Convolutional Neural Network for micro-CT image classification of carbonate rocks samples

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Abstract

Developing the Brazilian pre-salt reservoirs remains a challenge, mainly because of its geological peculiarities, as the heterogeneity of carbonate rocks. These difficulties stimulate the application of several methods that help in the characterization of reservoirs, such as X-ray computed tomography (CT). It is a useful non-destructive technique for imaging features within rocks, based on variations in material compositions. Another technique that has been studied is artificial intelligence, its implementation grants to automate some activities related to oil exploration. Given the above, this work aims to propose a convolutional neural network for lithology classification using microtomography images of carbonate rock samples from Brazilian pre-salt. For that, a set of images of 60 rock samples with distinct characteristics was used. The results obtained achieved 52.46% of accuracy on the validation set, which were within expectation, given the level of uncertainty associated with the lithological classification in this type of reservoir. More complex models and different image preprocessing are a future research line and are already being investigated.

Keywords: pre-salt carbonate rocks, deep learning, microtomography.

Introduction

Classifying carbonate rock remains a challenge in the field of sedimentology. Since the 1960s, efforts are made to develop a categorization, mainly based on the recognition of the main constituents of the rock (TERRA *et al*., 2010) besides the diagenetic events that becomes the assignment even more difficult.

The complexity and lithological variability of carbonate rocks are an object of study by geoscientists due to several diagenetic implications on permo-porous properties, what has motivated the search for new analytical techniques for a better understanding of the reservoir behavior

The experimental techniques of rock lithology analysis go through classification methods based on the structural and compositional aspects of the rocks, which allows a qualitative approach, on the other hand, do not enable a large scale visualization of the rock matrix and makes conventional petrophysical relationships unreliable (LUCIA, 2007).

As an alternative to this, the X-ray micro-computed tomography (micro-CT) has been extensively applied in the petroleum industry as a tool to assist 3D characterization of pore space and mineral distributions of reservoir rock samples (LOUIS *et al*., 2007). The physical principle of micro-CT is based on the different attenuation levels of the X-ray beam passing through the sample, as a function of X-ray energy, density and the atomic number of materials according to Beer's law (WELLINGTON E VINEGAR, 1987).

It is important to emphasize that classifying carbonate rocks has always been a significant challenge. Thus, the great development of studies on rocks by the geological and several other scientific communities come from decades, to add techniques that help in the process of classification of rocks.

A technique known as deep learning, specifically convolutional neural networks have shown notorious results on tasks of computer vision (KRIZHEVSKY *et al*., 2012). There are few works done on rock image classification using deep learning (CHENG e GUO, 2017; FERREIRA e GIRALDI, 2017). However, those works were done on a different set of rock types and with images acquired from others sources, more standardized.

In this way, the purpose of this work is to use integrated analysis methodologies, microtomography images and neural networks, to develop a mechanism able to automate lithological classification, supporting the characterizations of the carbonate reservoirs.

Accordingly, the classification proposed in this work uses micro-CT images of carbonate rocks as an input of a convolutional neural network model for a lithological classification. Besides, this kind of architecture is not only suitable for microtomography images, but also to high-resolution scanning electron microscopy image and thin sections.

Dataset

The used samples were classified into three mains groups by geologists using thin sections extracted at the same depth. The dataset available for analysis is composed of 6000 16-bit grayscale data type images, obtained from 60 rock samples. The micro-CT images were acquired at Ge Vtomex with resolutions varying from 27 to 50 μm.

Due to the polychromatic nature of x-ray beam, its lower energy component is more easily attenuated when passing through a dense material, giving false information about the sample's composition (WILDENSCHILD e SHEPPARD, 2013).

For this reason, the images have variable bright conditions and artifacts generated by the acquisition process (Figure 1). Due to these irregularities, some preprocessing were applied to the images. For different luminous conditions, the images were scaled individually using their minimum and maximum intensity.

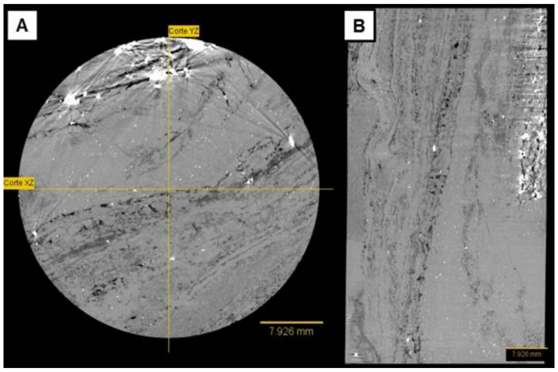

Figure 1: *Example of artifacts on the images: (A) XY Plane (B) XZ Plane.*

To maximize the use of the data, the regions of interests were cropped on different sizes. To deal with it, a resize preprocessing was used, reducing all images to a shape of 256x256. Even though applying this procedure might make the images lose information, it was chosen over cropping all slices to a fixed size, since it was not known if a crop of a smaller size would be enough to represent a lithology.

Through the thin section description was possible to classify of rock samples into 3 groups according to the lithological classes. Therefore, the study set consists of 18 spherulites, 24 stromatolites and 18 grainstones. Some examples of the classes can be seen in Figure 2.

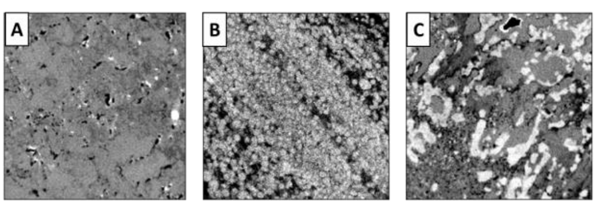

Figure 2: *Examples of (A) stromatolite, (B) spherulite and (C) grainstone.*

Model Details

Convolutional neural networks have presented excellent results on image classification tasks. Therefore this type of topology was chosen for implementation. The model proposed for lithology classification is shown in Figure 3. It consists of two parts, a convolutional part and a fully connected one.

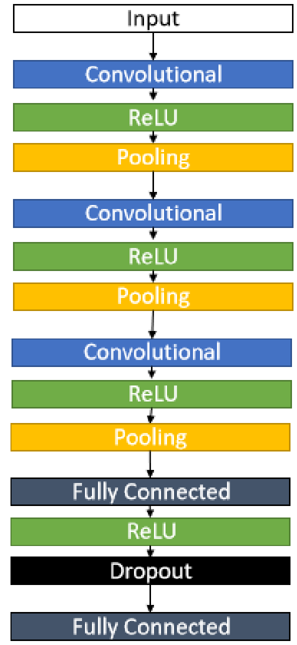

Figure 3: *Proposed model for lithology classification.*

The convolutional section has three convolutional layers with 3x3 kernels, stride of 1 and padding of 1 and ReLU as the activation function. Moreover, each of those layers is followed by a max pooling. The output of the last max pooling layer is then reshaped to be used as input of the fully connected part. This part consists of a fully connected layer with ReLU activation followed by a dropout (SRIVASTAVA *et al*., 2014) layer then a fully connected layer with linear activation function that is the output of the model, which is used as input on a softmax function.

The convolutional layers have 64, 48 and 32 filters respectively and the fully connected layer has 200 neurons.

Experiment

For a better analysis of the model performance on the dataset available, a nested k-fold (JAPKOWICZ e SHAH, 2011) is proposed. The first fold division is composed of 6 folds then the second use only 5 folds. That way, on our case, one possible scenario is using 6 folds, where 1 fold is used as a validation set, 1 as test set and 4 as training set, and we shift the folds to obtain the model statistics on the dataset. A simple visual representation of the method is shown in Figure 4. The distribution of the classes on each fold is 3 spherulites, 4 stromatolites, and 3 grainstones.

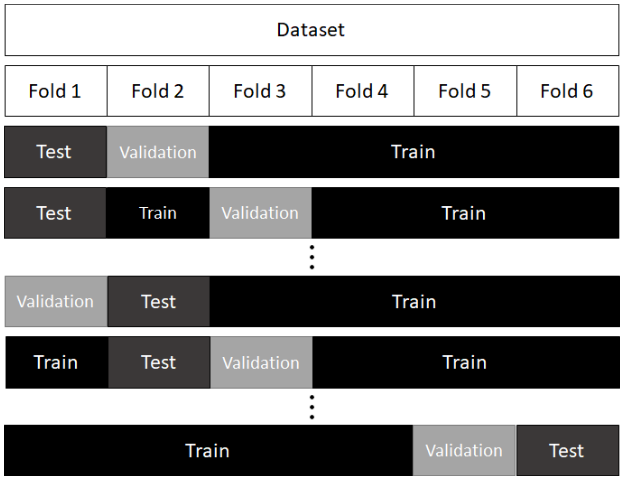

Figure 4: *Nested k-fold visual representation.*

For the model evaluation using this method, the accuracy was chosen as one of the metrics. However, the unbalanced dataset using only this approach would not be coherent for the model evaluation. Therefore, the sum-product index is used as well. The sum-product index formula is given by:

$$SP = \sqrt{\left(\frac{\sum_{i=1}^{N_{class}} Recall_i}{N_{class}}\right) \cdot \left(\sqrt[N_{class}]{\prod_{i=1}^{N_{class}} Recall_i}\right)}$$

Where N_{class} is the number of classes and $Recall_i$ is the recall of class *i*. The advantage of using this index is that with only one value it's possible to evaluate the model on all classes. If one of the class has a low recall, the index will converge to zero and the maximum possible value is 1.

The model was trained using weighted cross entropy as the loss function, due to the class imbalance. Adam (KINGMA e BA, 2014) was the optimizer chosen and its hyperparameters were a learning rate of 0.001 and betas of 0.9 and 0.999. The whole process of training was performed on a TITAN X sponsored by NVIDIA and the entire process took 4 hours.

Results

Nothing that the focus of this paper is to evaluate a deep learning model on lithological classification, the achieved results are presented in Tables 1 and 2. The results shown are the mean values and the standard deviations from all folds merit figures.

Table 1: *SP index results.*

Train	Validation	Test
0.642 ±0.217	0.474 ±0.191	0.423 ±0.164

Table 2: *Accuracy results.*

Train (%)	Validation (%)	Test (%)
68.10 ±13.74	52.46±13.13	47.95 ±10.94

It's feasible to infer that on some of the folds the model had difficulty in predicting the correct labels, given the high variance on the results. Further analysis is necessary to infer which were the cases with most error rate.

Analyzing the accuracy, Figure 5, there were folds which it was 95.63% on the training set, 76.60% on the validation set and 69.30% on the testing set, which would be promising results if the model could sustain such accuracy over all folds. However, it also had cases which it was 39.43%, 30.70% and 27.30%, respectively.

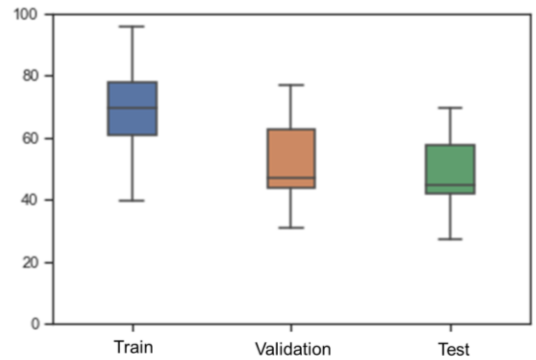

Figure 5: *Boxplot of the accuracy results.*

As previously stated, the accuracy alone is not enough to evaluate the model on our unbalanced case. When analyzing the SP index, Figure 6, there are cases as high as 0.96, 0.77 and 0.69, on the train, validation and test sets respectively. Though, there were also cases with 0.00, 0.00 and 0.00, which means the model couldn't output any slice of at least one of the classes correctly.

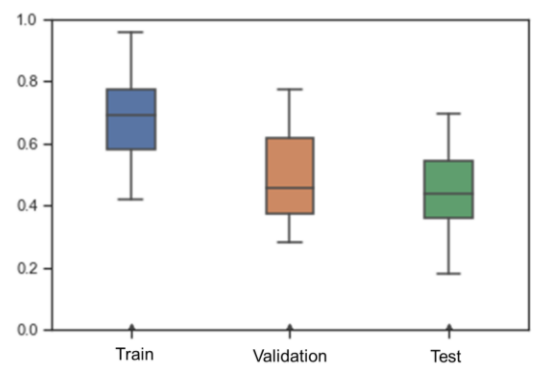

Figure 6: *Boxplot of the SP index results.*

Some reasons that could justify the low value on accuracy and SP index on some of the folds, would be that some slices of different lithologies are vastly similar and also was modified by the resizing process, which made information be lost with the image reduction. Using the original image as input might return better results, however it is not an easy task to deal with different image sizes as input on a neural network that has a fixed output size.

Conclusions and Future Work

This work presented a convolutional deep learning model using micro-CT images as input for a lithological classification task. The obtained results were within our expectation given the uncertainty level associated with the lithology classification task, as stated in the dataset section.

This work, although very preliminary, serves as an initial reference for classification of micro-CT images of Brazilian pre-salt carbonate rocks.

As for future works, the primary goal is using the original images and testing other preprocessing approaches for solving the bright conditions matter. An implementation to deal with images of different sizes is already on work by the authors. Additionally, more complex models and different tasks with the same dataset are part of a future research line.

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