# Stylolite detection and image classification from whole core images using convolutional neural networks

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## Abstract

## Stylolites are natural rock-rock interlocked interfaces that may produce spectacular rough patterns in formation rocks [1]. They form by a localized dissolution process, and their interface contains minerals at concentrations different from that in surrounding host rocks. The presence of stylolites, with various amounts of clays, may affect fluid flow in hydrocarbon formations or underground geological storages (e.g., Hydrogen, CO2). Stylolites could act as seals and stop the upward migration of fluid in formations [2]. Recent observations indicate that the stylolite permeability is anisotropic and that they may act both as seals and fluid pathways depending on the material that collects in them and the offset of sealing material at teeth [3]. Therefore, detecting stylolites in reservoir core samples can help us to have a better estimate of fluid flow through porous media.

In this study, a deep learning technique were used to detect and classify well depths showing stylolites from slabbed core images. The main approach of this study was using Convolutional Neural Networks (CNN) for analyzing core images. The CNN architecture was developed in Python using TensorFlow and Keras libraries and validated by the ground truth. The core data from of one the Iranian carbonate reservoirs with a length of 150 m were used. In the first step, the raw data of whole core images, photographed in white light, were pre-processed. 3,600 smaller square-shape images with a size of 300x300 pixels were extracted. Five various classes were defined for core images: stylolite, induced cracks, vertical plug, horizontal plug, and intact rock. The data geometric augmentation method (e.g., flipping, cropping, rotating, contrast and brightness changing) was implemented to increase the size of the training database to 5,000 images per class (25,000 images for all classes). Two main networks (ResNeXt-50 and manually modified ResNeXt-50) were trained on the images of each class to measure the effect of network architecture and number of training image dataset on the classification performance. 80 % of each class data set were used for training and the rest 20 % used for testing. The pre-trained parameters of CNN models on more than million natural images from the ImageNet dataset were used as an input. Both architectures were then retrained on our core database for 500 epochs, where the models converged, and further training would result in minimal or no improvements. After improving and altering the model's hyperparameters, including the batch size and learning rate, the stylolite classification model could predict the five classes on unseen core tray images (20 % of the initial data set) with an accuracy of 94%. The results show that the deep learning approach used in this study can be easily implemented on core-scale images to classify macroscopic features from core image samples. Moreover, this approach can reduce the time for macroscopic core studies usually done by hand.

## Keywords

Stylolite, Classification, Deep Learning, Whole Core Images

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