Automated Carbonate and Siliciclastic Core Lithotypes Classification with Convolutional Neural Networks

Evgeny E. Baraboshkin[1], Evdokiya A. Panchenko[2], Andrey E. Demidov[1], Ardiansyah Koeshidayatullah[3], Denis M. Orlov[1], Dmitry A. Koroteev[1]

[1]Digital Petroleum
[2]CJSC MiMGO
[3]King Fahd University of Petroleum and Minerals

Abstract

Convolutional neural networks are applied to distinguish different lithotypes, including siliciclastic, carbonate, and volcanic rocks. The work aims to demonstrate the abilities of convolutional neural network to generalize and optimize lithofacies classification.

A total of 15351 cropped core images were utilized as dataset in this study. The dataset contains 3923 limestones, 1142 dolomite and 2891 sandstones, 2000 siltstones, 4414 argillaceous and 981 calcareous shale 10x10cm full-bore image samples was prepared based on publicly accessible dataset. This dataset was used to train several models with different numbers of lithotypes. The carbonate lithotypes follows Dunham (1962) classification with boundstone, mud- wackestone, wack-packstone, and pack-grainstone texture; calcareous shale; dolomite. The siliciclastic rocks include sandstone, siltstone, and shale.

A Pytorch Image Models (Timm) deep learning library was used to conduct experiments. Several architectures were compared in performance, EfficientNet-B1 was chosen for the experiments. The dataset was split into several training groups: carbonates only, carbonates as a single class, dolomites and siliciclastic classes, all carbonates, and siliciclastic classes as separate classes.

The developed algorithm successfully distinguish siliciclastic and carbonate lithotypes, while dolomites and limestones are challenging to be differentiated due to its shared similarities. In the case of 3 classes (dolomite, limestone, sandstone), overall test set macro- precision is 73%, and micro-precision is 79% (sandstones classified correctly, but the dolomites and limestones are mixed up), 5 classes (siliciclastic classes; calcareous shale and limestone) got 87% and 89% precision, 6 classes (siliciclastic classes; calcareous shale, limestone, and dolomite) 80% and 82% precision accordingly. During training, an algorithm with 7-classes consisting of Dunham textures, dolomite, calcareous shale, and sandstone received 90% micro- and macro-precision on a test set, interestingly to note that dolomites were mixed up with boundstones mostly both during training and test period. The developed algorithms can classify the rocks with a speed of up to 1 m/s.

A wide set of experiments on full-bore carbonate and siliciclastic core images were conducted. Previous works did such experiments on thin-section, which may not apply to archive data. The convolutional neural networks can differentiate carbonate and siliciclastic textures and rock types. The developed algorithms could be used during the explorational stage to help geologists better understand and gain information about the object, even on archive data faster. In addition, the proposed model can be deployed to categorize siliciclastic and carbonate reservoirs robustly and rapidly.