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Recognizing facies in the Red River Formation of North Dakota using a Convolutional Neural Network

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ABSTRACT

Recent developments in machine vision technology suggests an alternative approach to the conventional way in which geologists evaluate "visual" aspects of sedimentary structures and texture. The reason for this new approach is the development of massively intricate algorithms known as Convolutional Neural Networks (CNN) or Deep Neural Networks. These algorithms use large arrays (650,000) of individual nodes or "neurons" within large arrays that act as banks of adjustable, nonlinear filters. These arrays are arranged into architectures that can be "trained" with labelled data, or in the case of this study, images. This process involves training the network with hundreds, or preferably thousands of images, each coded to an identified feature or texture. Once trained, validation of the network is provided by queries using images not included in the training set to evaluate the ability of the network to classify unknown images. Validation is obtained by comparing the classification provided by the trained network with one that is obtained independently. The neural network employed in this study uses the Berkeley Vision and Learning Center's (BVLC) Caffe CNN architecture, which is a reference implementation of ImageNet, by Krizhevsky, Sutskever, and Hinton. Training and validation images are from core photos of the Red River Formation (Ordovician) available through the North Dakota Department of Mineral Resource's online inventory of core photography. The images were downloaded, cropped to cover roughly half of a slapped four inch core and resized to 256 X 256 pixels. Images with noticeable defects such as edges, fractures and plug holes were discarded. The images are divided into the following visible texture categories: 1) mosaic to enterolithic anhydrite, 2) finely laminated to thrombolytic dolostone/anhydrite and 3) Thallisinoides burrowed carbonates. The training set consists of 768 "anhydrite", 622 "laminated" and 652 "burrowed" images. The validation set contains 85 "anhydrite", 95 "laminated" and 858 "burrowed" images. The network was trained using stochastic gradient descent with a batch size of 512 example images, momentum of 0.9, and weight decay of 0.0005. The learning rate was initialized to 0.01 and reduced by one- tenth every 5000 iterations. After 23,000 iterations the loss function (measure of inaccuracy) was reduced to less than 1X10-3 indicating that the CNN successfully "learned" the training set. The trained network, when applied to the validation set, correctly predicted 93% of the classifications. All of the "laminated" images were correctly identified. Of the remaining "anhydrite" or "burrowed" images less than 3% were falsely classed as "laminated". 96% of "anhydrite" validation images were correctly classified as were 92% of the "burrowed" facies. Most of the errors that did occur involved "anhydrite" classed images being mistaken for "burrowed" (2%) or "burrowed" examples being classed as "anhydrite" (5%). Errors on the order of 1% to 3% were made in classing "anhydrite" or "burrowed" images as "laminated". These results suggest that a trained CNN will produce classifications that are highly consistent with those of the supervising geologist.