Stylolite Detection and Image Classification From Whole Core Images, Using Convolutional Neural Networks

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Quick Overview

- Background on Stylolites
- Literature review
- Image data preparation
- Methodology
- Results and discussion
Stylolites

Main characteristics and how they may form:
- Natural rock-rock interlocked interfaces.
- Containing spectacular rough patterns (Rolland et al. 2012).
- Formed by localized dissolution process and compaction (Toussaint et al., 2018)
- Interface contains minerals that are different from surrounding host rock.

Stylolite generates permeability anisotropy.
- They can act as either seals or fluid pathways depending on material that collects within stylolite (Koehn et al. 2016).
Stylolite as potential seal

(Bruna et al. 2019)
Stylolite as potential fluid pathways

(Bruna et al. 2019)
**Convolutional Neural Networks (CNNs)**

- **CNN** is a particular implementation of a neural network used in machine learning.
  - Exclusively processes array data such as **images**.
- A **CNN** typically consists of the following architecture:

  ![Diagram of CNN architecture]

  - **Input** Image *Pre-processed*
  - **Feature Extraction**
  - **Classification Output**
  - **Containing Stylolite?**
    - Yes
    - No
  - **Classification Output**
<table>
<thead>
<tr>
<th>Author</th>
<th>Year</th>
<th>Researched topic</th>
<th>Applied Network(s)</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alzubaidi et al.</td>
<td>2021</td>
<td>Lithology classification from whole core images</td>
<td>ResNext-50, Inception V3</td>
<td>Up to 90%</td>
</tr>
<tr>
<td>Pires de lima et al.</td>
<td>2020</td>
<td>Petrographic microfacies classification</td>
<td>VGG 19, Inception V3</td>
<td>Up to 95%</td>
</tr>
<tr>
<td>Evgeny E.Baraboshkin et al.</td>
<td>2020</td>
<td>Rock typing using image color distribution and CNN</td>
<td>AlexNet, VGG, GoogleNet, ResNet</td>
<td>Up to 95%</td>
</tr>
<tr>
<td>Alzubaidi et al.</td>
<td>2022</td>
<td>Automatic fracture detection and characterization from unwrapped whole core images</td>
<td>Mask R–CNN</td>
<td>Approximately 95%</td>
</tr>
<tr>
<td>Houlinzhang et al.</td>
<td>2022</td>
<td>Permeability prediction of low-resolution porous media images</td>
<td>AE-CNN</td>
<td>Approximately 90%</td>
</tr>
</tbody>
</table>
Image Dataset

Whole core images of an Iranian carbonate reservoir. (3 wells, 150 m)

 Extraction of 3,600 smaller images in a size of 300 X 300 pixels.

Five various classes:
- Horizontal plug
- Vertical Plug
- Crack
- Intact rock
- Stylolite

Non-Detectable (QC)
- Low brightness
- Low quality
- Non-core intervals
- Crushed intervals
Image Data Preparation

- **Data Augmentation** to increase and normalize the size of each class in the database
  - Rotation 90°,
  - Horizontal and Vertical Flipping,
  - Brightness changes

- **2,000** (10,000 images in total) and **5,000** (25,000 images) image per class.
- **80% of dataset used for training**, the rest for testing.

- **Main objectives:**
  - Effects of network hyperparameters
  - Size of image dataset

On Stylolite Classification (Target Class)
ResNext-50 (32x4d)

- It was introduced by Xie et al. (2017)
- It uses a "split-transform-merge" strategy, similar to Inception architectures
- The principle is stacking the same topology blocks (with a cardinality number).
- Hyper-parameters (width and filter sizes) are shared within the residual block
- Trainable parameters: \( \sim 25 \times 10^6 \)
Transfer learning was applied for classifying images

CNN Networks:
- Untrained ResNeXt-50 (32x4d) (pre-trained on ImageNet dataset)
- Tuned ResNext-50

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Untrained ResNeXt-50</th>
<th>Tuned ResNeXt-50</th>
</tr>
</thead>
<tbody>
<tr>
<td>LR</td>
<td>0.1</td>
<td>0.001</td>
</tr>
<tr>
<td>Epochs</td>
<td>500</td>
<td>500</td>
</tr>
<tr>
<td>LR Gamma</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>Momentum</td>
<td>0.9</td>
<td>0.5</td>
</tr>
<tr>
<td>Batch Size</td>
<td>32</td>
<td>32</td>
</tr>
<tr>
<td>LR Step Size</td>
<td>30</td>
<td>30</td>
</tr>
<tr>
<td>Weight Decay</td>
<td>0.0001</td>
<td>0.0001</td>
</tr>
</tbody>
</table>
## Results

### Training and Validation Accuracy of Stylolite

<table>
<thead>
<tr>
<th>Network Architecture</th>
<th>Image Dataset</th>
<th>Training Accuracy</th>
<th>Validation Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Untrained ResNext50</td>
<td>10,000 (2,000 each)</td>
<td>0.78</td>
<td>0.77</td>
</tr>
<tr>
<td></td>
<td>25,000 (5,000 each)</td>
<td>0.85</td>
<td>0.84</td>
</tr>
<tr>
<td>Tuned ResNext50</td>
<td>10,000 (2,000 each)</td>
<td>0.83</td>
<td>0.81</td>
</tr>
<tr>
<td></td>
<td>25,000 (5,000 each)</td>
<td>0.93</td>
<td>0.90</td>
</tr>
</tbody>
</table>
Stylolite Training and Validation Accuracy

5,000 image per class (25,000 in total)

Untrained ResNext-50

Tuned ResNext-50

Validation accuracy:
Approximately 0.84

Validation accuracy:
Approximately 0.90
## Results

### Classification of all classes in Confusion Matrix

<table>
<thead>
<tr>
<th>True Label</th>
<th>Stylolite</th>
<th>Crack</th>
<th>Intact Rock</th>
<th>H-Plug</th>
<th>V-Plug</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stylolite</td>
<td>907</td>
<td>37</td>
<td>4</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Crack</td>
<td>79</td>
<td>948</td>
<td>0</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>Intact Rock</td>
<td>12</td>
<td>1</td>
<td>996</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>H-Plug</td>
<td>2</td>
<td>5</td>
<td>0</td>
<td>994</td>
<td>0</td>
</tr>
<tr>
<td>V-Plug</td>
<td>0</td>
<td>8</td>
<td>0</td>
<td>1</td>
<td>997</td>
</tr>
</tbody>
</table>

- Confusion matrix for the test dataset (1,000 images per class)
- The most common error was between Stylolite and Crack.
Conclusion

◎ Deep learning approach on whole core images for macroscopic feature classifications.

◎ This approach reduces the time and user bias for macroscopic core studies.

◎ Increasing of data size in our scenario resulted in rising of network accuracy.

◎ Performance of tuned ResNext50 was more convenient.

◎ Future studies:
  ○ Finalize Net. tunning, dataset size, sensitivity on hyperparameters
  ○ Implementing other architectures
  ○ Stylolite type classifications


Thank you!

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