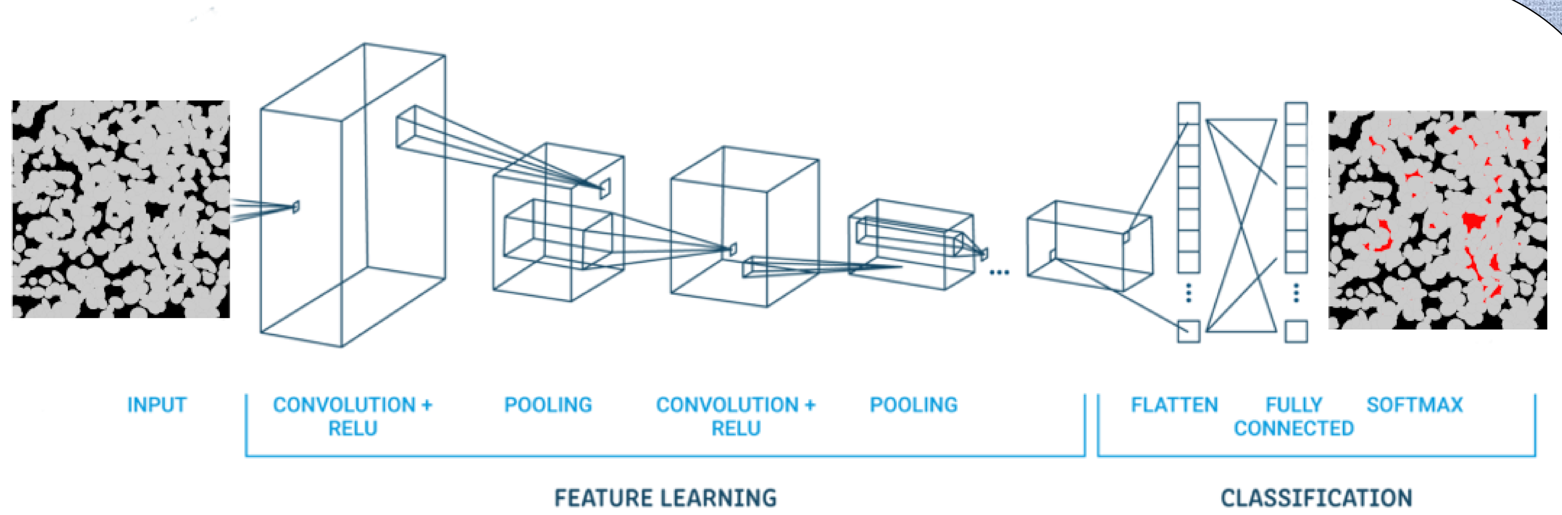
Aims and Objectives

To utilize machine learning for measuring various types of connected and isolated porosity and their correlations with enclosing mineralogies and diagenetic histories, we need to:

- Build 2D digital approaches to train a deep learning model recognising the complex pore networks and relationships between porosity and mineral compositions.
- Continuously introduce more grains with different characteristics to the dataset, continuously updating and training our chosen CNN model on this ever-evolving dataset.
- Expand the analysis of synthetic 2D pore structures to real SEM images with the goal of identifying interconnected and isolated pores while effectively thresholding the images.
- Analyse the pore system quantitatively to give the fraction of every phase in the rock, and their connections.
- Extend our approach by using a 3D CNN model with the 3D images through the use of Focused Ion Beam (FIB-SEM) and SIM technology.

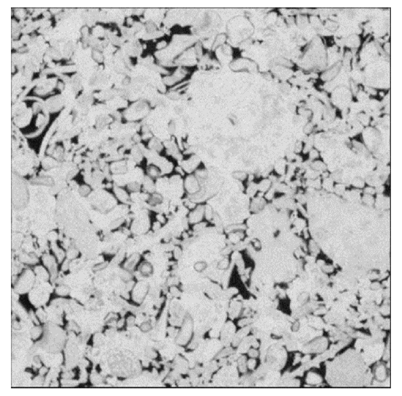
Methodology

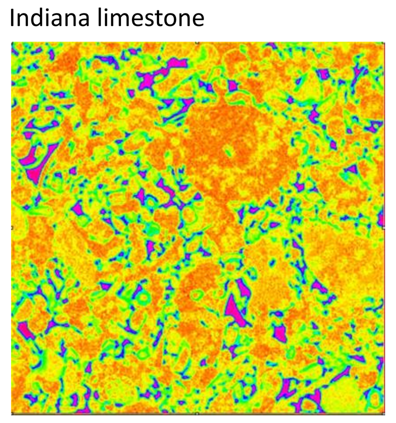
- **Generating training dataset**
  Generating synthetic porous media images along with a CSV file.
- **Training the CNN model**
  Train a neural network using synthetic images and their corresponding parameters as input.
- **Validate and test the model**
  the trained model must be tested on new images that are not in the training database.



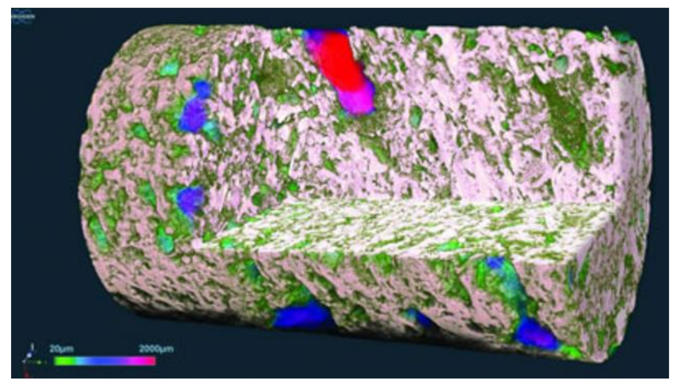
First, automatic identification of different types of porosity (here connected) using convolutional neural networks and our own models

Then, moving from models to 2D SEM





Finally using SIM and FIB-SEM to apply it to 3D



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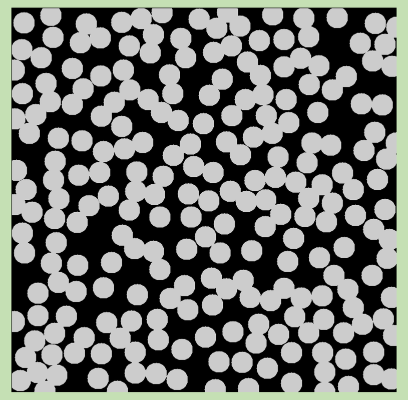
Generation of Dataset

The primary objective is to employ machine learning (ML) to compute and identify porosity structures within SEM images. However, commencing this process directly with these images poses challenges. Therefore, our approach begins from the ground up. We initiate by training the machine to recognize porosity within synthetic images. These synthetic images commence with a single grain (ball) size and progressively incorporate two, three, and so forth grain sizes. Through this step-by-step process, we aim to train a Convolutional Neural Network (CNN) model to gradually discern and quantify porosity:

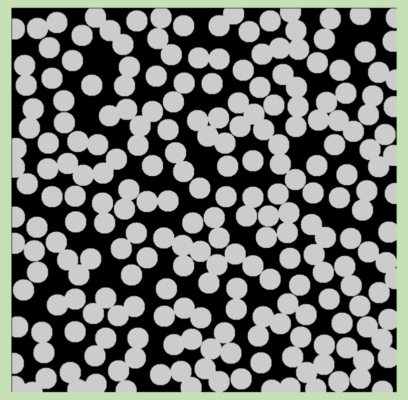
- **One Grain Size**

```python
import numpy as np
import cv2
import os

# Set random seed for reproducibility
np.random.seed(42)

# Constants and parameters
Kbn = 1.2
ballColor = 0.80
imageCut = 1024
BoxSize = int(np.ceil(imageCut * 1.2))
x_min, z_min = 1, 1
x_max, z_max = BoxSize, BoxSize
desired_percentage = 0.00
min_radius, max_radius = 20, 20
```

The packages and parameters used in Python



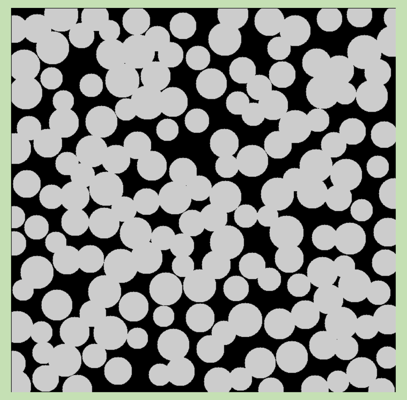
Φ=42.36%



Φ=42.71%

- **Two Grain Sizes**

```python
import numpy as np
import cv2
import os

# Set random seed for reproducibility
np.random.seed(42)

# Constants and parameters
Kbn = 1.2
ballColor = 0.80
imageCut = 1024
BoxSize = int(np.ceil(imageCut * 1.2))
x_min, z_min = 1, 1
x_max, z_max = BoxSize, BoxSize
desired_percentage = 0.90
min_radius, max_radius = 20, 45
```



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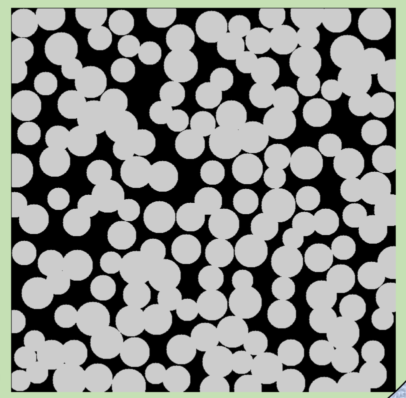
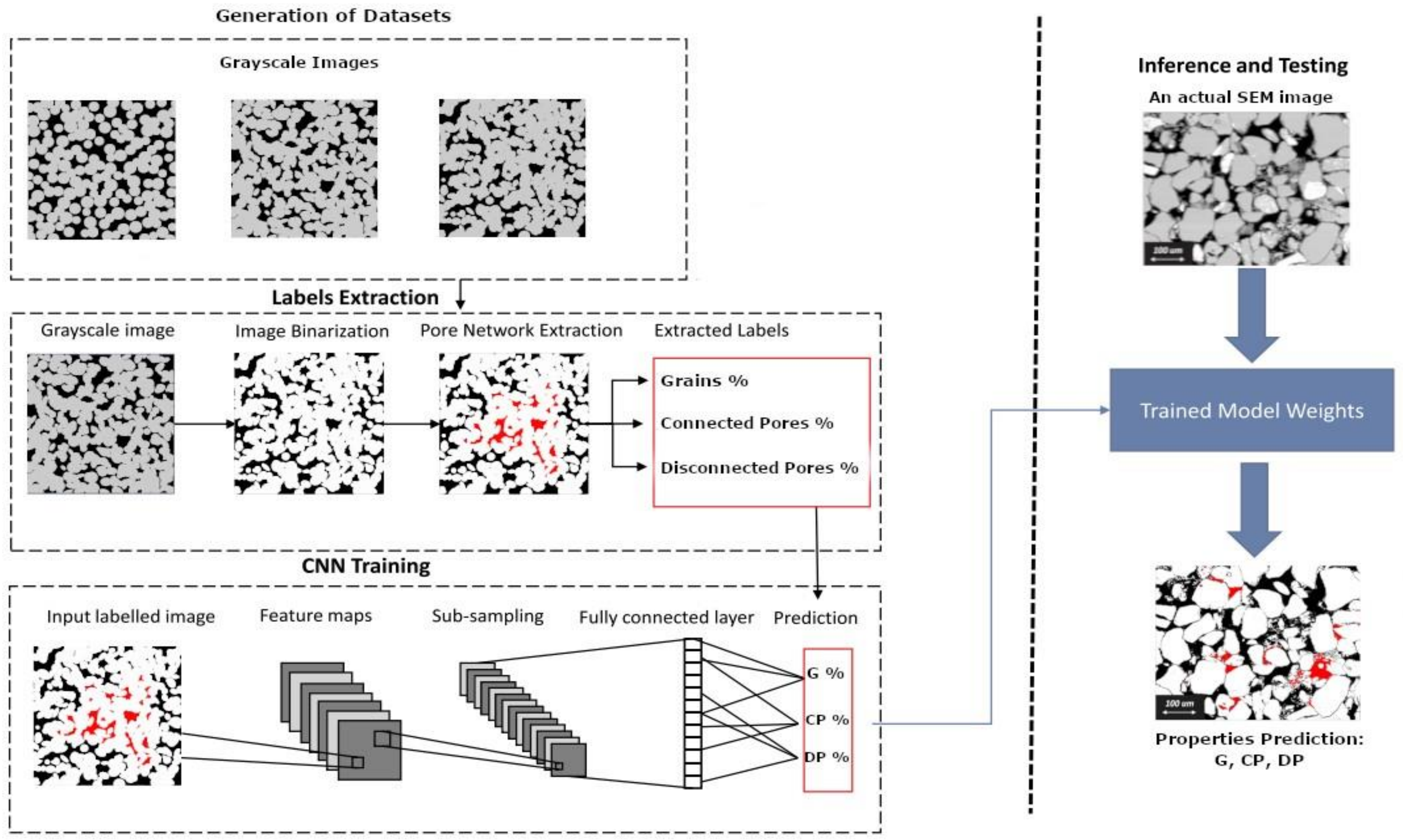


Φ=34.38%

Training and Test Data

After training the CNN model to quantitively distinguish between grains and porosity in binary images as an initial step, and subsequently augmenting the dataset with additional grain shapes, particularly ellipsoids, we proceeded to train another CNN model, alongside the two-phase recognition, to differentiate between two types of porosity. Specifically, isolated porosity was highlighted in red, while connected porosity was maintained in black.



Conclusions

We are going to develop deep learning models based on CNN for predicting the different types of porosity of 2D porous media from their binary images. the dataset we have examined suggest that machine learning is a viable tool for this subject. Its application is made feasible by the abundance of data that can be generated and the ready availability of real-world data, such as SEM images.

Innovative and multidisciplinary petrophysics combining experiment with modelling and the development of new AI approaches to allow automatic analysis of the microstructure of reservoir rocks and The outcomes will undoubtedly create opportunities for predicting permeability with greater accuracy.

Research that will open excellent perspectives for future applications in conventional and transition petrophysics, including:

- **Enhancement** of extraction or CO_2 emplacement methods.
- **Reduction in operational costs** through automation that is reliable and robust.
- Opening the door to **enhanced modelling** to maximize resource recovery or storage in carbonate reservoirs.
- Greater understanding of the **links between porosity, the mineral matrix and diagenesis**.