Tortuosity and permeability of random porous medium using deep learning

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Abstract

We presents the results of our recent work on tortuosity (T) and permeability (k) calculated using the deep learning framework presented in [1]. In brief, the idea is to obtain an algorithm that can predict the porosity (ϕ), tortuosity, and permeability based on the analysis of the binary figure of obstacles. To achieve this goal, we consider the deep learning method. The **convolutional neural network (CNN)** relates configurations of obstacles and the porosity, tortuosity, and permeability. We show that the CNN can predict tortuosity and permeability with reasonable accuracy.

1 Deep Learning Approach

The CNN gives the map between the complex space of configuration of obstacles and the tortuosity and permeability. The main features of the approach:

- Given obstacle configuration, (see e.g. input configuration in Fig. 2), is represented by binary figure of the size 400×400 re-scaled to the input of size 200×200 (in [1] we consider 400×400 input figures too).
- The input data are generated as described in Sec. 2. We collected more than 100000 of patterns.
- To train the network, the two data subsets are distinguished; namely, the training (85000) and validation (15000) data set. The best model has the lowest value of the loss on the validation data set.
- Because the data distribution in the output space is not uniform, see Fig. 2 a), weighted sampling of the data during the training.
- The CNN contains **six** blocks. Each of them consists of one convolutional layer with 10, 20, 40, 80, 160 and 400 kernels, respectively, and with ReLu activation function. After convolutional layer there is the max pooling layer and the batch normalization layer.
- The stochastic gradient descent (SGD) algorithm, in the mini-batch version, has been utilized for the training. The PyTorch library [5] has been used to construct the deep learning environment.

2 Porous medium and Fluid Flow data

To train the network we generate the data using simple, yet controllable, random porous medium model build of overlapping quads of equal sizes used before i.e. in [4]. Using this model we can smoothly vary porosity in permeable range $\varphi \in (0.35; 1.0)$ at dimensionless permeability in range $k/R_0 \in (2.5 \cdot 10^{-4}; 25.5)$ and tortuosity $T < 2$ (R_0 is a hydraulic radius of single obstacle). The input is a configuration of obstacles represented by binary figure. Effectively, the input has the size 200×200.

For the fluid flow the standard Lattice Boltzmann method is used. We implement the simulation using Palabos library [3].

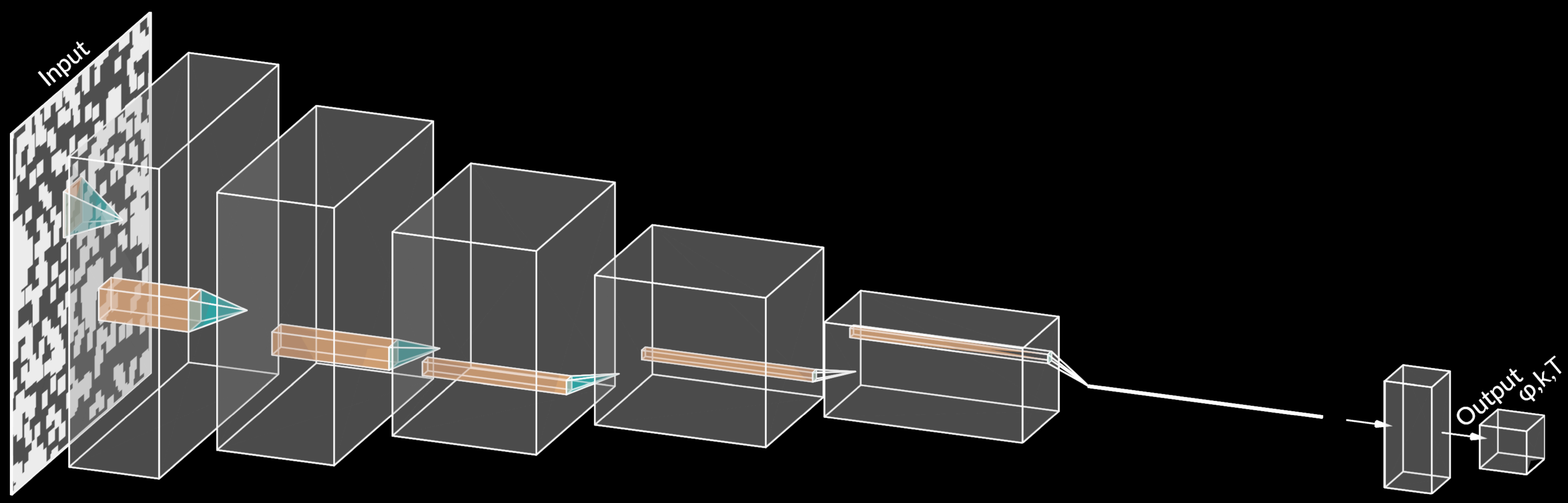

Figure 1: The structure of CNN model used in this work (source: [1]).

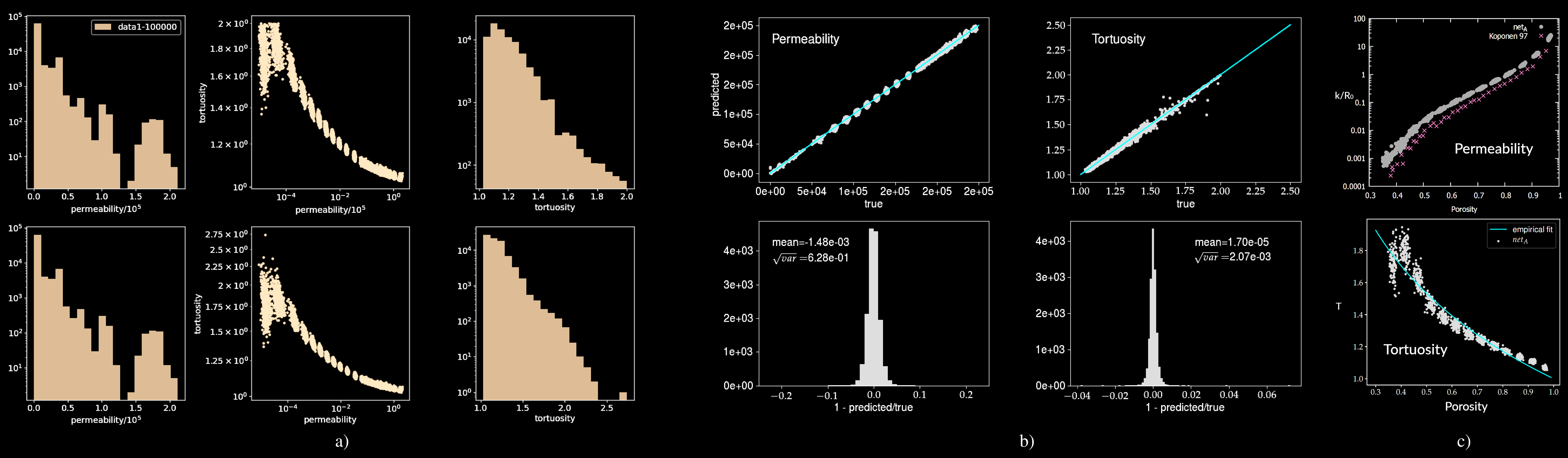

Figure 2: a) Distribution of physical properties of input data set, b) accuracy of NN predictions on tortuosity and porosity, c) permeability and tortuosity of random media obtained using neural networks only [1].

3 Results and Summary

Figs. 2 c) show the comparison of the predictions of permeability and tortuosity made by the CNN for the validation data set. We see that the difference between 'true' and 'predicted' is of the order of 6% and 1% for permeability and tortuosity, respectively.

To verify the quality of the model, we consider additional test data set not considered in the optimization process. It consists of 1300 of samples. In Fig. 2 b) we plot the predictions of the permeability vs porosity. We see that it agrees with theoretical expectations. While in Fig. 2 c) we show the comparison of the network predictions vs. empirical fit $T(\phi)$. We see a pretty good agreement. However, the empirical fit of tortuosity does not reproduce the drop in the low values of ϕ, in contrast to the network model. We compare network results for permeability in Fig. 2 c) with the work on similar system [2]. The agreement is satisfactory. A small, systematic deviation is due to differences between physical samples (there were no margins in [2], and thus, permeability is a bit lower there).

We showed that CNN can effectively predict porosity and tortuosity of random porous medium. The work has been summarized in [1]. The challenge now is to to perform study in more realistic porous media, i.e. highly anisotropic samples or complex geometries based on real samples.

Acknowledgements: Research project partly supported by program "Excellence initiative - research university" for years 2020-2026 for University of Wroclaw.

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