Automated Core-Based Ichnological Descriptions Using Machine Learning

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Summary

Core-based visual observations require identification of crucial parameters that aid oil and gas exploration, yet they can be difficult to discern and time consuming to collect. Depending on the main objective, these parameters vary remarkably, ranging from identification of lithology (grain size), physical sedimentary structures, bioturbation intensity, rock classification, fractures, etc. In many cases, the core logger needs to record multiple parameters at the same time for long periods of time. This may cause distraction, errors, and bias, particularly when continuously logging long formations. Moreover, many of these parameters require specialized training in order to accurately assess. For example, ichnological analysis, particularly bioturbation intensity, is a critical parameter to determine in core-based studies. It can provide information on reservoir quality, paleodepositional conditions, total organic carbon preservation potential, and redox conditions, among others. However, assessing bioturbation intensity requires long hours of training and practice

In order to alleviate this issue, we propose an automated technique to determine some of the critical parameters in cores by harnessing the capabilities of deep convolutional neural networks (CNNs) for image classification.

Methodology

The images used in our experiments were collected from a variety of subsurface cores and outcrop exposures, representing siliciclastic sedimentary facies from several Cretaceous-aged stratigraphic formations in the Western Canada Sedimentary Basin of Alberta Canada. The majority of the images are derived from sandstone and siltstone facies, with some mudstone intervals as well as rare conglomerate beds and mud-clast breccia units. All images are derived from facies recording relatively shallow-water settings, including estuaries, bays, shorefaces, offshore-shelf, delta fronts, and prodeltas.

Among the popular computer vision tasks such as object detection, image segmentation, and image-resolution enhancement, image classification is one of the most addressed application areas using deep convolutional neural networks (DCNNs) (Goodfellow et al., 2014; Krizhevsky et al., 2012; Mikolov et al., 2013; Simonyan and Zisserman, 2014; Vaswani et al., 2017). DCNN is a class of deep networks formed by a series of interconnected neurons that has led to great achievements on image classification problems. For example, Krizhevsky et al. (2012) proposed AlexNet, a DCNN designed to classify images from the ImageNet dataset, which contains 1.2 million high-resolution human-annotated images with 1000 different classes. Later, Simonyan and Zisserman (2014) introduced a deeper architecture for better classification accuracies for the

ImageNet dataset. Their proposed architectures, namely the VGG networks (e.g., VGG-16 and VGG-19) could also be applied to other image recognition tasks as well.

We carry out two main experiments in this study. First, we train a DCNN to differentiate between bioturbated and unbioturbated facies. Next, we extend this task to a 3-class classification problem that seeks a model mapping the input images to one of the three classes of unbioturbated (BI 0), moderately bioturbated (BI 1-2), or intensely bioturbated (BI 3-6) facies. For both experiments, we define our models (Fig. 1) based on the VGG-16 architecture (Simonyan and Zisserman, 2014), which is a DCNN containing 16 layers composed of 3x3 convolution filters. The input of the network is a 224x224 pixel image with 3 color channels (red, green, and blue).

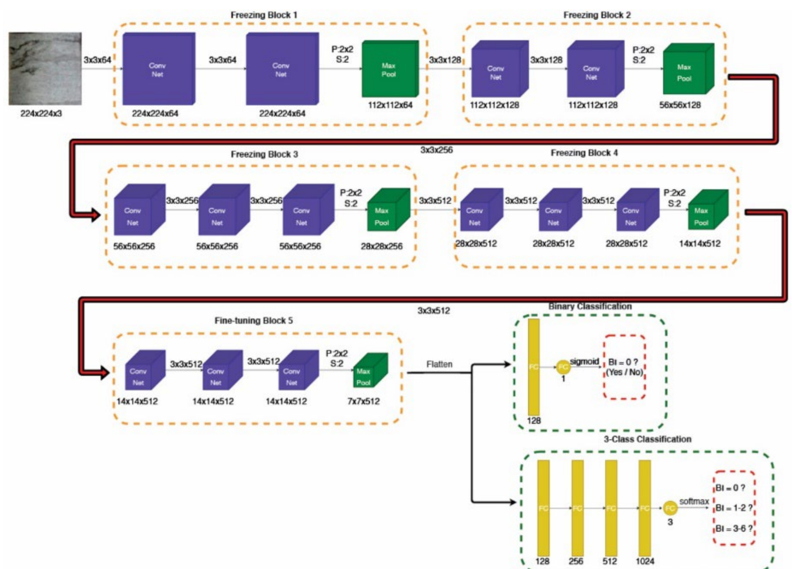

Figure 1. A convolutional neural network architecture based on VGG-16 with fully connected layers at the end. The architecture describes the routines for both binary and multi-class classifications. The input is a three-channel (red, green, blue) image. The binary classification problem outputs whether the input image is bioturbated or not. The multi-class classification problem outputs the class of the given image in terms of its bioturbation index range.

Results, Observations, Conclusions

In order to determine the applicability of deep learning to ichnological analysis, we run two main experiments. The first experiment is for differentiating unbioturbated facies (BI 0) from bioturbated facies (BI 1-6) (Figure 2). To achieve this, we train our algorithm using BI 0 images and BI 1-6 images (Table 1). The algorithm was run ten times on a test data set comprising 106 BI 0 and 156 BI >0 test images (Table 1). Accuracy values range between 93.8% and 97.7%, with an average accuracy value of 95.9%.

Figure 2. Examples of the expert-labeled training images used in our algorithm. Overall, 1303 core and outcrop images are labeled based on their bioturbation indices.

Experiment #1					
	Total number of images	Number of training images	Number of test images	Accurate	Misclassified
BI 0	530	424	106	104 (98.1%)	2 (1.9%)
BI 1-6	773	617	156	152 (97.4%)	4 (2.6%)
Total	1303	1041	262	256 (97.7%)	6 (2.3%)

Experiment #2					
	Total number of images	Number of training images	Number of test images	Accurate	Misclassified
BI 0	530	424	106	100 (94.3%)	6 (5.7%)
BI 1-2	360	287	73	62 (84.9%)	11 (15.1%)
BI 3-6	413	330	83	71 (85.5%)	12 (14.5%)
Total	1303	1041	262	233 (88.9%)	29 (11.1%)

Table 1. Results of experiments #1 and #2.

The second experiment is to test whether we can construct a 3-class bioturbation index classification using the same deep learning model. All images were grouped into three categories: (1) unbioturbated (BI 0), (2) moderately bioturbated (BI 1-2), and (3) intensely bioturbated (BI 3-6) (Figure 3). We run the algorithm on test data set of 106 BI 0, 73 BI 1-2, and 83 BI 3-6 images. Again, we train our algorithm ten times, starting with different initializations for the trainable parts of the model, and test them on the same test data. The lowest accuracy we obtain is 85.1%, whereas the highest is 88.9%, with an average of 86.8% for the three-class classification problem (Figure 3 and Table 2).

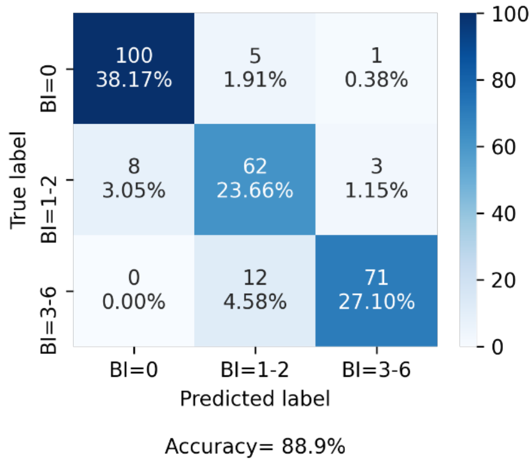

Figure 3. Confusion matrix for Experiment #2 indicating classification performance for the three bioturbation classes.

Novel/Additive Information

Our results clearly show high accuracies in predicting bioturbation indices in various siliciclastic sedimentary rock formations. These applications can be vital in oil and gas exploration through reducing uncertainty, lowering the cost and labor time of experts, maximizing efficiency by directing the experts' attention to more problematic intervals (i.e., those yielding low accuracy results), and in academia by facilitating accurate, reliable, comparable and consistent paleoenvironmental interpretations.

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