Advances in Geo-Energy Research

Vol. 8, No. 1, p. 5-18, 2023

Invited review

Advances in the application of deep learning methods to digital rock technology

Xiaobin Li[1], Bingke Li[1], Fangzhou Liu[2], Tingting Li[3], Xin Nie[1,4]*

[1]*School of Geophysics and Petroleum Resources, Yangtze University, Wuhan 430100, P. R. China.*

[2]*Department of Civil and Environmental Engineering, University of Alberta, Edmonton AB T6G 2R3, Canada*

[3]*School of Earth Sciences, Northeast Petroleum University, Daqing 163318, P. R. China*

[4]*Key Laboratory of Exploration Technologies for Oil and Gas Resources, Yangtze University, Wuhan 430100, P. R. China*

Keywords:
Digital rock
reconstruction
super resolution
segmentation
parameter prediction
deep learning

Cited as:
Li, X., Li, B., Liu, F., Li, T., Nie, X. Advances in the application of deep learning methods to digital rock technology. Advances in Geo-Energy Research, 2023, 8(1): 5-18.
https://doi.org/10.46690/ager.2023.04.02

Abstract:
Digital rock technology is becoming essential in reservoir engineering and petrophysics. Three-dimensional digital rock reconstruction, image resolution enhancement, image segmentation, and rock parameters prediction are all crucial steps in enabling the overall analysis of digital rocks to overcome the shortcomings and limitations of traditional methods. Artificial intelligence technology, which has started to play a significant role in many different fields, may provide a new direction for the development of digital rock technology. This work presents a systematic review of the deep learning methods that are being applied to tasks within digital rock analysis, including the reconstruction of digital rocks, high-resolution image acquisition, grayscale image segmentation, and parameter prediction. The results of these applications prove that state-of-the-art deep learning methods can help advance and provide a new approach to scientific knowledge in the field of digital rocks. This work also discusses future research and developments on the application of deep learning methods to digital rock technology.

1. Introduction

In recent years, the demand for oil and for greater efficiency and benefits in oil exploration has steadily increased. However, conventional reservoir exploration has been unable to meet the vast requirements of the market. Therefore, unconventional reservoir exploration has received increasing attention, and digital rock technology has become increasingly important for its realization (Wang et al., 2021a; Yang, 2022). Digital rock images can be used to describe pore and grain morphology (Blunt et al., 2013; Xia et al., 2019). Moreover, physical properties of rocks, such as permeability, resistivity and elasticity, can be obtained through numerical simulations based on three-dimensional (3D) digital rocks (Nie et al., 2016a, 2016b; Zhu and Shan, 2016; Zhu et al., 2019; Andhumoudine et al., 2021). Establishing 3D digital rock models, converting from low- to high-resolution rock images, segmenting grayscale rock images, and obtaining rock properties from digital rocks are essential procedures in digital rock technology. However, these procedures are time-consuming and expensive. For example, the widely used Lattice Boltzmann method (LBM) is highly accurate in permeability calculation, the size of the sample is limited due to the method's high computational cost (Okabe and Blunt, 2004; Wu et al., 2006; Liu et al., 2022).

The rapid development of artificial intelligence over the last decade has made the application of deep learning methods a promising solution to these intractable problems in digital rock technology (Cai et al., 2020; Wang et al., 2021c; Xiao, 2022). This work presents some successful examples of the use of deep learning methods in the reconstruction of digital rocks, acquisition of high-resolution digital rock images, automatic

*Corresponding author.
E-mail address: lxb7309102023@126.com (X. Li); lbk8589@126.com (B. Li); fangzhou.liu@ualberta.ca (F. Liu); dkyltt@163.com (T. Li); niexin_cugb@126.com (X. Nie).

Yandy Scientific Press

2207-9963

Received December 12, 2022; revised January 9, 2023; accepted January 26, 2023; available online February 2, 2023.

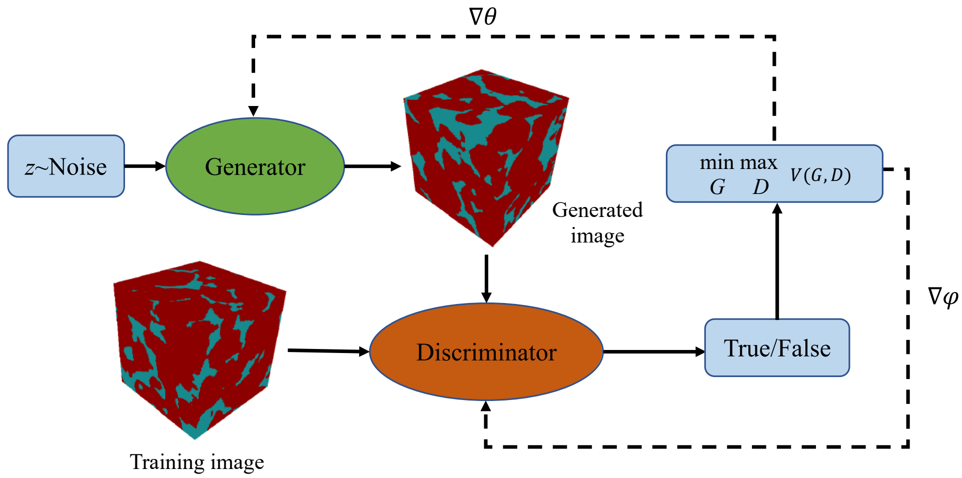


Fig. 1. GANs structure (modified from Hu et al., 2022).

segmentation of grayscale digital rock images, and prediction of rock parameters. The results and computational costs of traditional methods are compared with these innovative examples to demonstrate the superior performance of deep learning methods. Finally, some understanding and future research directions are stated for the use of deep learning methods in digital rock technology.

2. 3D digital rock reconstruction

Digital rocks are the images of rocks. There are three traditional digital rock reconstruction methods: physical experiments, numerical reconstruction, and hybrid modelling (Lin et al., 2018; Zhao et al., 2020). Physical experiments mainly include scanning electron microscopy (SEM), focused ion beam scanning (FIB-SEM), and X-ray computed tomography (CT). All these physical procedures require expensive experimental equipment, take a long time to complete even when scanning a small-sized core, and cannot guarantee both large imaging volume and high resolution (Yang et al., 2021). Numerical reconstruction methods include process-based modeling and stochastic methods including simulated annealing method, Markov chain Monte Carlo method, truncated Gaussian random field method, multiple-point statistics, and so on (Wang et al., 2013; Yao et al., 2013; Yang et al., 2015; Yao et al., 2018). Although the 3D digital rocks obtained from numerical reconstruction methods have good pore structures, the reconstruction results are controlled by different constraints. The more the conditions, the better the reconstruction results and the higher the calculation cost. The hybrid modelling method combines the advantages of the first two methods, obtaining two-dimensional (2D) slice data of rocks via SEM and other physical methods, and then reconstructing the 3D digital rocks through numerical reconstruction. However, this reconstruction method is often aimed at highly homogeneous rocks, making it unsuitable for unconventional reservoirs with complex and heterogeneous pore structures, such as shale (Cao et al., 2022).

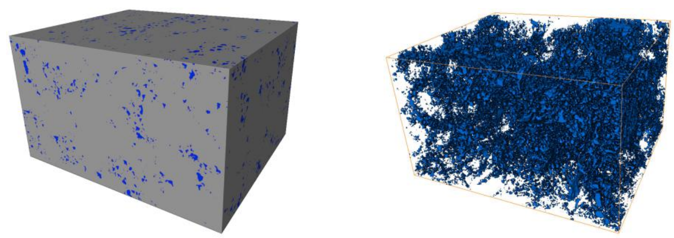
Deep learning algorithms that can be used to generate images are primarily composed of generative adversarial networks (GANs) and variational autoencoders (VAEs) (Cang et al., 2018; Zhang et al., 2021a). Compared to VAEs, GANs can generate more realistic images. Therefore, various variants of GANs are primarily used to reconstruct digital cores. The GANs have powerful image-generation abilities (Goodfellow et al., 2014), which are mainly composed of generator and discriminator networks. The generator is used to learn the distribution characteristics of real data samples and generate fake samples that are similar to the real ones. The goal of the discriminator is to accurately distinguish the input samples from real or fake training samples. As the number of training epochs increases, the capabilities of the generator and discriminator continue to improve, as shown in Fig. 1. Once the training process is completed, the generator can be used directly to generate realistic images.

Although GANs have achieved remarkable results in generating high-quality images, they have problems such as difficult training, only generate a single image, and the lack of indicators to monitor the training progress (Hu et al., 2022). In response to these problems, many researchers have improved GANs by developing different variants. Table 1 compares the advantages and disadvantages of several common GANs variants, including Deep Convolutional Generative Adversarial Networks (DCGANs), Least Square Generative Adversarial Networks (LSGANs), Wasserstein Generative Adversarial Networks (WGANs), Wasserstein Generative Adversarial Networks with Gradient Penalty (WGANs-GP), Large-scale Generative Adversarial Networks (BigGANs), Cycle-Consistent Generative Adversarial Networks (CycleGANs). As can be seen, the emphasis on reconstruction models varies between different GANs variants. In practice, additional experimental requirements are set to choose a suitable GANs that provides adequate results according to our needs.

Many scholars have studied the use of GANs for digital rock reconstruction. Mosser et al. (2017) creatively used DCGANs to achieve the rapid reconstruction of a bead pack, Berea sandstone, and Ketton limestone. The synthetic rocks were compared to the original ones using two-point statistics,

Table 1. Comparison of common GANs variants.

Variant name	Advantage	Disadvantage	Reference
DCGANs	Fast training and small memory occupied	Chessboard effect resulting in poor picture quality	Radford et al. (2015)
LSGANs	Less gradient disappearance and high generative quality	Not good enough for generating large-scale images	Mao et al. (2017)
WGANs	High training stability	Producing bad samples and complex convergence	Arjovsky et al. (2017)
WGANs-GP	Short convergence time and stable training	Unable to generate high-resolution images	Gulrajani et al. (2017)
BigGANs	High resolution and good quality	Complex network structure and high computational cost	Brock et al. (2018)
CycleGANs	High realism and diversity of the results	Complex network structure and training process	Zhu et al. (2017a)



(a) (b)

Fig. 2. Original shale digital rock (Yang et al., 2021).

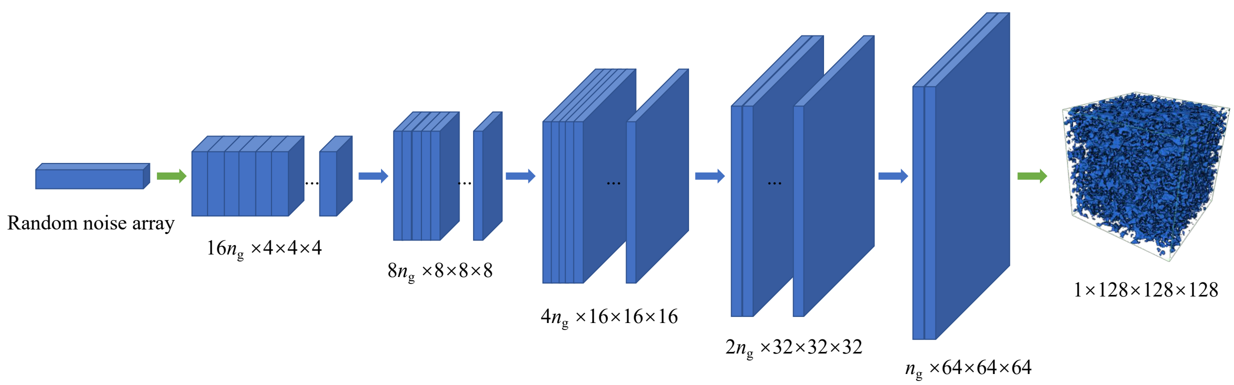


Fig. 3. Schematic diagram of the generator structure (Yang et al., 2021).

morphological characteristics, and single permeability. The results showed good consistency between the synthetic and original cores. This work used 3D digital rocks composed of pores and grains, whereas posterior studies focused on the reconstruction of 3D grayscale rocks based on 2D grayscale slices. Based on previous work, Mosser et al. (2018) reconstructed Oolitic limestone in grayscale. Likewise, Zha et al. (2020) used WGANs to generate realistic 2D grayscale images of shale, demonstrating that GANs can also achieve good results in the reconstruction of highly heterogeneous. Valsecchi et al. (2020), Feng et al. (2020) and You et al. (2021) realized the reconstruction of 3D digital rocks from 2D slices. In addition, the time consumption and average use of CPU, GPU, and memory by GANs and traditional methods were compared, proving that the reconstruction speed of GANs was faster (Feng et al., 2020; Zhang et al., 2021b).

The application of GANs to digital rock reconstruction were illustrated through the 3D digital rock reconstruction of shale by Yang et al. (2021). They obtained large-size training images based on three-dimensional FIB-SEM images of real shale cores, grouped the four mineral components of the skeleton phases of the original core images into one phase, and recombined them with pore phases into a new three-dimensional volume data (Fig. 2). Then, a six-layer deep convolution neural network was used as the generator (Fig. 3) and discriminator.

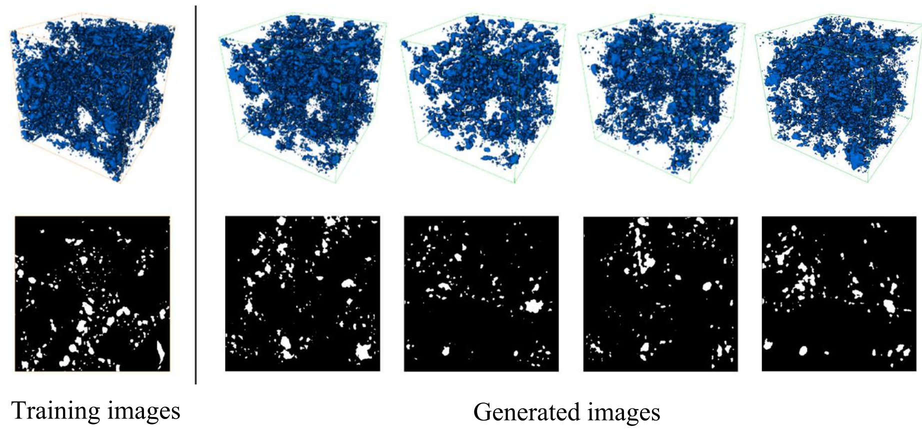


Fig. 4. 3D digital rocks and corresponding 2D slices produced by the generator (Yang et al., 2021).

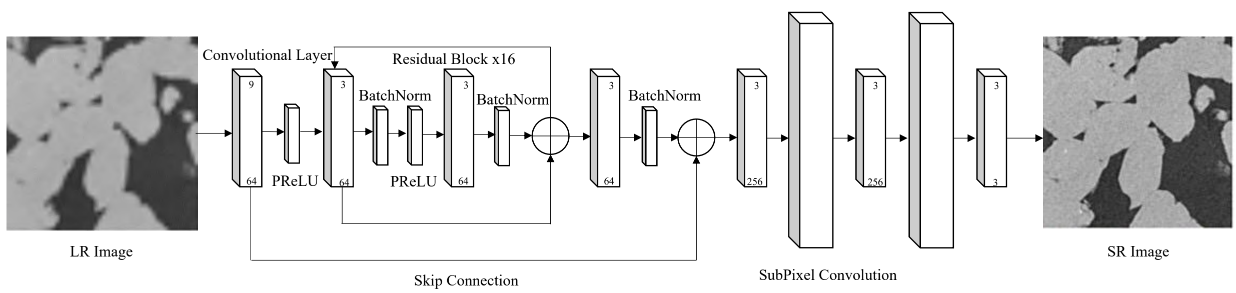


Fig. 5. Structure of SR-Resnet.

Partial displays of the 3D cores and 2D slices are shown in Fig. 4. The digital rock synthesized by the generator can not only restore the pores of the original core but also capture their spatial distribution, which gives a good description of the pore space of the original core. These results show that the trained GANs model can generate digital shale cores that satisfy the given pore structure information.

3. Image resolution enhancement

Microcomputed tomography (micro-CT) is widely used to describe the microstructure of conventional rocks (Flannery et al., 1987; Coenen et al., 2004; Shan et al., 2022). However, owing to the inherent limitations of micro-CT, the field of view of high-resolution (HR) images is small and the resolution of images with a large field of view is low (Li et al., 2017).

To overcome the limitations of micro-CT, a super-high-resolution (SR) algorithm was proposed in the 1960s. As an effective method to overcome the tradeoff between the field of view and image resolution, the SR algorithm can reconstruct rock micro-CT images from low-resolution (LR) to HR images. However, in most cases, existing SR methods cannot satisfactorily produce HR images, lack flexibility in the generation stage, and have problems such as a high computational cost (Yang et al., 2008). Some deep learning methods, such as super-resolution convolutional neural network (SRCNN) (Wang et al., 2019a), super-high-resolution cycle-consistent generative adversarial networks (SR-CycleGAN) (Wang et al., 2019a), and hybrid spatiotemporal deep learning (HSDL) (Kamrava et al., 2019), have been applied in continuous exploration to effectively improve the image resolution. Dong et al. (2015) proposed an SR with convolutional neural network SRCNN. Through mapping and reconstruction, the algorithm can convert LR images into SR images. Wang et al. (2019a) applied the SRCNN technique to the trained HR source and twice to the LR source to generate high-resolution images of sandstone and carbonate rocks. Compared with the bicubic interpolation, the experimental results show that the image quality improved and the relative error reduced by 50%-70%, indicating that the SRCNN can generate high-quality, high-resolution images by processing sandstone and carbonate images. Compared with the traditional method, the recovery quality significantly improved, indicating that the SRCNN method can be used as a feasible processing step in the digital rock workflow. Three models were subsequently developed from the SRCNN (Wang et al., 2019a): SR-Resnet, enhanced deep SR (EDSR), and wide-activation deep SR (WDSR), all of which had similar structures (Figs. 5-7. LR Image: Bentheimer (50 $\times$ 50), 15.2 micron resolution, 0.76mm $\times$ 0.76mm; SR Image: Bentheimer (200 $\times$ 200), 3.8 micron resolution 0.76mm $\times$ 0.76mm).

The application of GANs to high resolution image generation can also achieve good results. Ledig et al. (2017) proposed to apply the GANs to image super resolution, namely SRGAN. Zhu and Zheng (2022) used SRGAN to carry out research on super-resolution reconstruction of rock micro-CT images, and achieved good results. Training SRGAN requires a large number of paired data, which is usually difficult to achieve. Therefore, the Cycle-GAN network is proposed to

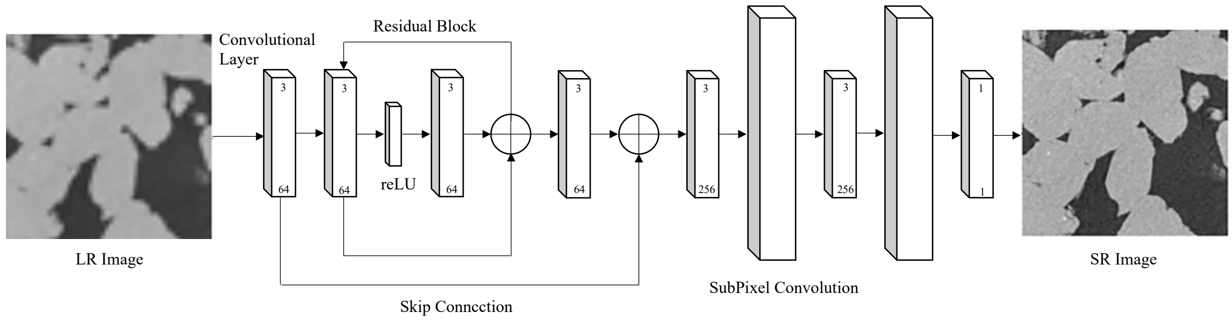


Fig. 6. Structure of EDSR.

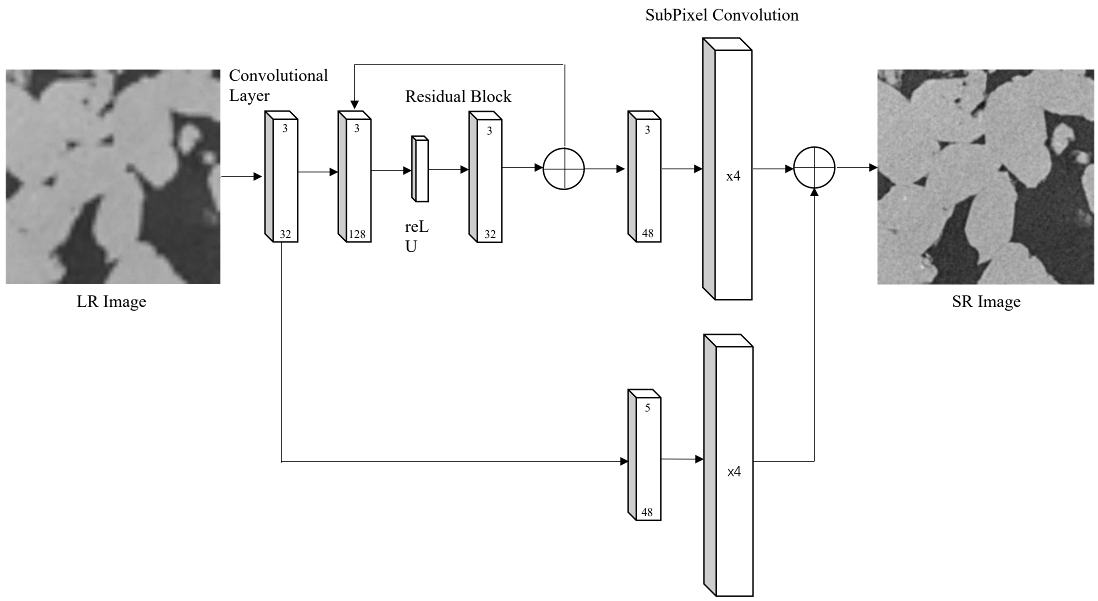


Fig. 7. Structure of WDSR.

solve this problem (Zhu et al., 2017b). Chen et al. (2020a) proposed a simple rock micro-CT image reconstruction based on an SR-CycleGAN (Fig. 8). The SR-CycleGAN transcends the limitations of imaging systems in terms of field of view and resolution and can simultaneously obtain a large field of view and HR rock micro-CT images. This method consists of two stages: offline training and online testing (Fig. 9). The offline training stage uses a set of unpaired rock micro-CT images to train the network. In the online testing phase, the mapping between micro-CT images is modeled and the SR-CycleGAN improves the resolution of the LR input by learning the mapping. Compared with the HR results generated by LR rock images and bicubic interpolation (Fig. 10), the experimental results show that the SR-CycleGAN algorithm can significantly improve the quality of the simulated and real rock micro-CT images.

The problem of lacking training image, which limit the usage of deep learning algorithms for image super resolution. To address this issue, Kamrava et al. (2019) proposed using an HSDL algorithm for generating a large number of plausible shale. This method uses very few input images to train a deep learning stochastic convolutional network at a meager cost while improving image resolution (Kamrava et al., 2019; Wang et al., 2019a; Chen et al., 2020a). In addition, Kamrava et al. (2019) used the HSDL algorithm to analyze and model complex shale formations with irregular pores. The results showed that the accuracy of the HSDL algorithm is higher than that of the conventional deep learning algorithm without reinforcement training. The frequency distribution of the images generated by the HSDL algorithm was close to that of the reference images, and the enhanced images generated by the HSDL algorithm were consistent with the original HR images (Fig. 11).

4. Image segmentation

In the field of digital rock, image segmentation usually only needs to divide the pore space and solid particle space. However, the binary images containing pore and solid grain are not applicable in the case of P- and S- wave speed simulation (Andrä et al., 2013), hybrid moisturizing flow simulation (Akai et al., 2019), and non-response transport simulation (Liu et al., 2018). It is necessary to segment the grayscale image of rock into the image containing multiple mineral components. However, traditional image segmentation methods (Seo et al., 2020), such as multi threshold segmentation, edge detection, clustering segmentation, are difficult to accurately segment

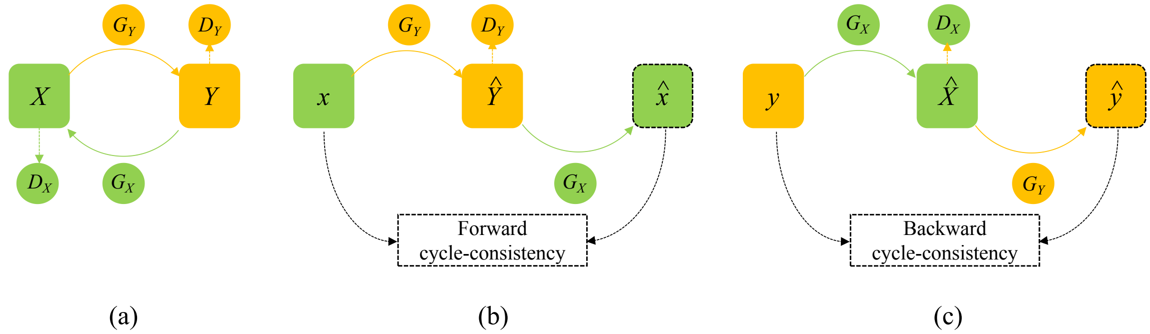


Fig. 8. The architecture of the SR-CycleGAN which comprises (a) two generators ($G_X : Y \to X$ and $G_Y : X \to Y$) and two associated discriminators (D_X and D_Y), (b) forward cycle consistency: $x \approx G_X(G_Y(x))$. (c) Backward cycle consistency: $y \approx G_Y(G_X(y))$.

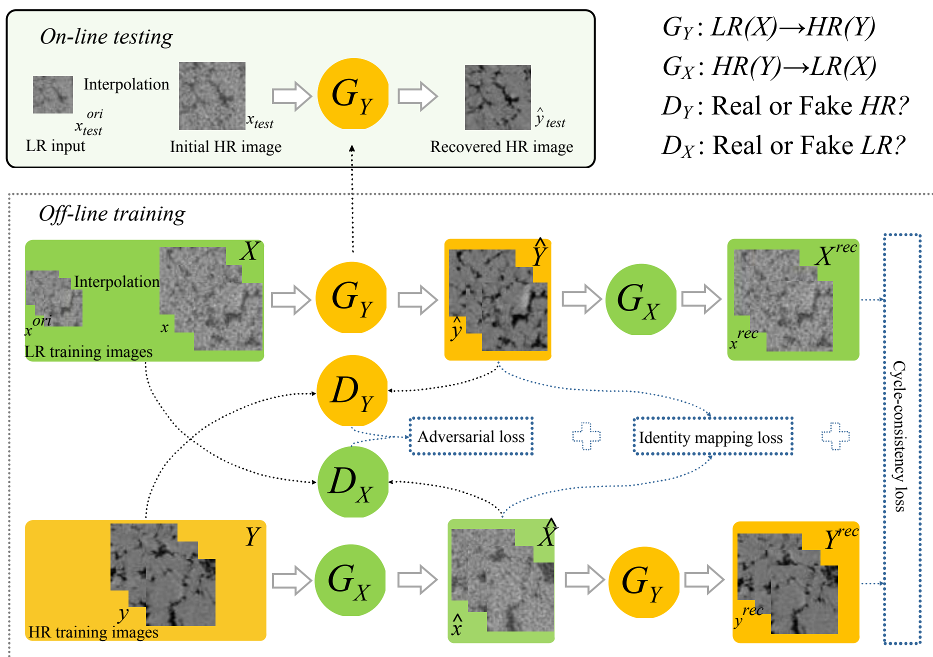


Fig. 9. The off-line training phase (bottom) and the on-line testing phase (top) of the SR-CycleGAN (Chen et al., 2020a).

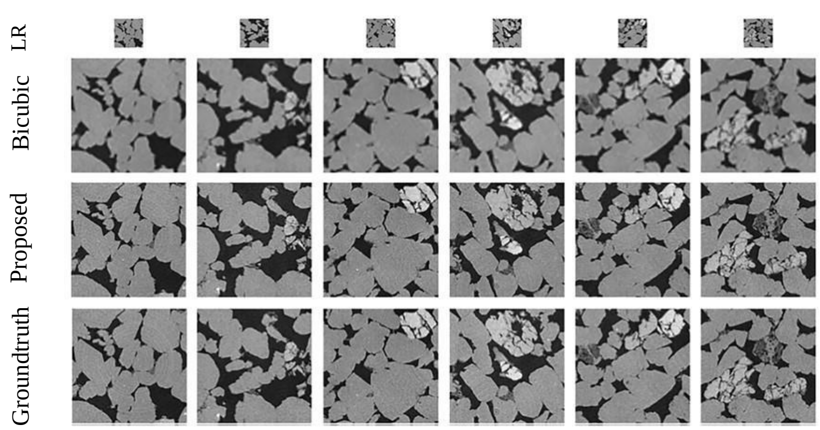


Fig. 10. LR rock images: (top) HR results produced through bicubic interpolation, (middle) HR results produced by the SR-CycleGAN, and (bottom) ground truth (Chen et al., 2020a).

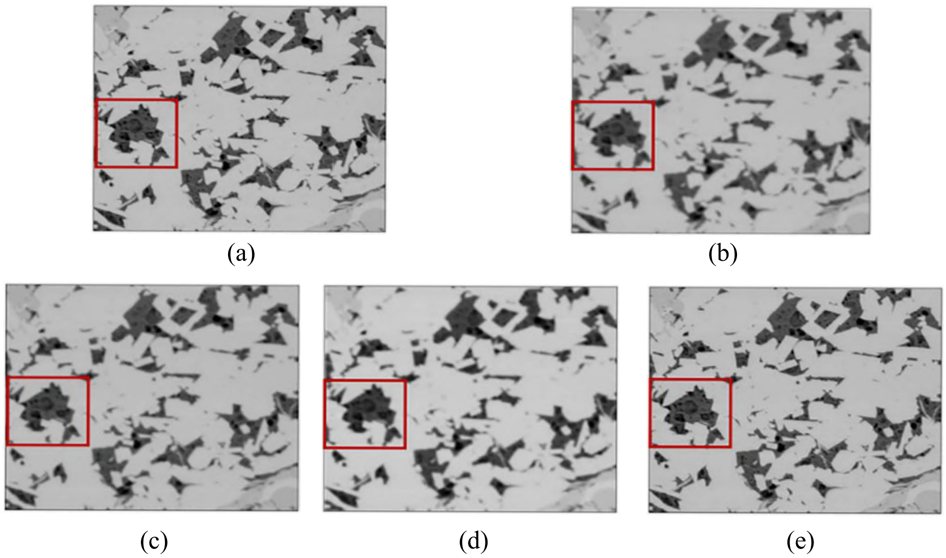


Fig. 11. Comparison of image resolution enhancement methods: (a) reference image, (b) low-resolution input image, (c) regular deep learning image, (d) bicubic interpolation image and (e) HSDL-generated image (Kamrava et al., 2019).

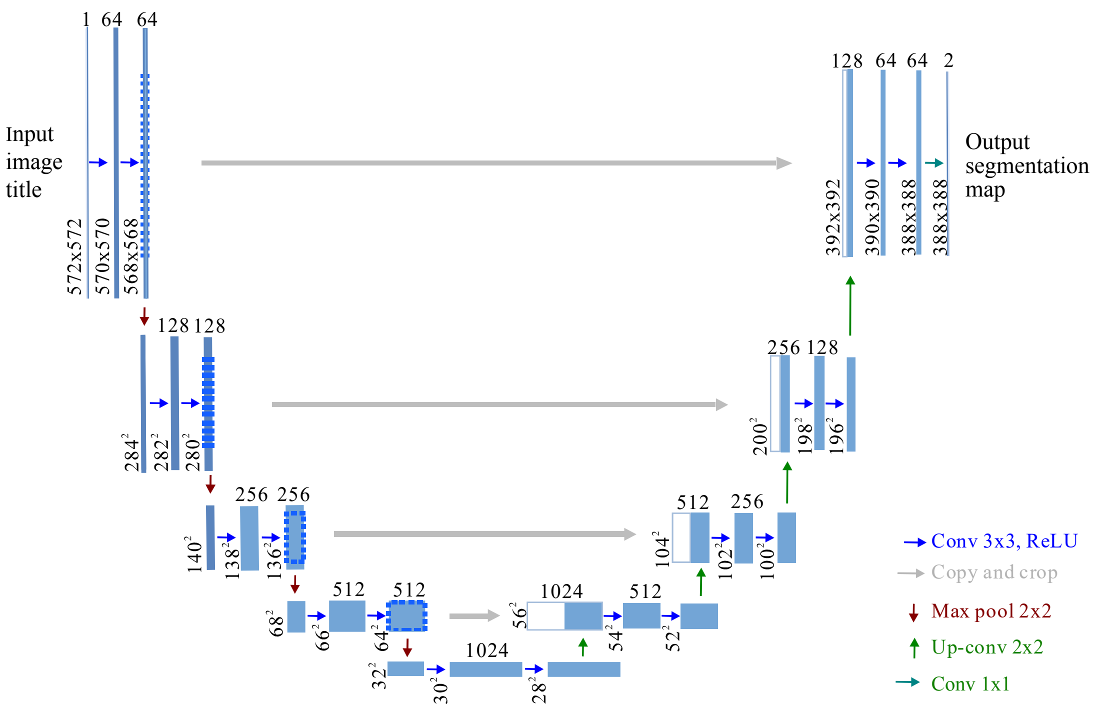


Fig. 12. U-Net structure (Ronneberger et al., 2015).

rock images. To address the lack of traditional image segmentation, some scholars have used convolution neural network (CNN) for image semantic segmentation (Ning et al., 2005; Cireşan et al., 2012; Farabet et al., 2012; Ganin and Lempitsky, 2014; Gupta et al., 2014; Pinheiro and Collobert, 2014). Deep learning methods such as fully convolutional networks (FCN) (Long et al., 2015), U-Net (Ronneberger et al., 2015), DeepLab (Chen et al., 2014), and SegNet (Badrinarayanan et al., 2017) have been applied in semantic segmentation. Since the U-Net network was proposed, the U-shaped network structure of encoders and decoders connected by skip connection has been widely used in the field of image segmentation and the improvement structures were proposed, such as SegNet, U-Net++ (Badrinarayanan et al., 2017; Zhou et al., 2018). The U-Net structure is illustrated in Fig. 12, the left side of the network is the encoder, the right side is the decoder, and the two sides are connected using the skip connection layer.

SegNet uses the pooling index obtained by the maximum pooling step of the encoder corresponding to the decoder for nonlinear samples (Fig. 13), which not only improves the image resolution but also reduces the need for the learning about up-sampling. For different aspects and the outlook re-

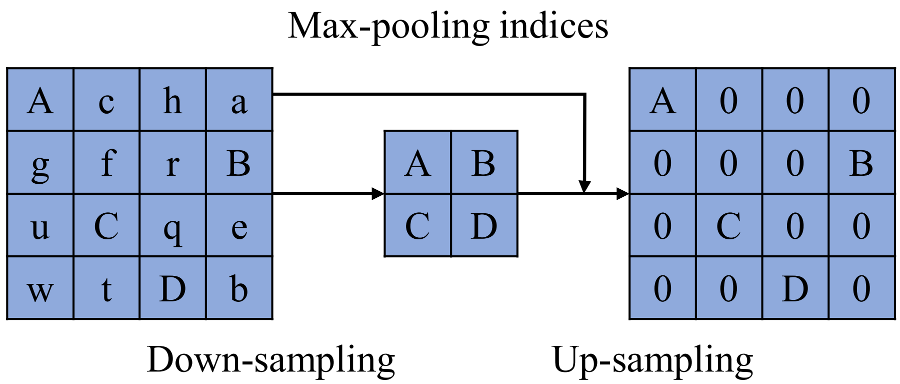


Fig. 13. The max pooling index is used for up-sampling low-resolution graphs in SegNet (Badrinarayanan et al., 2017).

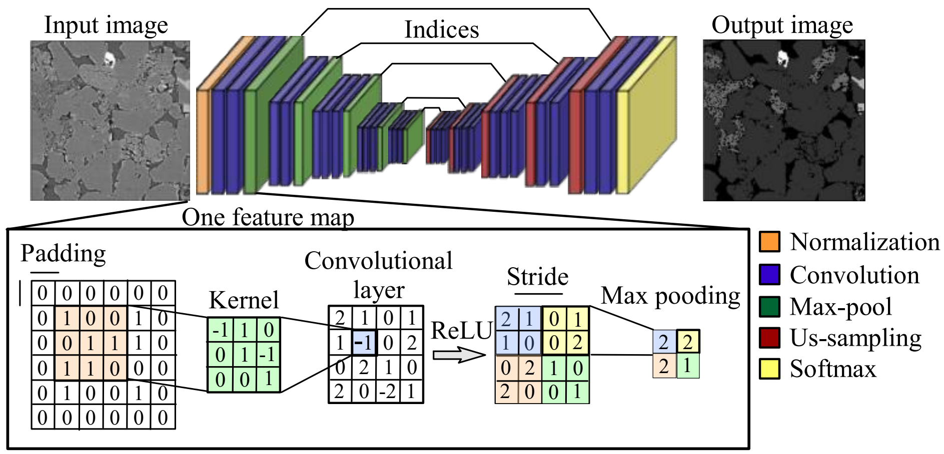


Fig. 14. The basic internal structure of SegNet (Karimpouli and Tahmasebi, 2019a).

sults (Kendall et al., 2015; Garcia-Garcia et al., 2017; Nanfack et al., 2017), the internal structure of the SegNet is shown in Fig. 14. Karimpouli and Tahmasebi (2019a) used the SegNet to realize the automatic segmentation of rock image of Berea sandstone, which can achieve more accurate results compared with the multi-threshold segmentation method.

Table 2. Prediction of performance of different learning models (Li et al., 2021).

Models	Fl-score		
	Micro	Weighted	Macro
Logistic regression	0.8705	0.8691	0.8691
Linear SVM	0.7980	0.7778	0.7778
K-Nearest neighbors	0.9150	0.9139	0.9139
Random forest	0.9238	0.9215	0.9215
ANN	0.8869	0.8873	0.8873
U-Net	0.8832	0.8784	0.7301

Previous research shows that the U-Net network can achieve good results in segmenting digital rock images. Wang et al. (2021b) realized automatic segmentation of 2D and 3D sandstone CT images using 2D and 3D U-Net network models. Experiments have proved that with revised weight function the U-Net architecture can effectively distinguish clay sets of mixed matrix mineral particles and organic matter. Chen et al. (2020b) used the U-Net architecture with modified the weight function to segment the scanning electron microscope images of Duvernay shale samples. The experimental results (Fig. 15) show that there is an obvious separation between the clay collection and matrix mineral particles, and the boundary is acceptable. This method proves that extracting deep-learning features based on texture is feasible, economical, and timely.

In addition, Li et al. (2021) used a variety of image segmentation methods, including support vector machine, k-nearest neighbor, random forest, artificial neural network and U-Net network model to perform multi-component segmentation of shale SEM images. The image segmentation effects of different methods can be seen in Table 2, and the U-Net model can achieve better results. Meanwhile, compared with the machine learning method used in this paper, the U-Net model uses the whole image as the input to achieve end-to-end image segmentation, without manually extracting image features, but also considering the neighborhood information of pixels. As for multi-component segmentation of shale CT images, Li et al. (2022) used U-Net network model to obtain a 3D shale

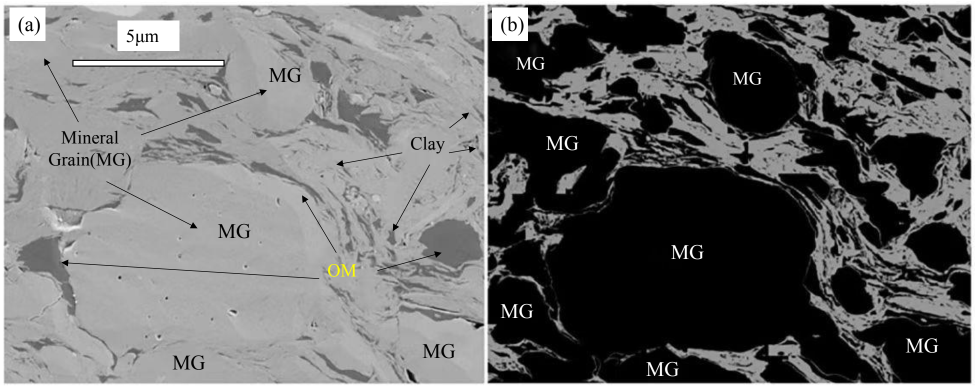


Fig. 15. (a) Comparison of the original image and (b) segmented clay minerals (Chen et al., 2020b). MG: matrix mineral grain, OM: organic matter.

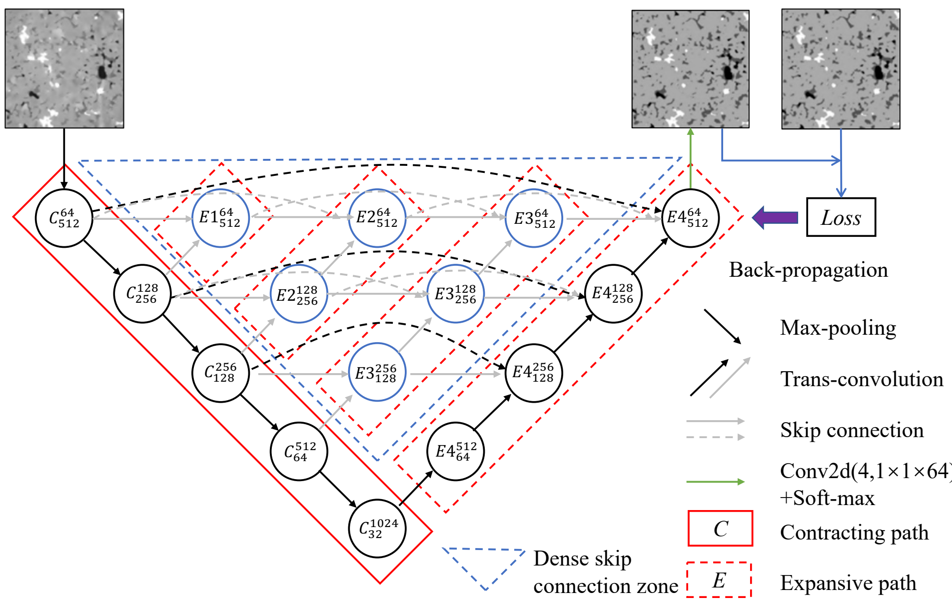


Fig. 16. The structure of U-Net++ model containing four regular U-Net models (Wang et al., 2022).

core model with multiple mineral components by combining shale CT images and QEMSCAN images containing mineral information. It is challenging to segment the small targets and the pixels near the boundary accurately in the rock image. To solve this problem, Wang et al. (2022) used the U-Net++ structure to carry out image segmentation experiments, compared the segmentation results of U-Net++ with those of the commonly used U-Net and wide U-Net model, and found that U-Net++ can achieve satisfactory results in terms of pixel-wise and physics-based evaluation metrics. The network structure of U-Net++ (Fig. 16) contains four conventional U-Net networks, the blocks and skip connections shown in the black are for the fourth U-Net. Comparison of segmentation results of different segmentation methods is shown in Fig. 17.

5. Digital rock parameter prediction

Rock parameters prediction is essential for formation evaluation (Wang et al., 2020). For example, permeability and porosity, which are inherent properties of the rocks whose values depend only on the pore structure, are important parameters used to characterize the heterogeneity and anisotropy of reservoirs (Haagsma et al., 2021; Ishola and Vilcáez, 2022). Numerical simulation has been used to calculate rock's parameters. Zhu et al. (2008) used the LBM to study the seepage characteristics of porous rocks. Song et al. (2015) used a structured pore network model of the rock samples to predict their permeability. Since the calculations involved are very time-consuming, the application of numerical simulation methods tends to be limited to small domains depending on the computational resources available. Therefore, the rapid prediction of core parameters has attracted great research interest.

Achievements have also been made in the parameter prediction of digital rock using deep learning algorithm. Alqahtani et al. (2020) used CNNs to predict the porosity, specific surface, and average pore size of binary and grayscale 2D X-ray images of sandstone. The results showed that the parameters predicted were consistent with ground truth, with a relative

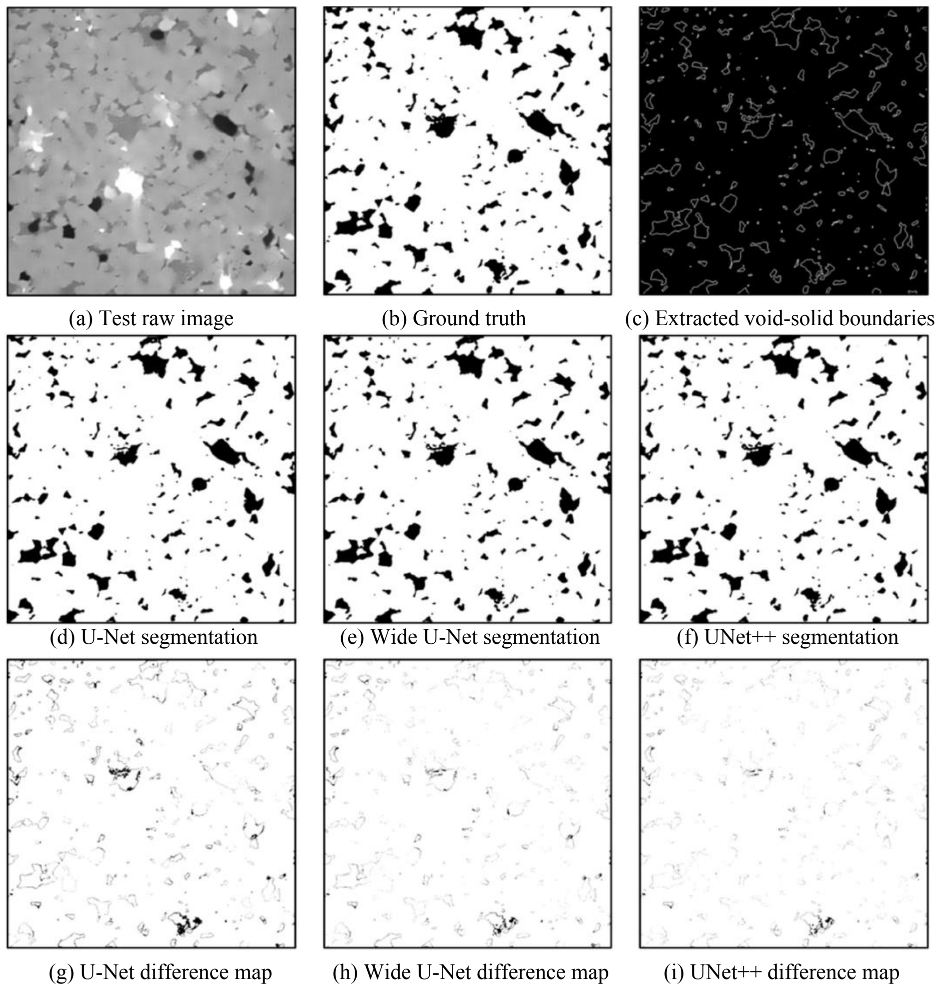


Fig. 17. Comparison of segmentation results of different segmentation methods (Wang et al., 2022).

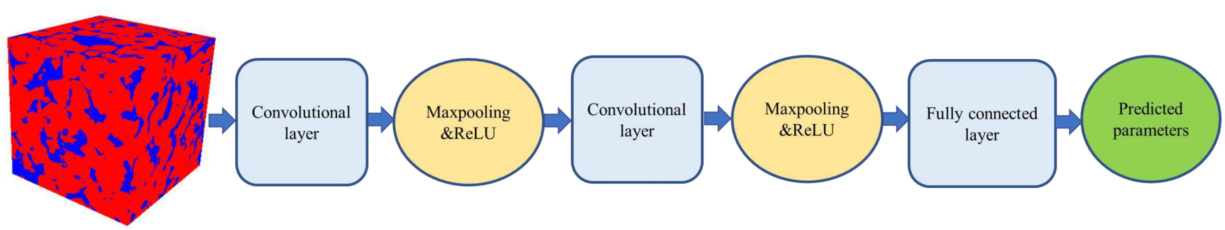


Fig. 18. Schematic of the CNN network for the prediction of parameters.

error of less than 7% for both binary and grayscale CT images. Misbahuddin (2020) utilized CNNs to predict properties from grayscale SEM images of shale. The relative errors in the predicted porosity and average pore radius were 0.4% and 1%, which are considered negligible. For 3D digital rocks, methods based on CNNs can also achieve excellent results (Srisutthiyakorn, 2016; Alqahtani et al., 2018; Yang et al., 2018; Karimpouli and Tahmasebi, 2019b). The schematic of the CNN network for the prediction of rock's parameters in shown in Fig. 18. Karimpouli and Tahmasebi (2019b) used CNNs to estimate P- and S- wave velocities from digital rock images, the estimated properties were compared with the numerical simulation results, indicating thar CNNs perform outstanding in predicting the physical parameters. Tembely et al. (2021) used CNNs to predict the porosity, formation factor, and permeability of 3D CT images with high accuracy. Rabbani et al. (2020) proposed a workflow based on CNNs to estimate a wide range of morphological, hydraulic, and electrical properties for binarized 3D CT images. Compared with traditional methods, the workflow proposed by Rabbani is compatible with any physical size. Zhang et al. (2022) proposed to predict the permeability of porous media from low-resolution images and achieved outstanding results.

A specific example was illustrated regarding the use of CNNs to predict the parameters of digital rocks. Wang et al. (2019b) established a 3D pore network model based on the OpenFOAM framework and calculated the porosity and permeability of pore network model. Then the 3D CT images

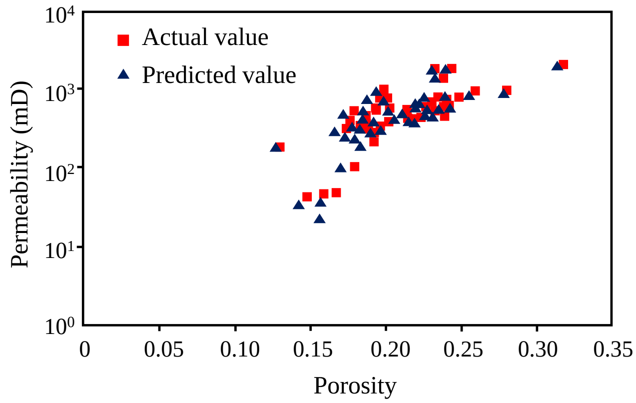


Fig. 19. Test data porosity-permeability distribution (Wang et al., 2019b).

and corresponding porosity and permeability are as training dataset for the CNNs model training. The actual data exhibits a strong matching relationship between pores and permeability (Fig. 19). This experiment shows that the fast prediction digital rock model established based on the 3D CNN has excellent potential and generalization ability for digital rock feature extraction. The prediction time of a good deep learning model was only 0.03 s. In contrast, the average time of the OpenFOAM numerical simulation method was 1.58 h, thus demonstrating a significant improvement in the calculation speed and providing an effective solution for the rapid prediction of digital rock permeability. In summary, deep learning methods can predict parameters of digital rocks accurately and improve prediction speed in one order of magnitude compared with traditional numerical simulation methods, effectively reducing computational costs, and significantly improving work efficiency.

6. Conclusions

This work provides an overview of the application of deep learning methods to 3D digital rock reconstruction, image resolution enhancement, image segmentation, and digital rock parameter prediction. Although digital rock technology has been developed for decades, many research challenges are yet to be addressed. The methods mentioned in this study have partially overcome the challenges posed by reconstruction, resolution enhancement, segmentation, and parameter prediction tasks. However, these methods are still unable to simultaneously consider the training speed, image size, and modeling accuracy. Therefore, the application of artificial intelligence methods in the field of digital rocks should be more comprehensively developed. The reconstruction of the digital rocks should be constrained by physical properties to make sure the reality and diversity of the generated samples. The component segmentation procedures by now are mostly based on 2D slices, which cannot assure the continuity of the components in all directions. Therefore, the ortho-slice segmentation should be considered. Parameter prediction should not only based on the image itself, but also the physical properties such as porosity and pore space distribution. In addition, the accuracy of segmentation can be further improved and attempts to predict more rock parameters are needed.

Moreover, as the future development of intelligent digital oilfields becomes a general trend, researchers are suggested to make full use of the powerful capabilities of deep learning and other artificial intelligence methods to continuously learn and update the collected core data and properties. Unlike other common tasks for machine learning such as number or animal identification, its application in digital rock area is relatively new and lack of solid data. Therefore, it is necessary to build an open source and renewable database containing rocks' digital images and their physical properties. This should enable the combination of geological and geophysical data to allow a comprehensive and systematic development of reliable strategies for integrating microscopic and local digital rock technology into macroscopic and overall exploration and development processes.

Acknowledgements

This research was supported by the National Natural Science Foundation of China (No. 41504094), the Undergraduate Training Program of the Yangtze University for Innovation and Entrepreneurship (No. Yz2020042), and Heilongjiang Provincial Natural Science Foundation of China (No. LH2020D008).

Conflict of interest

The authors declare no competing interest.

References

Akai, T., Alhammadi, A. M., Blunt, M. J., et al. Modeling oil recovery in mixed-wet rocks: Pore-scale comparison between experiment and simulation. Transport in Porous Media, 2019, 127: 393-414.

Alqahtani, N., Alzubaidi, F., Armstrong, R. T., et al. Machine learning for predicting properties of porous media from 2d X-ray images. Journal of Petroleum Science and Engineering, 2020, 184: 106514.

Alqahtani, N., Armstrong, R. T., Mostaghimi, P. Deep learning convolutional neural networks to predict porous media properties. Paper SPE 191906 Presented at SPE Asia Pacific Oil and Gas Conference and Exhibition, Brisbane, Australia, 23-25 October, 2018.

Andhumoudine, A. B., Nie, X., Zhou, Q., et al. Investigation of coal elastic properties based on digital core technology and finite element method. Advances in Geo-Energy Research, 2021, 5: 53-63.

Andrä, H., Combaret, N., Dvorkin, J., et al. Digital rock physics benchmarks-Part I: Imaging and segmentation. Computers and Geosciences, 2013, 50: 25-32.

Arjovsky, M., Chintala, S., Bottou, L. Wasserstein generative adversarial networks. Paper Presented at Proceedings of the 34th International Conference on Machine Learning, Sydney, Australia, 6-11 Augest, 2017.

Badrinarayanan, V., Kendall, A., Cipolla, R. SegNet: A deep convolutional encoder-decoder architecture for image segmentation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2017, 39: 2481-2495.

Blunt, M. J., Bijeljic, B., Dong, H., et al. Pore-scale imaging and modelling. Advances in Water Resources, 2013, 51: 197-216.

Brock, A., Donahue, J., Simonyan, K. Large scale GAN training for high fidelity natural image synthesis. ArXiv preprint, 2018, 1809: 11096.

Cai, J., Xu, K., Zhu, Y., et al. Prediction and analysis of net ecosystem carbon exchange based on gradient boosting regression and random forest. Applied Energy, 2020, 262: 114566.

Cang, R., Li, H., Yao, H., et al. Improving direct physical properties prediction of heterogeneous materials from imaging data via convolutional neural network and a morphology-aware generative model. Computational Materials Science, 2018, 150: 212-221.

Cao, D., Hou, Z., Liu, Q., et al. Reconstruction of three-dimension digital rock guided by prior information with a combination of InfoGAN and style-based GAN. Journal of Petroleum Science and Engineering, 2022, 208: 109590.

Chen, H., He, X., Teng, Q., et al. Super-resolution of real-world rock microcomputed tomography images using cycle-consistent generative adversarial networks. Physical Review E, 2020a, 101: 023305.

Chen, Z., Liu, X., Yang, J., et al. Deep learning-based method for SEM image segmentation in mineral characterization, an example from Duvernay Shale samples in Western Canada Sedimentary Basin. Computers and Geosciences, 2020b, 138: 104450.

Chen, L. C., Papandreou, G., Kokkinos, I., et al. Semantic image segmentation with deep convolutional nets and fully connected crfs. ArXiv preprint, 2014, 1412: 7062.

Cireşan, D. C., Giusti, A., Gambardella, L. M., et al. Deep neural networks segment neuronal membranes in electron microscopy images. Paper Presented at Advances in Neural Information Processing Systems, Lake Tahoe, U.S.A, 3-8 December, 2012.

Coenen, J., Tchouparova, E., Jing, X., et al. Measurement parameters and resolution aspects of micro X-ray tomography for advanced core analysis. Paper Presented at proceedings of International Symposium of the Society of Core Analysts, Abu Dhabi, The United Arab Emirates, 5-9 October, 2004.

Dong, C., Loy, C. C., He, K., et al. Image super-resolution using deep convolutional networks. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2015, 38: 295-307.

Farabet, C., Couprie, C., Najman, L., et al. Learning hierarchical features for scene labeling. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2012, 35: 1915-1929.

Feng, J., Teng, Q., Li, B., et al. An end-to-end three-dimensional reconstruction framework of porous media from a single two-dimensional image based on deep learning. Computer Methods in Applied Mechanics and Engineering, 2020, 368: 113043.

Flannery, B. P., Deckman, H. W., Roberge, W. G., et al. Three-dimensional X-ray microtomography. Science, 1987, 237: 1439-1444.

Ganin, Y., Lempitsky, V. N4-fields: Neural network nearest neighbor fields for image transforms. Paper Presented at 12nd Asian Conference on Computer Vision, Singapore, 1-5 November, 2014.

Garcia-Garcia, A., Orts-Escolano, S., Oprea, S., et al. A review on deep learning techniques applied to semantic segmentation. ArXiv preprint, 2017, 1704: 06857.

Goodfellow, I. J., Pouget-Abadie, J., Mirza, M., et al. Generative adversarial nets. Paper Presented at Advances in Neural Information Processing Systems, Montreal, Canada, 8-13 December, 2014.

Gulrajani, I., Ahmed, F., Arjovsky, M., et al. Improved training of wasserstein gans. Paper Presented at Advances in Neural Information Processing Systems, Long Beach, U.S.A, 4-9 December, 2017.

Gupta, S., Girshick, R., Arbeláez, P., et al. Learning rich features from RGB-D images for object detection and segmentation. Paper Presented at 13rd European Conference on Computer Vision (ECCV), Zurich, Switzerland, 6-12 September, 2014.

Haagsma, A., Scharenberg, M., Keister, L., et al. Secondary porosity prediction in complex carbonate reefs using 3D CT scan image analysis and machine learning. Journal of Petroleum Science and Engineering, 2021, 207: 109087.

Hu, M. F., Zuo, X., Liu, J. W. Survey on deep generative model. Acta Automatica Sinica, 2022, 48: 40-74. (in Chinese)

Ishola, O., Vilcáez, J. Machine learning modeling of permeability in 3D heterogeneous porous media using a novel stochastic pore-scale simulation approach. Fuel, 2022, 321: 124044.

Kamrava, S., Tahmasebi, P., Sahimi, M. Enhancing images of shale formations by a hybrid stochastic and deep learning algorithm. Neural Networks, 2019, 118: 310-320.

Karimpouli, S., Tahmasebi, P. Segmentation of digital rock images using deep convolutional autoencoder networks. Computers and Geosciences, 2019a, 126: 142-150.

Karimpouli, S., Tahmasebi, P. Image-based velocity estimation of rock using convolutional neural networks. Neural Networks, 2019b, 111: 89-97.

Kendall, A., Badrinarayanan, V., Cipolla, R. Bayesian segnet: model uncertainty in deep convolutional encoder-decoder architectures for scene understanding. ArXiv preprint, 2015, 1511: 02680.

Ledig, C., Theis, L., Huszár, F., et al. Photo-realistic single image super-resolution using a generative adversarial network. Paper Presented at Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, U.S.A, 21-26 July, 2017.

Li, B., Nie, X., Cai, J., et al. U-Net model for multi-component digital rock modeling of shales based on CT and QEMSCAN images. Journal of Petroleum Science and Engineering, 2022, 216: 110734.

Li, Z., Teng, Q., He, X., et al. Sparse representation-based volumetric super-resolution algorithm for 3D CT images of reservoir rocks. Journal of Applied Geophysics, 2017, 144: 69-77.

Li, C., Wang, D., Kong, L. Application of machine learning techniques in mineral classification for scanning electron microscopy-energy dispersive x-ray spectroscopy (SEM-EDS) images. Journal of Petroleum Science and Engineering, 2021, 200: 108178.

Lin, C., Wu, Y., Ren, L., et al. Review of digital core modeling methods. Progress in Geophysics, 2018, 33: 679-689. (in Chinese)

Liu, M., Shabaninejad, M., Mostaghimi, P. Predictions of permeability, surface area and average dissolution rate during reactive transport in multi-mineral rocks. Journal of Petroleum Science and Engineering, 2018, 170: 130-138.

Liu, C., Zhang, L., Li, Y., et al. Effects of microfractures on permeability in carbonate rocks based on digital core technology. Advances in Geo-Energy Research, 2022, 6: 86-90.

Long, J., Shelhamer, E., Darrell, T. Fully convolutional networks for semantic segmentation. Paper Presented at Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Boston, U.S.A, 8-10 June, 2015.

Mao, X., Li, Q., Xie, H., et al. Least squares generative adversarial networks. Paper Presented at Proceedings of the IEEE International Conference on Computer Vision, Venice (ICCV), Italy, 22-29 October, 2017.

Misbahuddin, M. Estimating petrophysical properties of shale rock using conventional neural networks CNN. Paper SPE 204272 Presented at SPE Annual Technical Conference and Exhibition, Virtual, 26-29 October, 2020.

Mosser, L., Dubrule, O., Blunt, M. J. Reconstruction of three-dimensional porous media using generative adversarial neural networks. Physical Review E, 2017, 96: 043309.

Mosser, L., Dubrule, O., Blunt, M. J. Stochastic reconstruction of an Oolitic limestone by generative adversarial networks. Transport in Porous Media, 2018, 125: 81-103.

Nanfack, G., Elhassouny, A., Thami, R. O. H. Squeeze-SegNet: A new fast deep convolutional neural network for semantic segmentation. Paper SPIE 10696 Presented at Tenth International Conference on Machine Vision (ICMV 2017), Vienna, Austria, 13-15 November, 2017.

Nie, X., Zou, C., Li, Z., et al. Numerical simulation of the electrical properties of shale gas reservoir rock based on digital core. Journal of Geophysics and Engineering, 2016a, 13: 481-490.

Nie, X., Zou, C. C., Meng, X. H., et al. 3D digital core modeling of shale gas reservoir rocks: A case study of conductivity model. Natural Gas Geoscience, 2016b, 27: 706-715. (in Chinese)

Ning, F., Delhomme, D., LeCun, Y., et al. Toward automatic phenotyping of developing embryos from videos. IEEE Transactions on Image Processing, 2005, 14: 1360-1371.

Okabe, H., Blunt, M. J. Prediction of permeability for porous media reconstructed using multiple-point statistics. Physical Review E, 2004, 70: 066135.

Pinheiro, P. O., Collobert, R. Recurrent convolutional neural networks for scene labeling. Paper Presented at Proceedings of the 31st International Conference on Machine Learning, Beijing, China, 21-26 June, 2014.

Rabbani, A., Babaei, M., Shams, R., et al. DeePore: A deep learning workflow for rapid and comprehensive characterization of porous materials. Advances in Water Resources, 2020, 146: 103787.

Radford, A., Metz, L., Chintala, S. Unsupervised representation learning with deep convolutional generative adversarial networks. ArXiv preprint, 2015, 1511: 06434.

Ronneberger, O., Fischer, P., Brox, T. U-net: Convolutional networks for biomedical image segmentation. Paper Presented at International Conference on Medical Image Computing and Computer-Assisted Intervention, Munich, Germany, 5-9 October, 2015.

Seo, H., Badiei Khuzani, M., Vasudevan, V., et al. Machine learning techniques for biomedical image segmentation: An overview of technical aspects and introduction to state-of-art applications. Medical Physics, 2020, 47: e148-e167.

Shan, L., Bai, X., Liu, C., et al. Super-resolution reconstruction of digital rock CT images based on residual attention mechanism. Advances in Geo-Energy Research, 2022, 6: 157-168.

Song, R., Liu, J., Li, G. Researches on the pore permeability of core sample based on 3D micro-CT images and pore-scale structured element models. Journal of Southwest Petroleum University (Science & Technology Edition), 2015, 37: 138-145. (in Chinese)

Srisutthiyakorn, N. Deep learning methods for predicting permeability from 2-D/3-D binary segmented images. SEG Technical Program Expanded Abstracts, 2016, 35: 3042-3046.

Tembely, M., AlSumaiti, A. M., Alameri, W. S. Machine and deep learning for estimating the permeability of complex carbonate rock from X-ray micro-computed tomography. Energy Reports, 2021, 7: 1460-1472.

Valsecchi, A., Damas, S., Tubilleja, C., et al. Stochastic reconstruction of 3D porous media from 2D images using generative adversarial networks. Neurocomputing, 2020, 399: 227-236.

Wang, Y. D., Armstrong, R. T., Mostaghimi, P. Enhancing resolution of digital rock images with super resolution convolutional neural networks. Journal of Petroleum Science and Engineering, 2019a, 182: 106261.

Wang, J., Cao, J., You, J., et al. Prediction of reservoir porosity, permeability, and saturation based on a gated recurrent unit neural network. Geophysical Prospecting for Petroleum, 2020, 59(4): 616-627. (in Chinese)

Wang, H., Dalton, L., Fan, M., et al. Deep-learning-based workflow for boundary and small target segmentation in digital rock images using UNet++ and IK-EBM. Journal of Petroleum Science and Engineering, 2022, 215: 110596.

Wang, Y., Jiang, H., Yu, F., et al. Researches on the pore permeability prediction method of 3D digital cores based on machine learning. Petroleum Science Bulletin, 2019b,

4: 354-363. (in Chinese)
Wang, S., Qin, C., Feng, Q., et al. A framework for predicting the production performance of unconventional resources using deep learning. Applied Energy, 2021a, 295: 117016.
Wang, Y. D., Shabaninejad, M., Armstrong, R. T., et al. Deep neural networks for improving physical accuracy of 2D and 3D multi-mineral segmentation of rock micro-CT images. Applied Soft Computing, 2021b, 104: 107185.
Wang, S., Yao, X., Feng, Q., et al. Molecular insights into carbon dioxide enhanced multi-component shale gas recovery and its sequestration in realistic kerogen. Chemical Engineering Journal, 2021c, 425: 130292.
Wang, C. C., Yao, J., Yang, Y. F., et al. Structure characteristics analysis of carbonate dual pore digital rock. Journal of China University of Petroleum (Edition of Natural Science), 2013, 37: 71-74. (in Chinese)
Wu, K., Van Dijke, M. I. J., Couples, G. D., et al. 3D stochastic modelling of heterogeneous porous media-applications to reservoir rocks. Transport in Porous Media, 2006, 65: 443-467.
Xia, Y., Cai, J., Perfect, E., et al. Fractal dimension, lacunarity and succolarity analyses on CT images of reservoir rocks for permeability prediction. Journal of Hydrology, 2019, 579: 124198.
Xiao, L. The fusion of data-driven machine learning with mechanism models and interpretability issues. Geophysical Prospecting for Petroleum, 2022, 61: 205-212. (in Chinese)
Yang, Y. Application progress of big data & AI technologies in exploration and development of Shengli Oilfield. Petroleum Geology and Recovery Efficiency, 2022, 29(1): 1-10. (in Chinese)
Yang, Y., Liu, F., Yao, J., et al. Reconstruction of 3D shale digital rock based on generative adversarial network. Journal of Southwest Petroleum University (Science & Technology Edition), 2021, 43: 73-83. (in Chinese)
Yang, J., Wright, J., Huang, T., et al. Image super-resolution as sparse representation of raw image patches. Paper Presented at 2008 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Anchorage, U.S.A, 23-28 June, 2008.
Yang, Z., Yabansu, Y. C., Al-Bahrani, R., et al. Deep learning approaches for mining structure-property linkages in high contrast composites from simulation datasets. Computational Materials Science, 2018, 151: 278-287.
Yang, Y., Yao, J., Wang, C., et al. New pore space characterization method of shale matrix formation by considering organic and inorganic pores. Journal of Natural Gas Science and Engineering, 2015, 27: 496-503.
Yao, J., Sun, H., Li, A., et al. Modern system of multiphase flow in porous media and its development trend. Chinese Science Bulletin, 2018, 63: 425-451. (in Chinese)
Yao, J., Wang, C., Yang, Y., et al. The construction of carbonate digital rock with hybrid superposition method. Journal of Petroleum Science and Engineering, 2013, 110: 263-267.
You, N., Li, Y. E., Cheng, A. 3D carbonate digital rock reconstruction using progressive growing GAN. Journal of Geophysical Research: Solid Earth, 2021, 126: e2021JB021687.
Zha, W., Li, X., Xing, Y., et al. Reconstruction of shale image based on wasserstein generative adversarial networks with gradient penalty. Advances in Geo-Energy Research, 2020, 4: 107-114.
Zhang, W., Li, H., Li, Y., et al. Application of deep learning algorithms in geotechnical engineering: a short critical review. Artificial Intelligence Review, 2021a, 54: 5633-5673.
Zhang, T., Li, D., Lu, F. A pore space reconstruction method of shale based on autoencoders and generative adversarial networks. Computational Geosciences, 2021b, 25: 2149-2165.
Zhang, H. L., Yu, H., Yuan, X. H., et al. Permeability prediction of low-resolution porous media images using autoencoder-based convolutional neural network. Journal of Petroleum Science and Engineering, 2022, 208: 109589.
Zhao, J., Chen, H., Li, N., et al. Research advance of petrophysical application based on digital core technology. Progress in Geophysics, 2020, 35: 1099-1108. (in Chinese)
Zhou, Z., Rahman Siddiquee, M. M., Tajbakhsh, N., et al. Unet++: A nested u-net architecture for medical image segmentation. Paper Presented at Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support, Granada, Spain, 20 September, 2018.
Zhu, J. Y., Park, T., Isola, P., et al. Unpaired image-to-image translation using cycle-consistent adversarial networks. Paper Presented at Proceedings of the IEEE International Conference on Computer Vision (ICCV), Venice, Italy, 22-29 October 2017a.
Zhu, W., Shan, R. Digital core based transmitted ultrasonic wave simulation and velocity accuracy analysis. Applied Geophysics, 2016, 13: 375-381.
Zhu, Y., Tao, G., Fang, W. Lattice boltzmann simulation of permeability in 3D porous medium. Well Logging Technology, 2008, 32: 25-28. (in Chinese)
Zhu, J. Y., Zhang, R., Pathak, D., et al. Toward multimodal image-to-image translation. Paper Presented at 31st Annual Conference on Neural Information Processing Systems, NIPS 2017, Long Beach, U.S.A, 4-9 December, 2017b.
Zhu, L., Zhang, C., Zhang, C., et al. Challenges and prospects of digital core-reconstruction research. Geofluids, 2019, 2019: 7814180.
Zhu, L., Zheng, Y. Applications of self-attention SRGAN in super resolution reconstruction of rock CT image. Journal of Xi’an Shiyou University (Natural Science Edition), 2022, 37: 131-137. (in Chinese)