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# Estimating Petrophysical Properties of Shale Rock Using Conventional Neural Networks CNN

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## Abstract

Digital Rock Physics (DRP) serves as a powerful computational tool for analyzing the petrophysical properties of rock. Obtaining the properties of a fine-grained sample, such as shale is very challenging due to its highly variable and complex nature. Capturing the micro-features of this structure requires advanced microscopy techniques such as SEM (scanning electron microscopy) and FIB-SEM (Focused ion beam- scanning electron microscopy). However, performing advanced microscopy techniques to capture the heterogeneity of the sample is quite difficult; the slow speeds of data collection and analysis are two critical problems that limit more extensive use of this technology. In this study, an alternative approach is proposed to quantify the physical properties of the rock sample. This study aims to accelerate the process of SEM image analysis and reduce the computational cost by using machine learning. A deep learning-based method, Convolutional Neural Networks (CNN), is utilized to predict the properties from the 2D grayscale SEM images of Marcellus shale. The image data set is segmented by applying watershed segmentation to extract the pore network of the sample. Porosity and average pore size are the two properties computed for this study. The SEM images are down sampled to low-resolution images which are fed as an input, and the computed properties are used for training and validation of the CNN network. A detailed description of the image segmentation process, CNN architecture and the predicted results are discussed in this work.

## Introduction

Estimating the physical properties of a rock are a crucial and time-consuming process of the exploration phase in the Oil & Gas industry. Drill cuttings and cores are the only way to know what is beneath the surface. Making the most of every centimetre of a core, or gram of a cutting sample has been a key driver for innovation and development, especially when it comes to characterizing the physical properties of a rock such as mineralogy, porosity, pore size distribution, etc. These physical properties are measured from slow laboratory-based experiments which are often time-consuming. The trend of conducting laboratory experiments has been complemented and, in some cases, replaced with digital rock physics (DRP). The DRP is conducted from 2D grayscale images generated from microscopic instruments such as X-Ray CT (Computed tomography), Micro CT, scanning electron microscopy (SEM), Focused ion beam – Scanning electron microscopy (FIB-SEM). These 2D grayscale images are reconstructed and transformed into a 3D representation of a rock sample(Hajizadeh et al., 2011). These three-dimensionally represented rocks are referred to as "Digital Rocks". DRP is a modern technique for visualizing the mineral spatial arrangements and pore structure in a rock sample. In some cases, the direct CT method may not be reliable, e.g. capturing the nano features of a heterogeneous sample is difficult on direct CT methods therefore, in cases like these, high-resolution microscopy methods such as SEM and FIB-SEM are used to examine the sample. The SEM & FIB-SEM are mostly used to capture the images on Nanoscale resolution (Goral et al., 2016). Constructing a digital rock is an expensive and time-consuming process, also it requires huge computational resource for highly dense mineral samples. These limitations have led to great interest from the researchers in developing a stochastic method to reconstruct a rock sample. A variety of stochastic models are used to generate reconstructed images of rock sample based on the limited information available from the 2D grayscale images. The stochastic methods include truncated Gaussian random field, simulated annealing, Markov Chain Monte Carlo, sequential indicator simulation, multiple-point statistics, phase-recovery algorithm and process-based or gain method. Multiple Point based statistics(MPS) was first proposed by (Deutsch, 1992), it is of one the most reliable methods among all the methods mentioned above as it can deal with the interpretation of the geometry and curvilinear structures in the sample (Tahmasebi, 2018). MPS has advanced substantially with many algorithms which have their pros and cons. However, slow speeds of data collection and image analysis is still an issue to be addressed with digital rock physics. To accelerate this process, our research involves the use of machine learning tools for predicting the properties of a rock sample. In this study, we are looking into two properties i.e., porosity and average pore radius.

The increase in advanced computational techniques and power have brought significant attention to digital rock physics. In recent studies, Machine learning was used to analyse the petrophysical properties of the rock. Microstructure classification, Image processing, Image segmentation and reconstruction of porous media of rocks are a few applications in evaluating the petrophysical properties of a rock. The methods used to determine these properties are Support vector machines (SVM), Convolution neural network (CNN), Decision tree method (DTM), Random forest, Generative adversarial network (GAN) and Spatial generative adversarial network (SGAN). (Alqahtani et al., n.d.; Budennyy et al., 2017; Chauhan et al., 2016; Chowdhury et al., 2016; Goodfellow et al., 2014; Laloy et al., 2017, 2018; Mosser, 2017/2019; Tang & Spikes, 2017; Wang et al., 2018).

However, among all the machine learning tools, CNN has been the most promising tool for predicting the properties of a rock sample. Take the example from the study conducted by (Wang et al., 2018) which illustrates the reconstruction of the porous media of a rock sample using CNN. The CNN's were used to improve the resolution of the porous structure extracted from micro CT image data of a rock sample. The micro CT data was fed as the input, and the corresponding image slices of the SEM images were used as output to train the CNN. The study concluded that the proposed method of CNN had dramatically improved the pore connectivity and exhibits a better performance than the conventional methods, including MPS.

Another recent study using CNN to predicting the properties of porous media was implemented by(Alqahtani et al., n.d.). The micro CT image data set for three different sandstone samples were segmented and trained as an input to the CNN and, the computed properties (porosity, coordination number and average pore size) were labelled with the image slice and fed to the CNN model as an output. The data set was divided into testing set and training set, with the testing set consisting of 2000 images and the training set containing 5680 images. The training took two days for each label on the CPU. The overall model estimated the properties with an error of 5%(porosity), 17% (Coordination number) and & 7% (Average pore size). These studies demonstrated that CNN's are the suitable tool in machine learning for image analysis, as it is frequently used tool for quick interpretation and quantification of a rock's physical properties.

However, performing ultra-high-resolution microscopy methods such as SEM & FIB-SEM to capture the heterogeneity of a sample is challenging. The slow speeds of data collection and analysis are two critical problems that limit more extensive use of this technology. In this study, an alternative approach is proposed to quantify the physical properties of the rock sample. A deep learning-based method, Convolution Neural Networks (CNN), is used to predict the properties from the 2D grayscale SEM images of Marcellus shale. Initially, we establish the ground truth by applying pore network extraction algorithm to the grayscale images. In this study, the two properties that were computed using CNN model was porosity and average pore size. Finally, the properties computed from the pore network extraction model are compared with the predicted values from the trained CNN model.

## Methodology

The methodology provides the description of materials used during the study, an explanation of image segmentation process and machine learning process. The methodology also explains the use of CNN in this study.

### Materials used

***Marcellus shale.*** A Marcellus shale sample was used for the study to test the CNN model on a heterogeneous sample, as Marcellus shale is a heterogenous sample. Estimating the properties of fine-grained samples is very challenging because of their highly variable and complex nature. Mudstone like Shale rocks are the best example of a complex and inherently heterogeneous sample. The ultra-high-resolution methods such as SEM & FIB-SEM is used to capture the complexity of the mudstone sample. The SEM sample size of 1879×1580×1700 with the resolution of 1um was used to test our machine learning model. Since this sample has only 1700 slices which are considered to be less data to train CNN, the data set was subsampled to a total of 16000 images with 512×512 resolution to get a definite amount of data for training.

### Image Segmentation

The main objective for image segmentation here is to detect the pores and throats to calculate the porosity of the sample. Watershed is an essential tool for morphological segmentation; it is a fast and efficient method for segmentation and separation of attached clusters of objects. Although watershed segmentation is one of the more powerful methods for image segmentation, its application on rock samples does not have acceptable results due to over-segmentation issues (overestimation of pores). An automated method for pore network extraction proposed by Rabbani (2014) (Rabbani, Jamshidi, & Salehi, 2014)has been used in this study, which is a combination of both watershed segmentation and distance function algorithm. The image segmentation was performed in MATLAB; the code is available open-source on MathWorks. The same code was previously used for shale SEM images by (Rabbani & Salehi, 2017) which worked fair enough to predict the petrophysical rock properties.

The algorithm proposed by (Rabbani et al., 2014) can successfully detect the pores and calculate the porosity and average pore size of the rock sample. The Figure 1, illustrates the procedure for identifying and measuring the pore size and porosity of raw SEM images. The distance transform function used in the watershed segmentation is city block combined with noise reduction and median filtering. Figure 1b is the intensity map of the raw SEM image after multi-level thresholding, which represents the highest void space (pores) of the rock with higher precision. In Figure 1c, the darkest section (grains) of the image is selected and represented by black pixels in a solid white background. The Figure 1d represents the segmented pores of the SEM image labelled with different random colours.

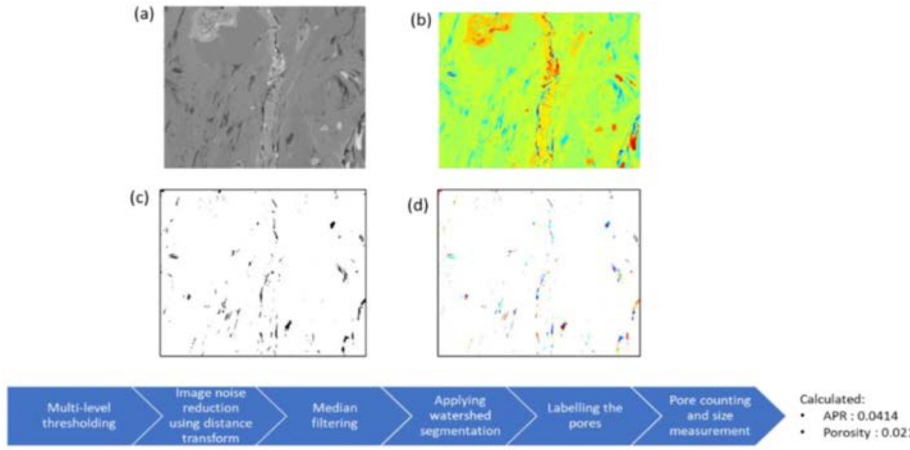



**Figure 1—Image segmentation process to detect and measure pore sizes of Marcellus shale**

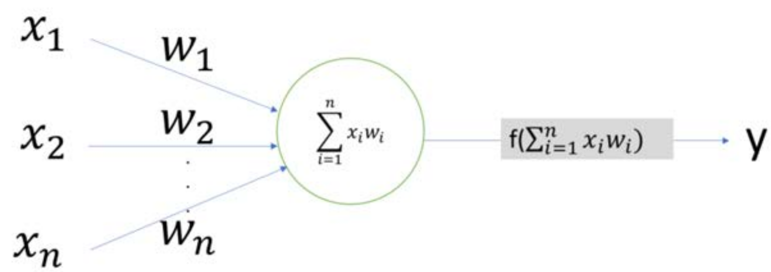
## Machine Learning

In image analysis, Machine learning is the most progressive techniques. The image analysis from the CT scans and MRI scans aids the treatment of diseases such as Alzheimer's, arrhythmia, autism, cancer, dental Cavities, diabetic retinopathy, gram stains, lung cancer, onychomycosis and pneumonia.(Lathia, 2017). Similarly, it has proven to be useful in digital rock physics for analyzing the petrophysical properties of rock. In this study, we used the CNN to predict petrophysical properties from SEM images. A brief explanation of neural networks and CNN's is described in the following section.

## Neural Networks

A neural network is the base structure of all machine learning models which resembles the human brain. It is noted that the primary unit of the human brain is a neuron, similarly the building block of the artificial neural network is a perceptron or artificial neuron shown in figure 2a. These neurons conduct signal and are connected to a large set of networks like a mesh. These are also known as Multilayer Perceptrons as shown in figure 2b.

(a)




(b)

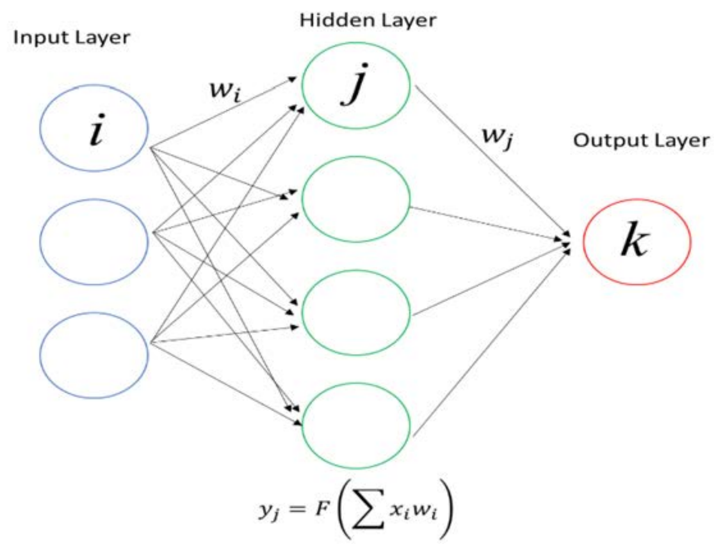



**Figure 2—(a) Artificial Neuron (b) Example of feedforward multi-layer neural network**

## Training

A conventional neural network learns through a gradient descent-based algorithm. The objective of this algorithm is to find the values of the weights that minimizes the error or difference between the estimated and output value. Since the neural network has multiple layers, all the weights need to be adjusted along with the hidden layers; for this reason, it is required to propagate the error backward from the output layer to the input layer (backpropagation). In the beginning, when the network is trained, all the weights are set at random. When training is initialized in a network, the data is propagated forward along with the layers through a non-linear transfer function or activation function. The actual output is then compared to the estimated output, and the error is propagated from the output towards input, this allows the gradient descent algorithm to adjust the weights accordingly. This process is done iteratively until the error is minimized. The most commonly used activation functions are (i) Sigmoid (ii) Tanh – Hyperbolic tangent and (iii) ReLu – Rectified linear units. In this study, ReLu had been used as the activation function.

## Testing

During the testing phase, the output of the neural network is compared to the predicted outputs. The difference is measured in either "accuracy" for classification or "error" for regression. This gives a good indication of the performance of the network. The curves of the training set and validation set represent the quality of a neural network model, whether the model is overfitting, underfitting or good fit Figure 3. A neural network can be tuned by looking at the behaviour of these curves between the training set and validation set. The main objective of using a validation set is to evaluate the model.

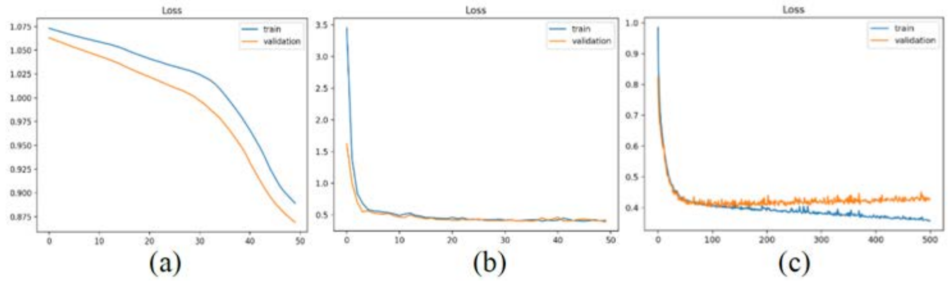



Figure 3—(a) Underfit Model (b) Good fit (c) Overfitting (Brownlee, 2019)

## Convolutional Neural Network

CNN's were established in 1989 (LeCun et al., 1989) but neglected due to a limitation in the availability of GPU's and access to an abundance of data for training huge models. A convolution neural network model has three main types of layers: Convolutional layer, pooling layer and a fully connected layer. Sometimes a flattening layer is also required to reshape the two-dimensional or three-dimensional neural nodes to be one-dimensional. All the layers are stacked to establish a CNN architecture as in (figure 4). A brief description of all the layers with application to this study is described below. More detailed information and background about CNN can be found at (Habibi Aghdam & Jahani Heravi, 2017)

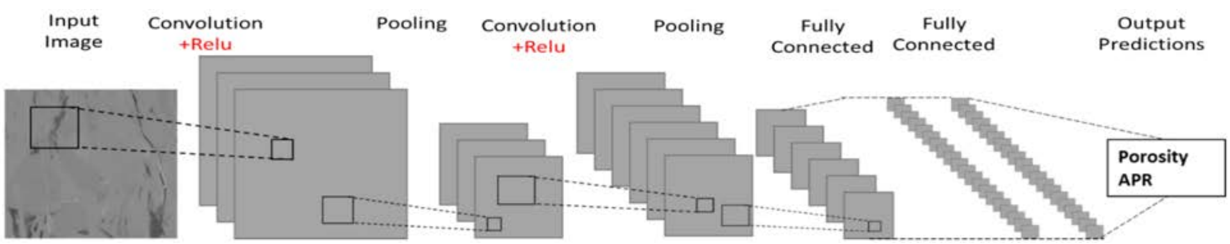



Figure 4—Sequence of CNN architecture

***Input Image.*** The input image in the convolution layer can be a grayscale or a colour (RGB) image. The image is read in terms of its pixel values. The Higher the dimensions of the image, the higher the computational time and the number of resources. In this study, grey-scale images with dimensions of 128×128 are used.

***Convolution Layer -The kernel.*** The main objective of this operation is to extract features from the given input image. CNN's need not be restricted to only one convolutional layer. One or more layers can be added to the architecture to adapt high-level features. For example, in figure 5 an input image with 5(Height) × 5(Breadth) × 1(Number of channels, e.g. Grayscale) is considered for demonstration and a kernel **k** of 3×3×1 matrix is applied to carry out the convolution operation. The kernel is shifted nine-times until the whole image is traversed. In the current study, the kernel size of 16×16×1 is used to extract the features from the SEM image data set.

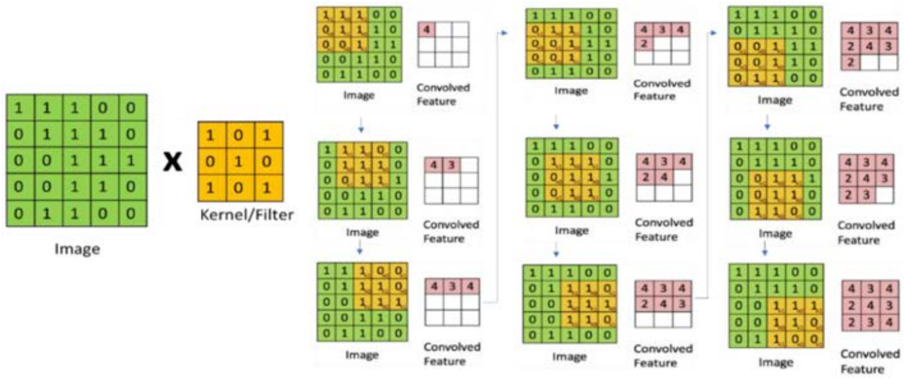



**Figure 5—Convoluting 5×5×1 image with 3×3×1 (Saha, 2018)**

***Pooling Layer.*** The objective of the pooling layer is to reduce the spatial size of the convolved feature. This helps in reducing the computational power required to process the data through dimensionality reduction. Max Pooling and Average pooling are the two types of pooling layers used in this network (figure 6). The most commonly used is max pooling since it performs better than the average pooling. Similarly, max pooling with 2×2 filter has been applied to the CNN model in this study.

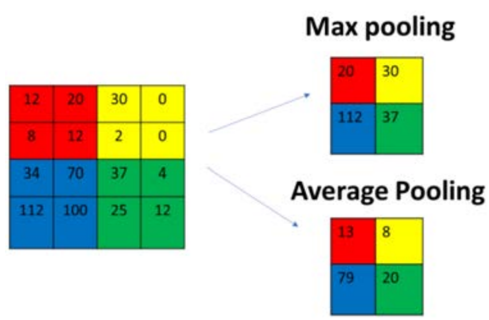



**Figure 6—Types of Pooling**

***Fully Connected layer.*** The output from the CNN layers represents high-level features in the data. This output is flattened and connected to the output layer, adding a fully connected layer. Adding this layer is (usually) an inexpensive way of learning non-linear combinations of the high – level features that are represented by the output of the convolutional layer.

## The framework to build CNN

The original sample consists of only 1700 slices with the image resolution of 1879×1580 which is considered as insufficient amount of data to train our CNN. For this reason, the SEM sample was cropped into nine cubes, and a total of 16000 slices with 512×512 resolution were extracted to get a definite amount of data for training. All 16000 images were segmented to calculate the porosity and average pore size of the sample. Each image was labelled with its estimated porosity and average pore radius values; these labels were used as an output data to our CNN model. The resolution of 512 ×512 images was reduced to 128×128 in ImageJ to decrease the computational time. (Figure 7) describes the framework adopted to build the CNN model in our study. The dataset was divided into 75:25% ratio for training and testing, i.e. from a total of 16000 images, 12000 images were used for training and the remaining 4000 images were used for testing or predicting.

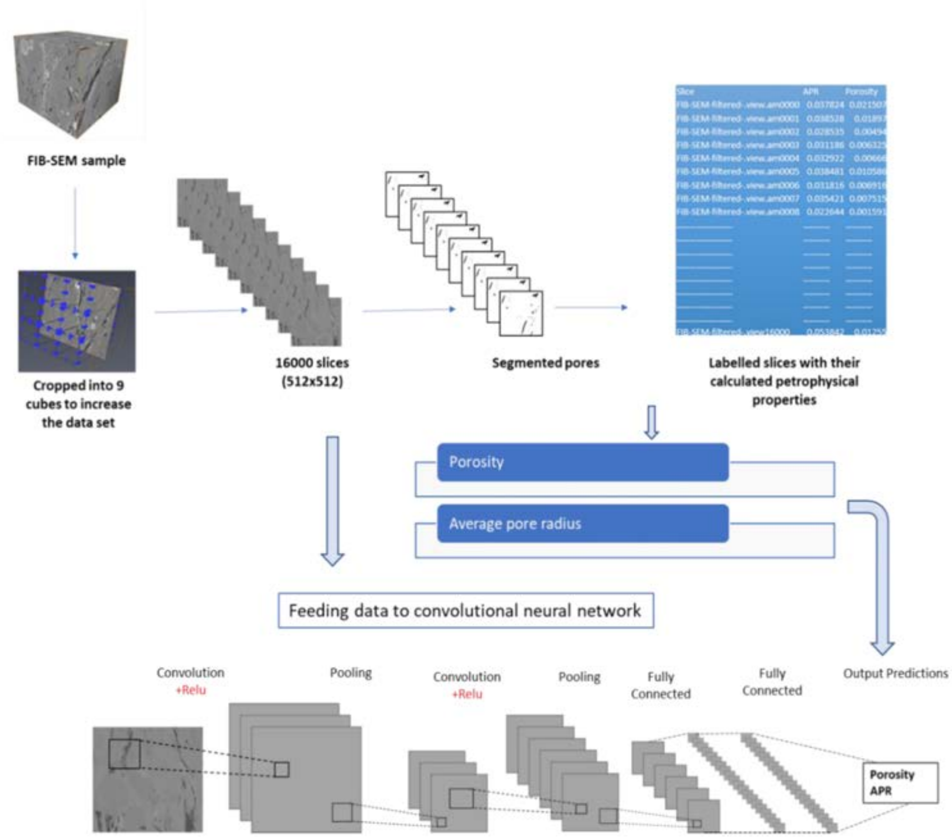



**Figure 7—The methodology used for preparing the data set for CNN and predicting the porous media properties**

Initially, this model was trained using the CPU. Training on CPU took a very long time; 35mins for each epoch. Later the same model was trained by using GPU which took only 11-12 seconds for each epoch. The TensorFlow library has the CUDA packages which works with the GPU and CPU in parallel to increase the training efficiency. The whole CNN model was trained on i7 intel processor with 16GB RAM using Nvidia GeForce GTX 1060 6GB graphic card.

## CNN architecture

The CNN model was built using Keras library. Keras is the most popular framework for deep learning; this library is written in python code and easy to use and customize. Instead of SoftMax function, we use mean absolute error to define the loss function, the error between the labels (Porosity & Average Pore Radius) and predictions. Figure 8 demonstrates the layers used to build out the CNN model.

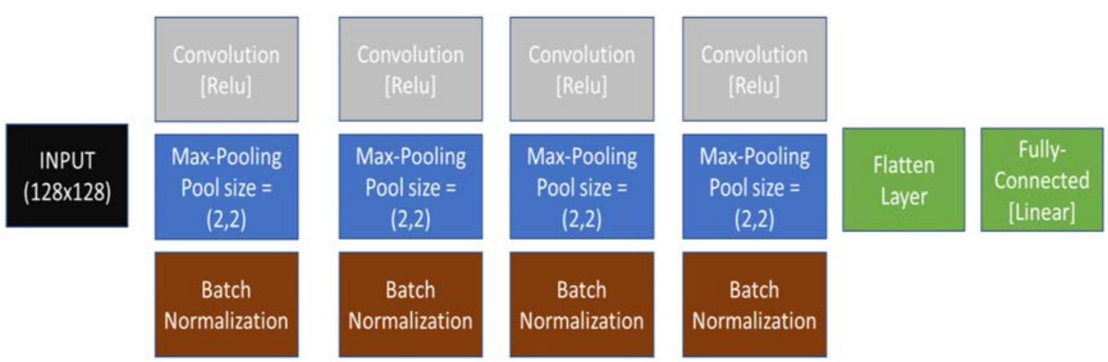
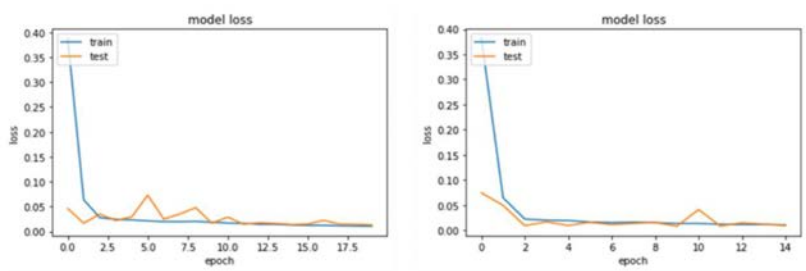



**Figure 8—CNN Architecture implemented in this study**

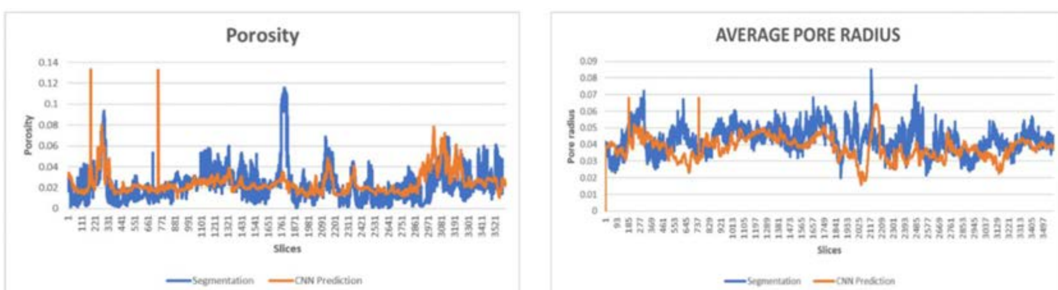
## Results and discussions

To establish the ground truth before the predictions, the watershed algorithm was implemented to extract the porous media of a Marcellus shale sample. Porosity and average pore size were calculated, and these results were used as ground truth and to train the CNN model developed in this study. As mentioned earlier, the training set and the test set were divided into 75:25% ratio, i.e., a total of 12000 images were used to train the model, and the remaining 4000 were used to test the accuracy of CNN model. Multiple iterations for each label (Porosity & Average pore size) were performed by tuning the parameters of our CNN model to achieve good accuracy. The model was trained separately for each label, i.e., for porosity and Average Pore Radius. The best fit for the model to estimate porosity was achieved with a batch size of 32 using 20 epochs, and the for average pore radius was achieved with a batch size of 32 using 15 epochs. The curves of the model are shown in figure 9, These curves demonstrate that our model worked effectively, as demonstrated by figure 3b. The accuracy of the model was determined by comparing the results of watershed segmentation and the results that were predicted using the CNN model (figure 10). The curves in the (figure10a) specify that CNN's were unable to detect the large size pores, which indicates that the model requires multiple data sets of images with is required for more accurate prediction.




(a). Porosity (b). Average Pore Radius

**Figure 9—Training curves for (a)Porosity & (b)Average pore radius**




(a) (b)

**Figure 10—CNN prediction in comparison to properties calculated from watershed segmentation (a)porosity & (b) average pore radius**

## Conclusion

A CNN model was built to predict the porosity and average pore radius of the shale SEM sample. Initially, these properties were estimated using the watershed segmentation algorithm, and the estimated properties were used as input data to train the CNN model. The accuracy of the predicted results matched with the computed values from watershed segmentation. The average error between CNN predictions and the ground truth (watershed segmentation) for porosity and Average pore radius was 0.4% and 1%, which is negligible.

This study aimed to test how the CNN model behaves in predicting the properties of highly heterogeneous rock sample like shale. The model proves to be successful in this case. The images used in training were down-sampled from 512×512 to 128×128 size. This shows that CNN can make the predictions from low-resolution images instead of using high-resolution imaging techniques like SEM. These studies were only tested on two properties i.e., porosity and Average pore radius. The results may vary in terms of accuracy if conducted on other properties. But still, this is an initiative to test how beneficial CNN's could be if used to estimate the properties of rock. The results from this study show that once the algorithm is trained, the properties of the rock can be estimated instantly with minimum computational resources. However, future studies can be conducted to unlock the full potential of CNN's by testing it on Nanoscale resolution images like FIB-SEM, which can be beneficial to get rid of using advance microscopic techniques. Further research can be conducted on 3D images by using 3D CNN's to predict the flow properties such as permeability which can help avoid expensive numerical simulations. One of the limitations using this method is, it initially demands large image dataset for training and the results may be varied if the same trained algorithm is used to predict the properties on different samples. However, these limitations can be solved if CNN's are tested aggressively using the same trained algorithm on different rock samples by predicting multiple properties. Therefore, furthermore, research is required to confirm the robustness of this metho

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