Multi-Class Pore type identification in Bombay Offshore Carbonate rocks using image analysis and Deep Neural Network

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Summary

A Deep Neural Network (DNN) based robust model has been proposed to classify carbonate porosities into their different types. More than 200 images are generated from thin sections of core samples obtained from carbonate reservoirs from the Bombay offshore region. The images are used for training the model into two vugs and channel type porosities. The testing was done on 50 images which were completely new to the network. The classifier achieved an accuracy of over 85%. The proposed method attempts to address the non-linearity and complexity inherent in the porosity classification using the image processing techniques and use of DNN methods.

1. Introduction

Porosity is an important parameter which is used for reservoir characterization. Porosity can be complex in a carbonate reservoir. Carbonate rocks have inherited this complexity and heterogeneity from its biological nature of formation. The outcome of the porosity classification can be used in reservoir modelling. Traditionally thin section petrography images are used for identification of different types of porosity. Mathematical models help us achieve the desired result more efficiently in less time. The objective of this work is to devise a model which can classify different pore types in carbonate rocks on the basis of Choquette and Pray (1983) classification scheme making use of thin section images using image processing, and neural network. Thin section image based analysis techniques have proved to become very important in petrophysics. Many researchers have utilized mathematical models for several applications. Some papers which have similar context are discussed below.

Yan LeCun (1995) describes about the ability of a backpropagation networks to solve complex and non-linear problems such as image classification and speech recognition. Furthermore, Geoffrey Hinton’s (2012) work on neural networks demonstrates the capability of such a model. They worked on over a million images to classify them into 1000 classes and achieved an accuracy of over 75%. Perring (2004) utilized image analysis technique for quantification of petrographic data on olivine phryic basalts. Martinez (2007) has developed neural neural network model and uses image analysis techniques for petrographic quantification of brecciated rocks. Chang et al. (2002) have prepared a self-organizing map for lithofacies identification with artificial neural network and achieved an accuracy around 80%.

This research paper proposes a method for addressing non-linearity and complexity inherent in the porosity classification using image processing techniques and DNN methods.

2. Methodology

In this section we describe the workflow of steps which were carried out to achieve the target (Fig. 1). Each step has been further described briefly in subsections.

2.1 Thin Section Preparation

Carbonates unlike igneous and metamorphic rocks are a soft rock so after the sample was cut it was baked to prevent sample loss during grinding. The samples are grinded using 80, 220, 400, 600, 800, 1000, 1200 grit silicon carbide powder one after the other in the mentioned order. Special care was taken to apply uniform pressure during manual grinding. Sample obtained after grinding was attached to glass slide
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using epoxy after that it was blue dyed so that pores can be clearly visible. Finally, the sample is dried for some time before can be brought under the microscope.

Figure 1: Sequence of steps followed to achieve the desired result in this paper.

2.2 Image Acquisition

After the thin section is prepared it is placed under microscope for visual examination. 6 images from each thin section is acquired under plane polarized light. After hit and trial we reached a conclusion that 10X magnification is suitable for obtaining high resolution image accurately. Few images have been shown in figure 2 with pore types marked on them on the basis of geological input. Other important parameters such as hue, contrast and brightness levels were kept constant for all the images acquired on 50 thin sections.

2.3 Image Processing

Images obtained from the microscope are of high quality.

However, during sample preparation some dust and other impurities are bound to stick to the sample. So a 3x3 median filter was applied to each image to remove salt and pepper noise from the image without distorting the image character. Good images were handpicked from sample and bad images such as blurred, sample washed, bubbles, images containing noise were discarded (Fig. 3a and 3b).
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Figure 2: Petrography images acquired from the microscope denoting different pore types. A) Fracture, B) Channel, C) Vugs, D) Intraparticle, E) Channel and F) Intraparticle porosity.

Figure 3a: Examples of a good dataset in which noise can be removed after image processing.

Figure 3b: Examples of a poor dataset. Object in the image are indistinguishable from the background due to poor resolution and high noise in the data.

2.4 Dataset preparation & Training the Model

After image processing is carried out on the images, we prepare dataset on which our model can be trained, validated and tested. The dataset is divided into two parts one is training set and the other is test set. Training set and test set have been divided into the number of pore classes we are going to identify, here 2 vug and channel type porosity. Training set consists of 80% of the images (160 images) and test set contains remaining 40 images. This dataset does not need to be preprocess again in neural network architecture. The network is trained on python using libraries of machine learning.

A Convolution Neural Network (CNN) is more powerful in comparison to a fully connected Neural Network (ANN). ANN is a basic architecture of the neural network which is a collection of nodes and neurons and tunable parameters such as weights and biases.

A CNN has extra convolutional layers in a fully connected Neural Network. A basic CNN may consist of Convolve operation followed by ReLU, Maxpool operation, and Flattening (Fig 4). Each extra layers in CNN serve important functions.

The Convolution operation reduces size of the image while preserving its features, so it’s easier to process the image. The resulting feature map has preserved important features of the image. With different feature detectors we create multiple feature maps so that important information in the image remains preserved.
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Unknowingly after convolution operation we increase the chance of linearity in the data which may yield inferior results. So, to break this linearity and increase non-linearity we use Rectified Linear Unit (ReLU) operation on data.

Pooling operation involves reducing the size of the image while introducing spatial invariance, and still preserving the features in the image. Reducing the size make the processing faster. This step also prevents overfitting which is a common problem faced while training a network. There are several types of pooling. Max-Pooling operation has been used in this study. The Flattening step involves putting these pooled feature maps into a column vector so that it can be called as input in the ANN structure.

Load Image data
Convolve
ReLU
MaxPool
Flattening
Full Connection
Softmax

Figure 4: Various layers in a CNN. Some operations can be used many times depending upon the tuning requirement.

2.5 Choosing activation function and Batch Size

There are different types of activation functions such as Sigmoid, Tanh, Softmax, ReLU, Leaky ReLU, Exponential Linear Unit (ELU), and Self-Normalizing ELU (SELU). Each of these activation functions have their pros and cons. We have utilized ReLU activation function for all hidden units and Softmax function in output layer. The advantage of Softmax function in the final layer is that the output pore types can be predicted and shown as probabilities.

Nitish et al. (2017) demonstrate in their paper on the choice of batch size. Common choice of batch size is 32, 64, 128 etc. However, choosing the large batch size degrades the quality of model and a low batch size i.e. 4 or 8 training time goes up before convergence. There is a sweet spot between low and high batch size. We have used 32 batch size in this study. The large networks with high batch size requires more computational power of the machine. Large networks require more time on a CPU machine. The benefit of using a small batch size is that it can be trained on a CPU.

3. Result & Discussion

This section deals with giving a meaning to the abstract features produced in convolution and max-pool layers and visualize them. An image can be thought of as an array of numbers stored in pixels. Each pixel value ranges between 0 to 255. Grayscale image has a single whereas a colored image has 3 channels Red, Green and Blue (RGB). Each channel is filled with pixel values depending upon the image. When a CNN network takes an image as input it identifies the features in the image with their pixel values. The convolution and max-pool operations pick different characteristics present in the image. In this way with multiple feature detectors the signature of either a vuggy pore or channel pore remains preserved by the network. The abstract looking features have been shown in Fig 5.

Carbonate reservoirs are extremely heterogeneous hence they display a complex porosity owing to their environment of formation and undergo a lot of diagenetic porosity modifications. These modifications can result in different types of microporosities and may enhance or suppress the interconnectivity of pores. Each pore type has a fixed hydrocarbon holding capacity. For example, a fracture in carbonate reservoir may enhance the interconnectivity between different pore types.

Identifying the correct porosity is extremely crucial for correct estimation of reserve potential. In manual classification there is always a chance of misinterpreting the pore-type which can result in incorrect estimation of hydrocarbon potential in the reservoir. This study aims to automate the process which will save time and cost of geoscientists.

4. Conclusion
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A six-layered neural network architecture was used in the study. There are two main issues that affect the model. First, the quality of dataset should be of high resolution so that different pore types can be distinguished with ease. Second, the network architecture which is an experimental parameter can be improved with training. The proposed classifier is very accurate and swiftly produces results in a moment on a standard computing system. However, the model is as good as the data we feed in the network and sometimes it can classify sample washed images or images containing bubbles incorrectly. Thus, it is important to ensure that high resolution and accurate data is acquired and quality check is performed before fed to the network.

The classifier designed has outst our expectations. At present the model is correctly identifying 2 types of pores i.e. Channel and Vuggy pores. We would take this study forward to classify all important pore types described by Lucia (1995). We aim to achieve a higher accuracy and exhaustive experimentation with hyper-parameter tuning of the model.

5. References


