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DETERMINING THE PROPERTIES OF ROCK SAMPLES USING DEEP MACHINE LEARNING

Porosity, absolute permeability, and diffusion coefficient are crucial characteristics governing fluid flow in the porous media of geological formations. Determining these properties traditionally involves resource-intensive and time-consuming processes. However, with the advancement of deep learning methods in the last 3–4 years, artificial neural networks have gained significant traction in predicting the transport properties of the fluid-porous medium system and the geometric characteristics of porous samples based on their images. This approach allows for the rapid determination of these properties with acceptable accuracy.

The aim of this article is to conduct a scientific review of literature from open sources on the determination of absolute permeability, diffusion coefficient, and porosity from their images acquired through various scanning methods. Additionally, this article incorporates proprietary data, specifically images from four carbonate samples. Convolutional neural networks were examined as the method of choice.

The results of this article comprise a scientific review of moderate depth regarding the effectiveness and applicability of the approach for determining important characteristics of porous media using deep machine learning methods based on sample images. In this article, we also present the results of predicting the open porosity of four carbonate samples based on their X-ray images using the convolutional neural network model we constructed. The conducted review has demonstrated that images (scans) of geological rock samples obtained through various scanning methods allow for the calculation of their transport properties with a high degree of accuracy using deep machine learning algorithms, and this can be achieved within a significantly short timeframe. This implies that deep machine learning can serve as a valuable alternative tool for estimating the properties of geological rock samples based on their images. The convolutional neural network model we constructed exhibited predictive capability for the porosity of three carbonate samples with a coefficient of determination ranging from 0.936 to 0.976.

Keywords: sample images, absolute permeability, diffusion coefficient, porosity, convolutional neural networks, machine learning, prediction.

1. Introduction

The transport properties of rocks, such as absolute permeability, diffusion coefficient, and porosity, are essential macroscopic characteristics that influence hydrocarbon production during the development of oil and gas fields, the assessment of CO_2 injection and storage capabilities in carbonate reservoirs, and the evaluation and monitoring of groundwater quality, among others. These properties are usually determined experimentally under laboratory conditions using specialized equipment or through numerical modeling. Laboratory measurements typically take a considerable amount of time and are costly, while numerical modeling also requires significant time, including processing numerous input parameters. Therefore, determining these properties through alternative methods based on existing analytical and experimental data about the porous medium is a relevant task.

Machine learning has become widely applied in data analysis and the prediction of important characteristics across many fields, such as medicine [1], economics [2, 3], geophysics [4–6], and others.

To date, many studies have been devoted to studying fluid flow in porous media at the pore scale [7–11] and predicting porous media characteristics [12–18] based on two-dimensional images combined with the lattice Boltzmann method.

This article presents a scientific review of the literature from open sources on determining the aforementioned key properties of porous materials based on their images acquired through various scanning methods. Additionally, the article provides the results of our research on calculating open porosity for four carbonate samples using their two-dimensional images obtained with an X-ray micro-computed tomography scanner.

2. Materials and Methods

2.1. Calculation of the Diffusion Coefficient

The study [18] focuses on predicting the effective diffusion coefficient of two-dimensional porous media using deep machine learningspecifically, convolutional neural networks (CNNs)based on their images. These two-dimensional porous media were generated using the pore structure reconstruction methoda quartet structure generation set. The effective diffusion coefficients were calculated using the lattice Boltzmann method (LBM), which served as the training data for the CNN model. The authors generated multiple media with porosity and diffusion coefficients ranging from 0.28 to 0.98 and 0.1 to 1, respectively (Fig. 1). As seen in Fig. 1, the lower diffusion coefficients are distributed with greater variability. The authors predicted the diffusion coefficient using CNN, which correlated with the diffusion coefficient calculated by LBM with an accuracy of 0.99 (Fig. 2a), whereas the widely used empirical Bruggeman equation allows for calculating the diffusion coefficient with comparatively lower accuracy (Fig. 2b), especially for low coefficient values. The authors of [18] also provide several ways to improve the accuracy of the diffusion coefficient prediction using CNN, particularly for low values (<0.1), such as using relative error instead of absolute error when minimizing the loss function and excluding dead-end pores from the overall pore network.

In study [16], the prediction of the diffusion coefficient of three-dimensional granular porous media using CNN with self-enhancement of pore structure information is considered. The diffusion coefficient was calculated using the lattice Boltzmann method, and the granular porous media were reconstructed by stochastically generating spheres of different diameters with porosity ranging from 0.39 to 0.79 (Fig. 3). The authors showed that images with any porosity can be used for training with the same media structure: if images of low-porosity media are used for training and the diffusion coefficient of high-porosity media is predicted, and vice versa, the predicted diffusion coefficient will deviate from the true value similarly in both cases (Fig. 4). The authors also demonstrated that using deep machine learning reduced the diffusion coefficient calculation time from 17 hours to 1 second, with the error between CNN and LBM results not exceeding 9%.

The prediction of the diffusion coefficient of sandy and fractured types of porous media is presented in study [19] using CNN based on their images. Notably, the considered porous media were reconstructed by randomly generating objects in a two-dimensional area, and their diffusion coefficients were calculated using the lattice Boltzmann method.

Figure 5 shows some of these media: the first two images correspond to sandy type porous media, and the last two images to fractured type. The main conclusion of this study is that the CNN model trained on data from sandy type porous media predicts the diffusion coefficient of porous media of the same type more accurately. This indicates that the question of developing a universal CNN model that predicts the diffusion coefficient of any type of porous media remains open.

2.2. Calculation of Absolute Permeability

The authors of the study [17] predicted the absolute permeability of carbonate and sandy samples based on their images using regression machine learning methods (shallow machine learning) and CNN. The input data consisted of images of a carbonate sample (Fig. 6) obtained using X-ray micro-computed tomography.

The results showed that CNN predicts the permeability of rocks better than regression machine learning methods. The petrophysical parameters of the considered samples were calculated using pore network modeling (PNM), LBM, and the full Navier-Stokes equations. PNM is the fastest method for calculating petrophysical parameters, whereas LBM and the full Navier-Stokes equations are the most accurate. As the authors demonstrated, all three methods were capable of predicting permeability with good accuracy. The main conclusions of this work are:

a) CNN can predict the permeability of a sample 1000 times faster than LBM;

b) The prediction accuracy of the permeability of sandy samples (Fig. 7b) is higher than that of carbonate samples (Fig. 7a) due to the complex pore structure of the latter.

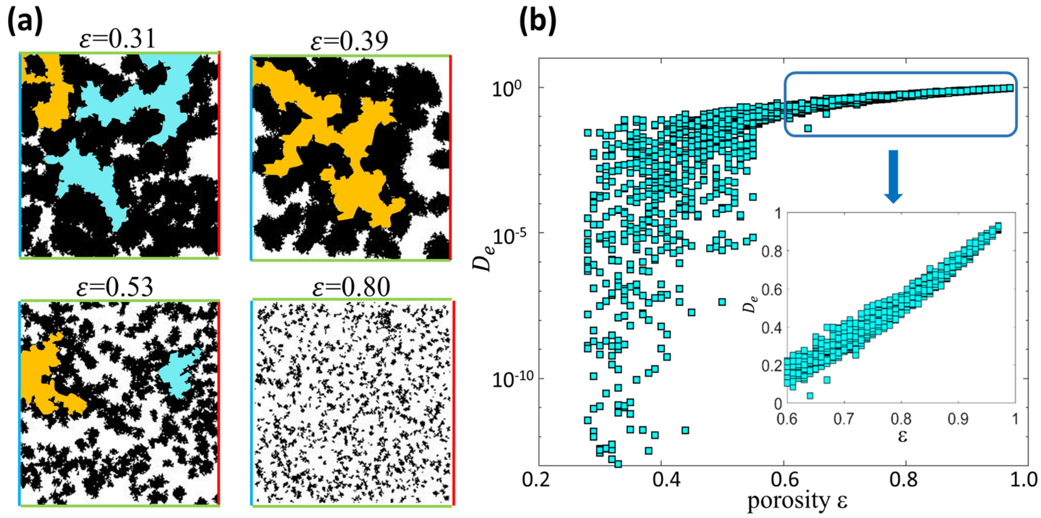

Figure 1 – Generated porous media (a) and their diffusion coefficient (b) [18]:
a) selected porous media; b) diffusion coefficient distribution on porosity

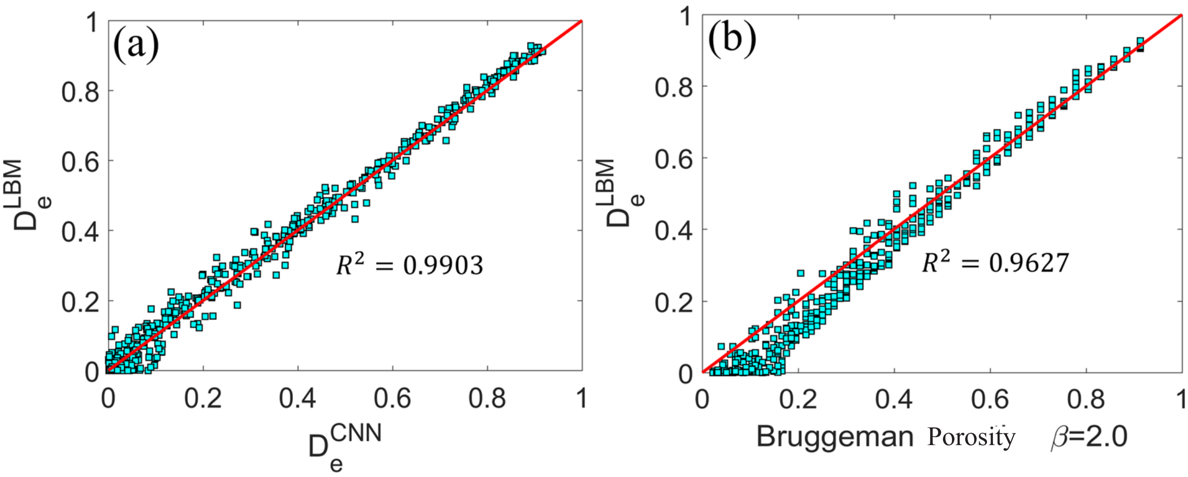

Figure 2 – Diffusion coefficients obtained by different methods [18]: a) CNN-predicted vs. LBM-predicted diffusion coefficients; b) LBM-predicted vs. Bruggeman equation-predicted diffusion coefficients

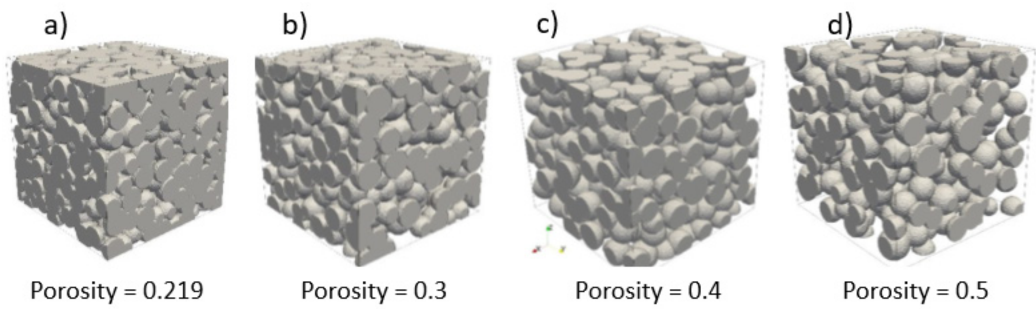

Figure 3 – Generated porous media with different porosities [16]: a) with porosity 0.219; b) with porosity 0.3; c) with porosity 0.4; d) with porosity 0.5

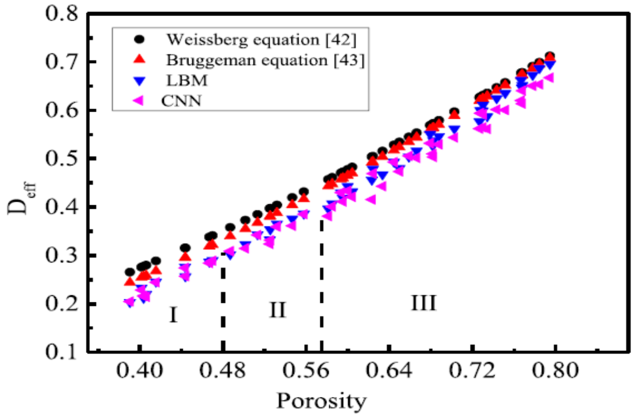

Figure 4 – Diffusion coefficient calculated by different methods [16]

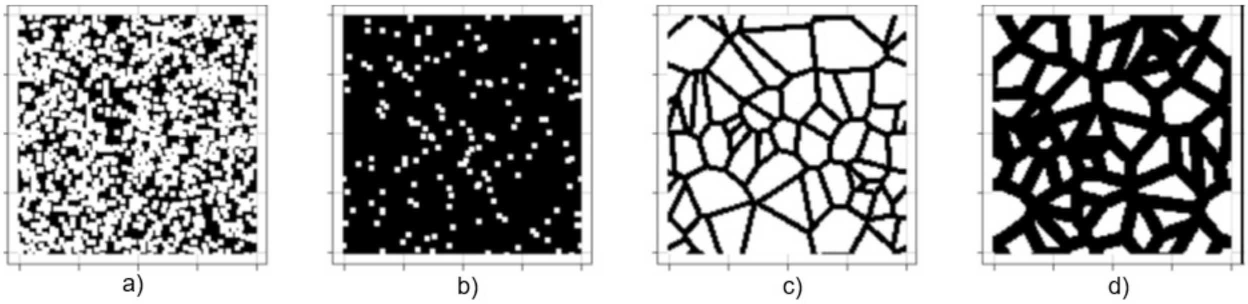

Figure 5 – Generated porous media with different porosities [19]: a) sandstone type with high porosity; b) sandstone type with low porosity; c) fractured type with high porosity; d) fractured type with low porosity

Some studies focus on predicting permeability based on images of samples obtained through various scanning methods, such as micro-computed tomography or electron microscopy, taking into account the petrophysical properties of rocks [15, 20]. In study [20], a new deep learning architecture (Fig. 8b) was proposed for more accurate prediction of the absolute permeability of synthetic rocks, considering their porosity and tortuosity. The authors examined the influence of different controlling parameters, such as the number of dense layers and the learning rate, on the predictive capability of the constructed architecture. They showed that accounting for porosity and tortuosity when predicting absolute permeability based on rock images can improve the prediction quality. Their results demonstrated an increase in prediction accuracy from 0.985 to 0.994 when using porosity and tortuosity as additional input data for training the CNN model (Fig. 9), while the permeability calculation time was reduced by 1000 times compared to the calculation time using LBM.

Figure 6 – 3D image of a carbonate sample [17]

It is evident that the quality of sample images affects the accuracy of predicting the transport properties of rocks, and it is not always sufficiently high. The quality of images depends on the resolution of the scanning equipment, such as X-ray micro-computed tomography or scanning electron microscopy. In study [21], a method for predicting the absolute permeability of porous media using deep learning based on low-resolution images is presented. This method relies on the combined use of CNN and an autoencodera specialized neural network architecture that allows for unsupervised learning using the backpropagation method. As the results showed, this approach not only enabled the use of low-resolution images for prediction but also improved the accuracy of predicting absolute permeability (Fig. 10).

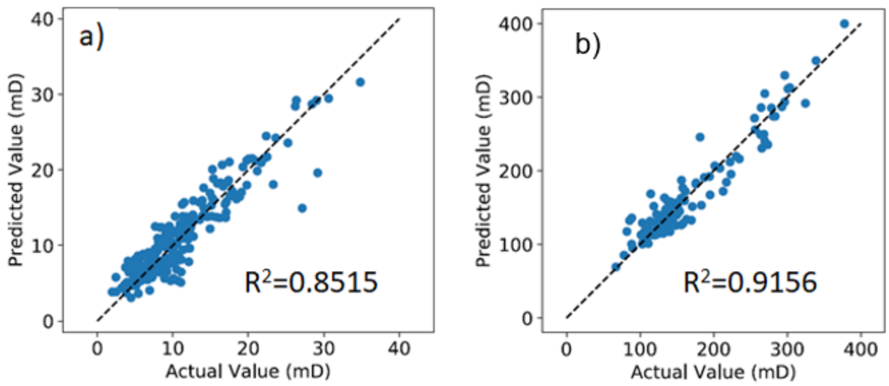

Figure 7 – Comparison of predicted permeability of carbonate and sandstone samples with permeability calculated using LBM [17]: a) carbonate sample; b) sandstone sample

2.3. Calculation of Porosity

Porosity describes the storage capacity of porous media, which is a fundamental factor in evaluating permeability, tortuosity, and the diffusion coefficient using various empirical equations, such as the Kozeny-Carman equation. It is typically determined by the fluid saturation method in laboratory conditions, which is time-consuming. Machine learning can be a tool for rapidly determining the porosity of media with acceptable accuracy.

In study [22], the results of predicting the properties of porous media, including porosity, using deep learning based on two-dimensional tomographic images of three sandy samples are presented. The results show that CNNs can predict the porosity of sandy samples with high accuracy on filtered and segmented images (Fig. 11a), whereas predictions on raw images lead to relatively low accuracy (Fig. 11b). This indicates that the quality of rock sample images is important when constructing (training) neural network models.

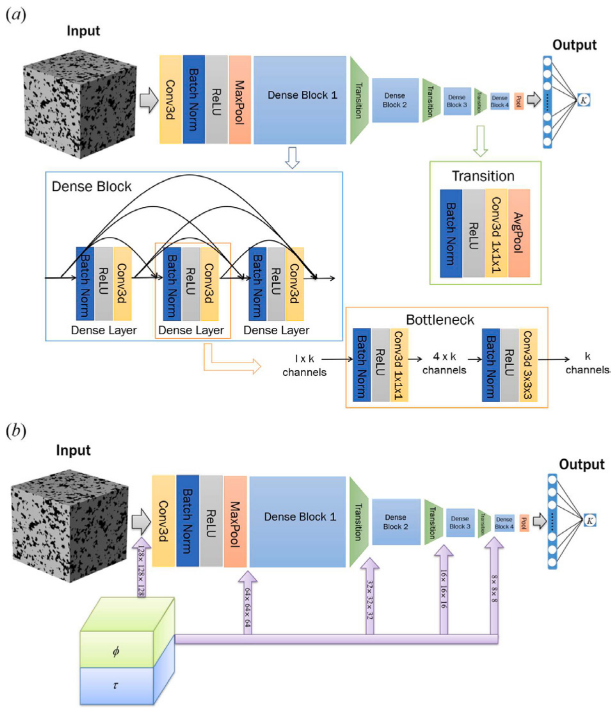

Figure 8 – CNN architectures [20]:
a) conventional; b) proposed

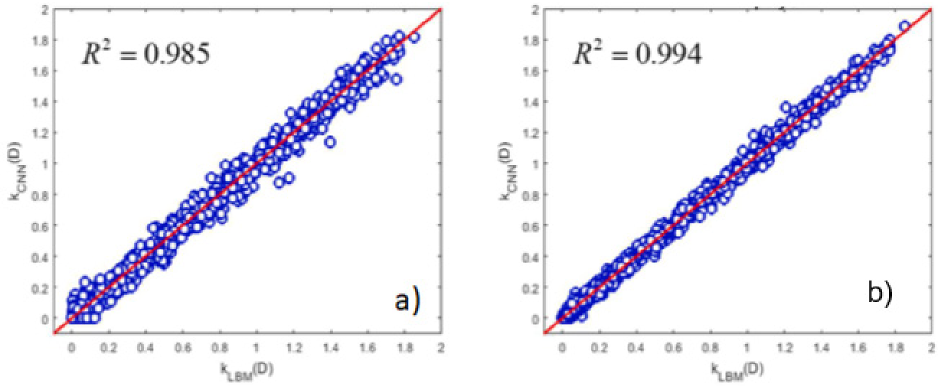

Figure 9 – Predicted permeabilities by conventional and proposed CNN architectures vs. LBM permeability [21]: a) conventional; b) proposed

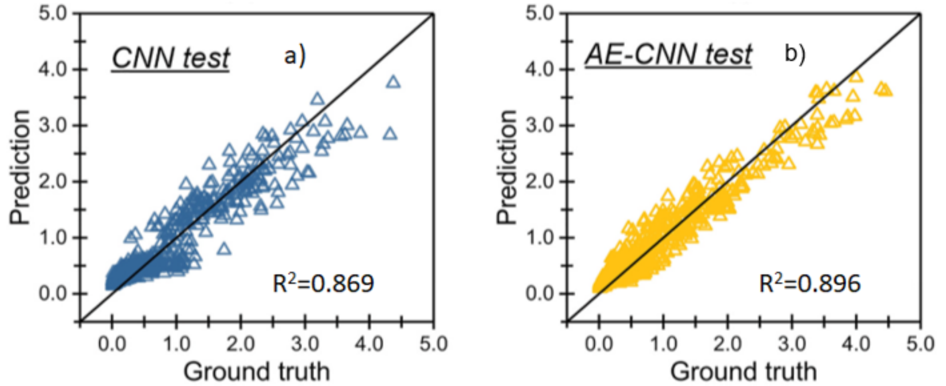

Figure 10 – Predicted permeabilities using the conventional and proposed methodologies compared with the true permeability [21]: a) conventional; b) proposed

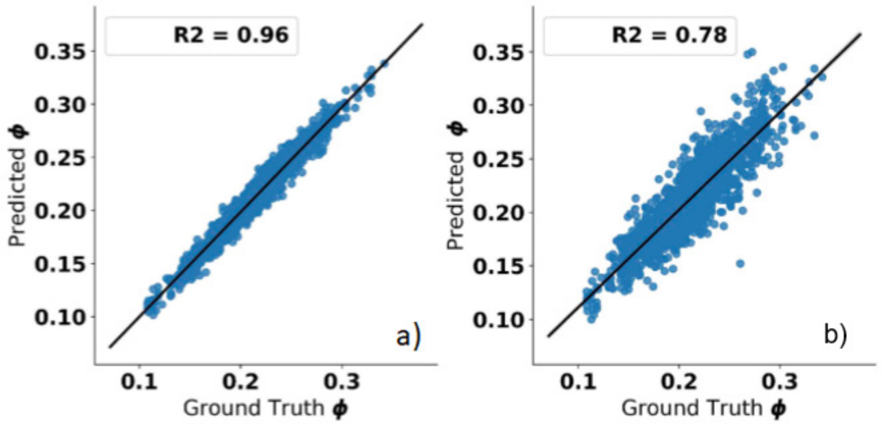

Figure 11 – Predicted porosities from processed and unprocessed images compared with true porosities [22]: a) from processed images; b) from unprocessed images

3. Results

This article also presents our own results on predicting the open porosity of carbonate samples using CNN based on their two-dimensional images obtained with an X-ray micro-computed tomography scanner. Rectangular samples, cut from four cylindrical carbonate samples, were used as input data for training and prediction. The extraction of a rectangular sample with a square cross-section is schematically illustrated in Fig. 12. In this figure, the pore space is shown in dark blue, with the circle and square representing the cross-sections of the cylindrical and rectangular samples, respectively (Fig. 12a). The pore space of the selected rectangular samples is shown in Fig. 13. The constructed CNN model was trained and tested on images of sample 1, and then the porosity of the remaining samples was predicted. The three-dimensional model of sample 1 consists of 2490 images.

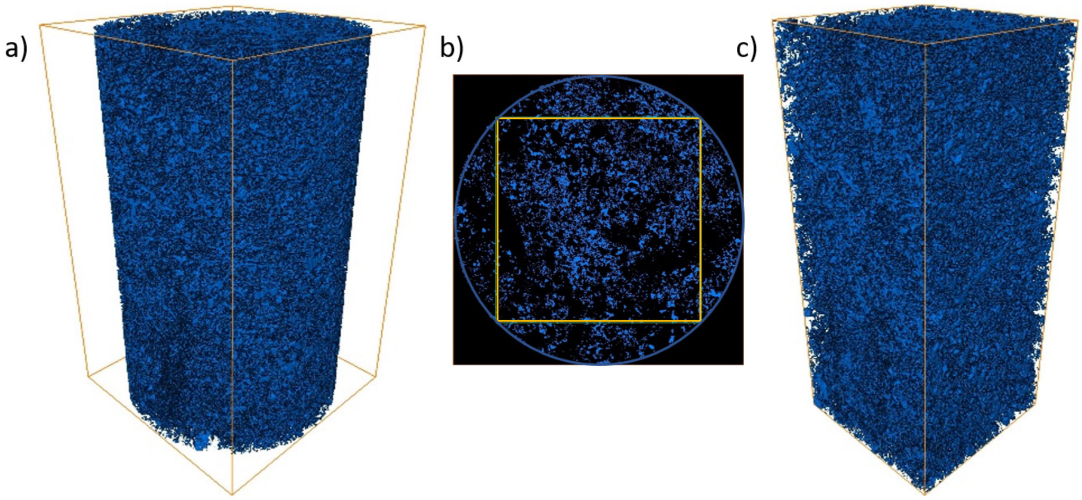

Figure 12 – Schematic representation of the extraction process of rectangular sample: a) cylindrical sample; b) cross-section of the samples; c) extracted rectangular sample

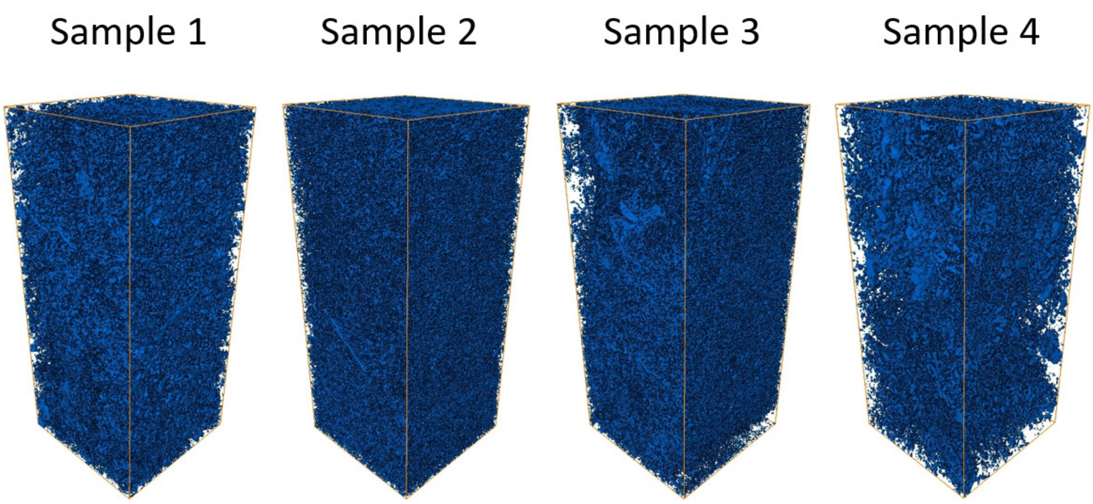

Figure 13 – Pore space of extracted rectangular samples: a) sample 1; b) sample 2; c) sample 3; d) sample 4

Figure 13 reveals the highly heterogeneous pore structure of the considered samples, which is confirmed by the distribution of the cross-section averaged porosity of the samples along their length (Fig. 14). As shown in Fig. 14, the samples exhibit varying degrees of heterogeneity. Sample 4 has relatively low porosity compared to the other samples. From the porosity distribution, regions of low and high porosity can be observed, indicating the presence of compacted layers and cavities within the rock structure.

For the purpose of analyzing the sample images, a CNN with two-dimensional images as input and a regression layer as output was selected to predict porosity. The CNN architecture is an efficient tool for image processing and can be applied to various tasks, including classification, object detection, and regression. In this case, a regression layer was used as the model's output. This layer typically consists of one or more fully connected layers that transform the features extracted by the convolutional layers into numerical predictions.

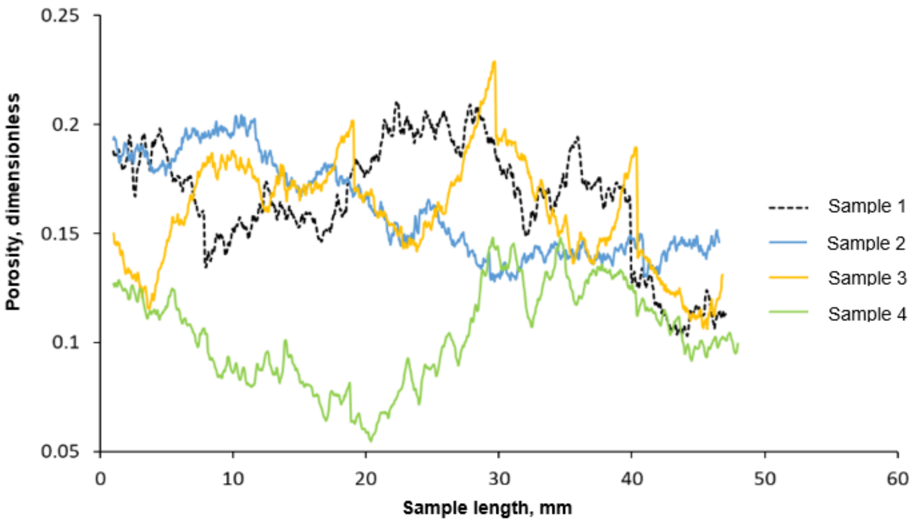

Figure 14 – Distribution of slice averaged porosity of considered samples along their length

The process of image analysis and porosity prediction using a Convolutional Neural Network (CNN) involves the following steps:

1. Data Preparation. It is crucial to properly prepare the data before training the neural network, including scaling them to a uniform size and normalizing pixel values. In this case, the images were normalized to a size of 120x120 pixels (Fig. 15), and the pixel values were scaled to 1 or 0 to enhance learning.

2. CNN Architecture. CNN consists of various layers, such as convolutional layers, pooling layers, fully connected layers, and activation layers. The network architecture defines the number and sequence of these layers. For example, in this model, two convolutional layers with ReLU activation functions, pooling layers, two fully connected layers, and a regression layer at the output were used (Fig. 15).

3. Training the Network. Training the CNN involves passing the training data through the network and adjusting the neuron weights through backpropagation. The model was trained on sample 1 and tested on others to evaluate its performance.

4. Optimization of Architecture and Hyperparameters. Experiments were conducted with different architectures and hyperparameters to optimize the model's performance. This included changing the number of layers, filter sizes, activation functions, pooling parameters, and other network characteristics.

5. Regularization and Overfitting Control. To prevent overfitting, regularization methods such as Dropout and L2 regularization were applied. These methods helped improve the model's ability to generalize data in the training set.

6. Optimization of Loss Function. Appropriate loss functions, such as mean squared error, and

optimizers like Adam were chosen for effective model training.

7. Evaluation and Comparison of Results. It is important to evaluate the model using various metrics, such as mean absolute error and prediction accuracy coefficient, and compare its results with other models or methods to determine its effectiveness.

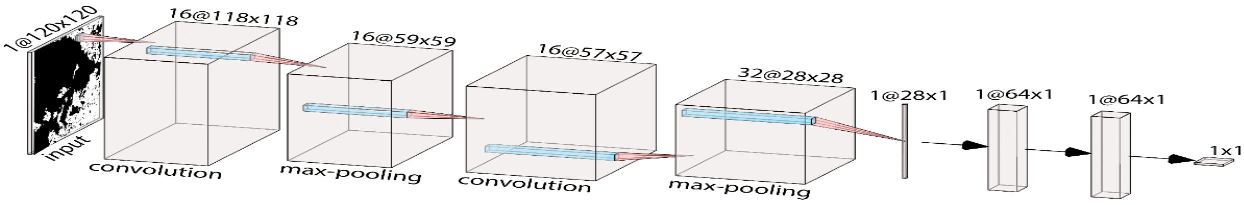

Figure 15 – CNN architecture

The CNN architecture used is shown in Figure 15. The code was written in Python using the Keras library. The total number of training epochs (iterations) was 25, during which the loss functions significantly decreased (Figure 16). The mean squared error between the predicted and actual porosity was used as the loss function, which should decrease during the iterations (Figure 16). As shown in Figure 16, the mean squared error is significantly lower during validation than during testing because the constructed CNN model is first comprehensively tested and then further validated.

Figure 17 shows the results of predicting the open porosity of samples 2-4 using the constructed CNN model in comparison with the actual porosity. As shown in Figure 17, the CNN predicted the porosity of samples 2-4 with high accuracy, despite the fact that the constructed CNN model was trained and tested only on the images of sample 1, with a coefficient of determination ranging from 0.936 to 0.976. This figure also demonstrates that machine learning is capable of distinguishing the heterogeneous structure of the samples, with the predicted porosity closely matching the actual porosity along the length of the samples. This indicates that deep learning can be a valuable tool for the rapid calculation of rock sample properties with acceptable accuracy based on their images obtained by one of the material scanning methods.

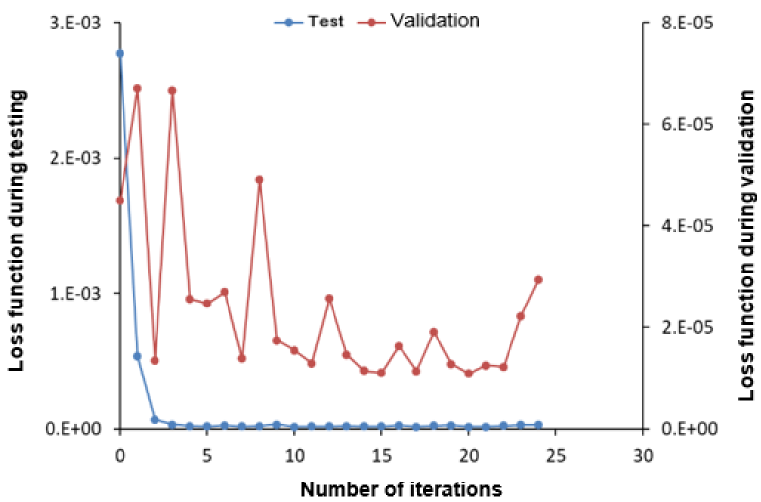

Figure 16 – Change of loss function during testing and validation

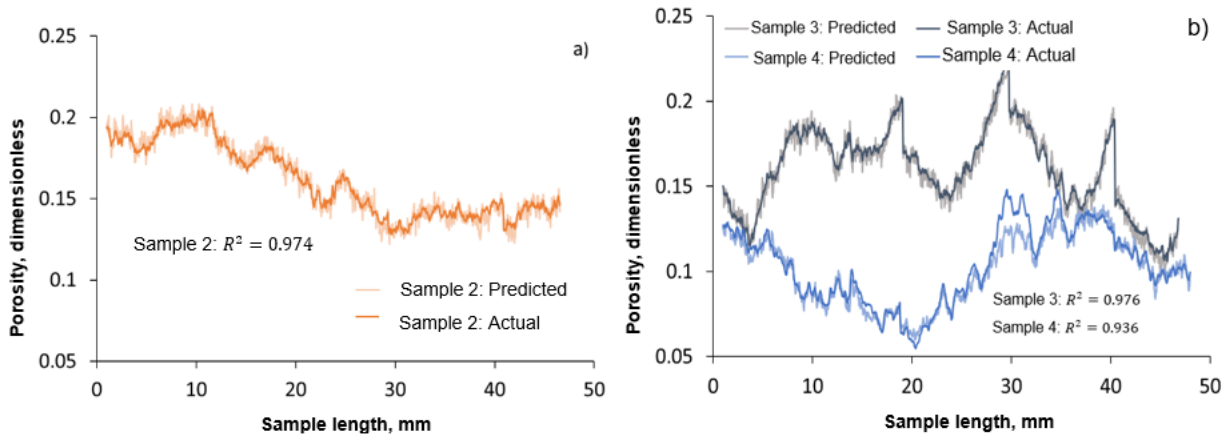

Figure 17 – Predicted and true porosity of samples: a) sample 2; b) samples 3, 4. Predicted (light lines) and actual (dark lines)

4. Conclusion

Based on the literature review conducted, we can conclude that images of rock samples obtained through various scanning methods allow for the calculation of their transport properties using deep machine learning with high accuracy and in a significantly shorter time. This indicates that deep learning can be a valuable tool for calculating the properties of rock samples based on their images obtained by one of the material scanning methods. CNNs are the primary deep learning algorithm for this task. However, we also note the following conclusions:

1) Deep learning can be applied to predict the properties of samples with various pore structures (fractured, heterogeneous, and cavernous carbonate and sandy rocks);

2) Deep learning significantly reduces the calculation time of transport properties of rock samples (from several tens of hours to several seconds) compared to the lattice Boltzmann method (LBM);

3) Deep learning models with additional options allow predicting sample properties based on low-quality images;

4) CNNs predict rock permeability better than regression machine learning methods;

5) In general, CNNs predict the properties of sandy samples better than carbonate samples due to the complex pore structure of the latter;

6) CNNs can recognize the spatial heterogeneity of sample porosity during training, which is considered in the prediction.

References

1. Rajalingam B, Priya R. Multimodal Medical Image Fusion based on Deep Learning Neural Network for Clinical Treatment Analysis. Int J ChemTech Res. 2018;11(6):160–176. doi:10.20902/IJCTR.2018.110621.

2. Cicceri G, Inserra G, Limosani M. A Machine Learning Approach to Forecast Economic Recessions – An Italian Case Study. Mathematics. 2020;8(2). doi:10.3390/math8020241.

3. Yoon J. Forecasting of Real GDP Growth Using Machine Learning Models: Gradient Boosting and Random Forest Approach. Comput Econ. 2021;57(1):247–265. doi:10.1007/s10614-020-10054-w.

4. Gholami R, Shahraki AR, Jamali Paghaleh M. Prediction of Hydrocarbon Reservoirs Permeability Using Support Vector Machine. Math Probl Eng. 2012:1–18. doi:10.1155/2012/670723.

5. Waszkiewicz S, Krakowska-Madejska P, Puskarczyk E. Estimation of absolute permeability using artificial neural networks (multilayer perceptrons) based on well logs and laboratory data from Silurian and Ordovician deposits in SE Poland. Acta Geophys. 2019;67:1885–1894. doi:10.1007/s11600-019-00347-6.

6. Tembely M, AlSumaiti AM, Alameri W. A deep learning perspective on predicting permeability in porous media from network modeling to direct simulation. Comput. Geosci. 2020;24(4):1541–1556. doi:10.1007/s10596-020-09963-4.

7. Xuan YM, Zhao K, Li Q. Investigation on mass diffusion process in porous media based on Lattice Boltzmann method. Heat Mass Transf. 2010;46(10):1039–1051. doi:10.1007/s00231-010-0687-2.

8. Wang Y, Lin G. Efficient deep learning techniques for multiphase flow simulation in heterogeneous porousc media. J Comput Phys. 2020;401. doi:10.1016/j.jcp.2019.108968.

9. Santos JE, Xu D, Jo H, et al. PoreFlow-Net: A 3D convolutional neural network to predict fluid flow through porous media. Adv Water Resour. 2020;138. doi:10.1016/j.advwatres.2020.103539.

10. Da Wang Y, Blunt MJ, Armstrong RT, Mostaghimi P. Deep learning in pore scale imaging and modeling. Earth-Science Rev. 2021;215. doi:10.1016/j.earscirev.2021.103555.

11. Bolysbek DA, Kulzhabekov AB, Bekbau B, Uzbekaliyev KS. Study of the pore structure and calculation of macroscopic characteristics of rocks based on X-ray microcomputed tomography images. Kazakhstan J oil gas Ind. 2023;5(2):17–30. doi:10.54859/kjogi108647. (In Russ).

12. Tian J, Qi C, Sun Y, et al. Permeability prediction of porous media using a combination of computational fluid dynamics and hybrid machine learning methods. Eng Comput. 2021;37:3455–3471. doi:10.1007/s00366-020-01012-z.

13. Graczyk KM, Matyka M. Predicting porosity, permeability, and tortuosity of porous media from images by deep learning. Sci Rep. 2020;10. doi:10.1038/s41598-020-78415-x.

14. Caglar B, Broggi G, Ali MA, et al. Deep learning accelerated prediction of the permeability of fibrous microstructures. Compos Part A Appl Sci Manuf. 2022;158. doi:10.1016/j.compositesa.2022.106973.

15. Araya-Polo M, Alpak FO, Hunter S, et al. Deep learning–driven permeability estimation from 2D images. Comput Geosci. 2020;24:571–580. doi:10.1007/s10596-019-09886-9.

16. Wang H, Yin Y, Hui XY, et al. Prediction of effective diffusivity of porous media using deep learning method based on sample structure information self-amplification. Energy AI. 2020;2. doi:10.1016/j.egyai.2020.100035.

17. Tembely M, AlSumaiti AM, Alameri WS. Machine and deep learning for estimating the permeability of complex carbonate rock from X-ray micro-computed tomography. Energy Reports. 2021;7:1460–1472. doi:10.1016/j.egyr.2021.02.065.

18. Wu H, Fang W-Z, Kang Q, et al. Predicting Effective Diffusivity of Porous Media from Images by Deep Learning. Sci Rep. 2019;9. doi:10.1038/s41598-019-56309-x.

19. Graczyk KM, Strzelczyk D, Matyka M. Deep learning for diffusion in porous media. Sci Rep. 2023;13. doi:10.1038/s41598-023-36466-w.

20. Tang P, Zhang D, Li H. Predicting permeability from 3D rock images based on CNN with physical information. J Hydrol. 2022;606. doi:10.1016/j.jhydrol.2022.127473.

21. Zhang H., Yu H., Yuan X., et al. Permeability prediction of low-resolution porous media images using autoencoder-based convolutional neural network. J Pet Sci Eng. 2022;208. doi:10.1016/j.petrol.2021.109589.

22. Alqahtani N., Alzubaidi F., Armstrong R.T., et al. Machine learning for predicting properties of porous media from 2d X-ray images. J Pet Sci Eng. 2020;184. doi:10.1016/j.petrol.2019.1

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