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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

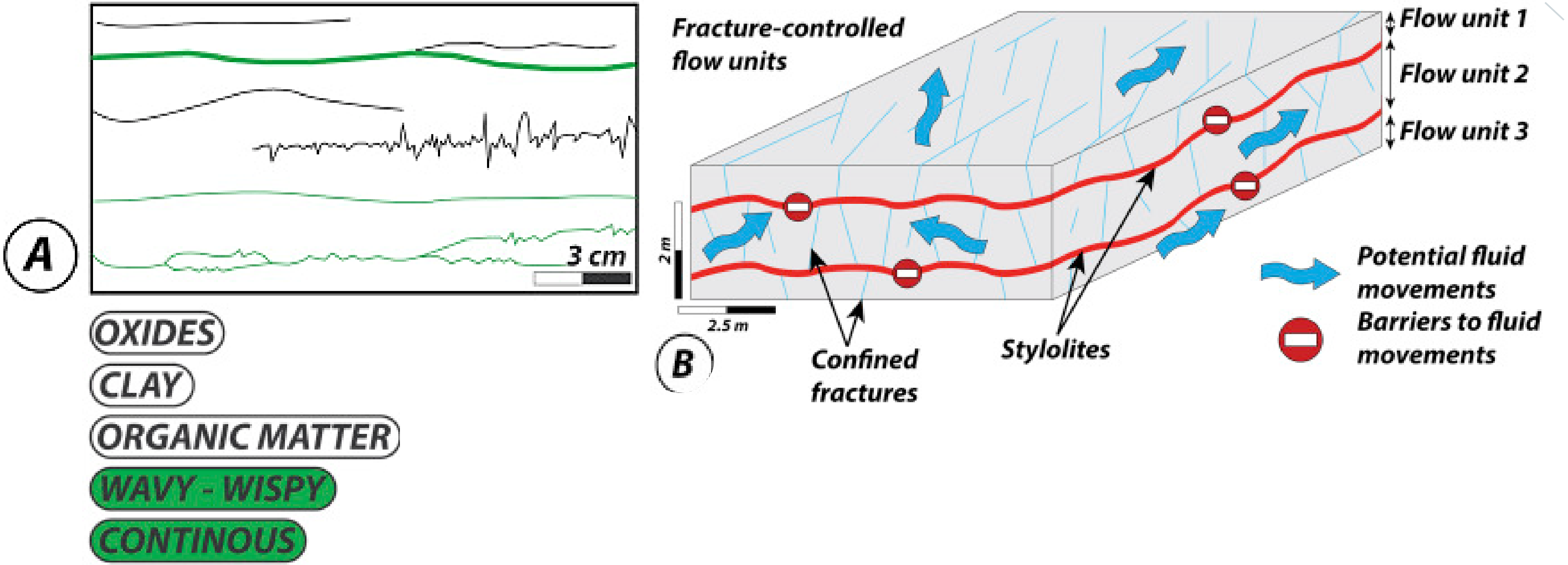
Main characteristics and how they may form:

- 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.

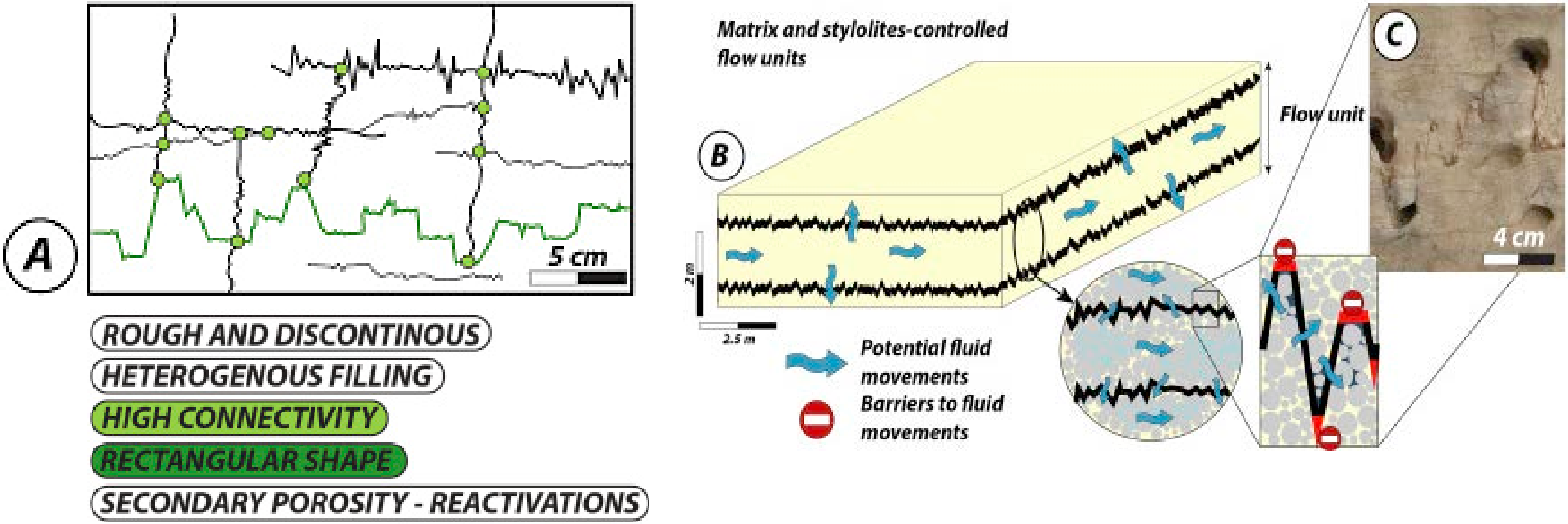
- **They can act as either seals or fluid pathways depending on material that collects within stylolite** (Koehn et al. 2016).

Stylolite as potential seal



(Bruna et al. 2019)

Stylolite as potential fluid pathways



(Bruna et al. 2019)

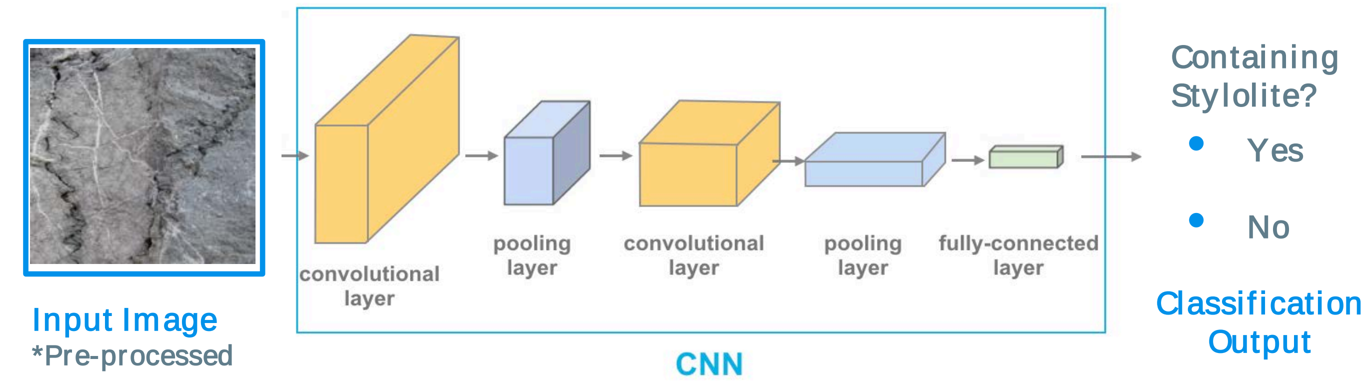
Convolutional Neural Networks (CNNs)

- **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:

Input

Feature Extraction

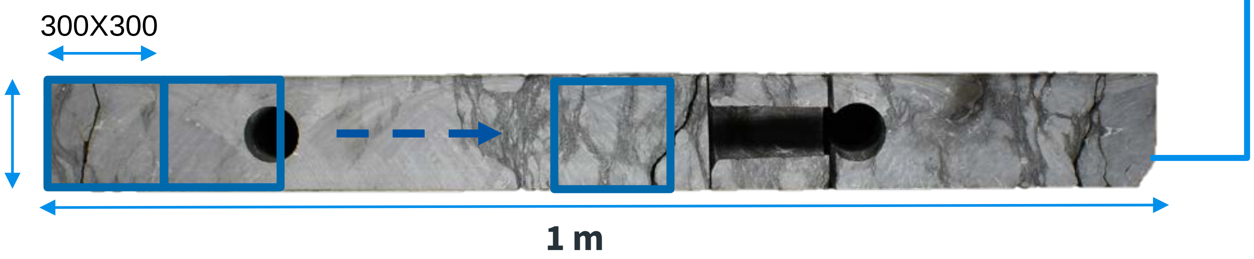
Classification Output



Literature review - CNNs

Author	Year	Researched topic	Applied Network(s)	Accuracy
Alzubaidi et al.	2021	Lithology classification from whole core images	ResNext-50, Inception V3	Up to 90%
Pires de lima et al.	2020	Petrographic microfacies classification	VGG 19, Inception V3	Up to 95%
Evgeny E.Baraboshkin et al.	2020	Rock typing using image color distribution and CNN	AlexNet, VGG, GoogleNet, ResNet	Up to 95%
Alzubaidi et al.	2022	Automatic fracture detection and characterization from unwrapped whole core images	Mask R–CNN	Approximately 95%
Houlinzhang et al.	2022	Permeability prediction of low-resolution porous media images	AE-CNN	Approximately 90%

Image Dataset



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

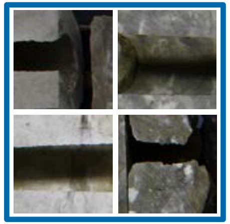
- **Extraction** of **3,600** smaller images in a size of 300 X 300 pixels.

- Non-Detectable (QC)
  - **Low brightness**
  - **Low quality**
  - **Non-core intervals**
  - **Crushed intervals**

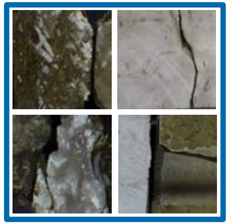
- **Five various classes:**

Horizontal plug

Vertical Plug



Crack



Intact rock

Stylolite

Image Data Preparation

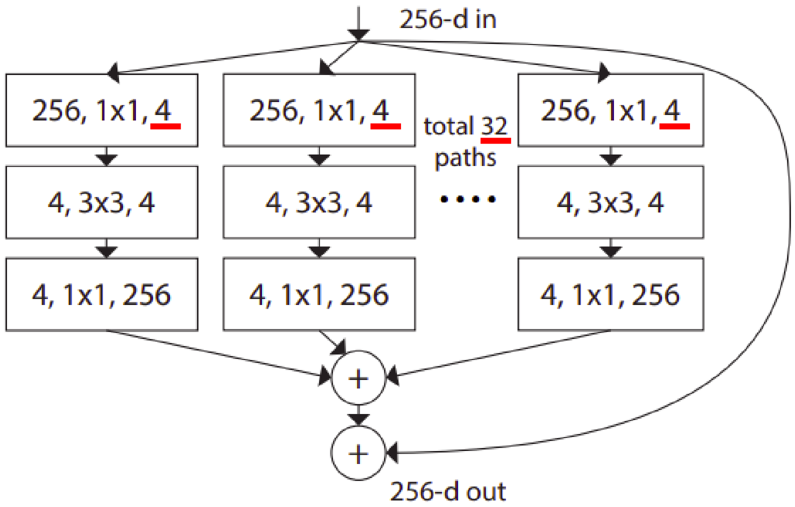
- **Data Augmentation** to increase and normalize the size of each class in the database
  - **Rotation 90°,**
  - **Horizontal and Vertical Flipping,**
  - **Brightness changes**

- **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 (32x4dغ

- 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: ~25x10^6



Research Methodology

Network Architecture

- Transfer learning was applied for classifying images
- CNN Networks :
  - Untrained ResNeXt-50 (32x4d) (pre-trained on ImageNet dataset)
  - Tuned ResNext-50

Parameters	Untrained ResNeXt-50	Tuned ResNeXt-50
LR	0.1	0.001
Epochs	500	500
LR Gamma	0.1	0.1
Momentum	0.9	0.5
Batch Size	32	32
LR Step Size	30	30
Weight Decay	0.0001	0.0001

Results

Training and Validation Accuracy of Stylolite

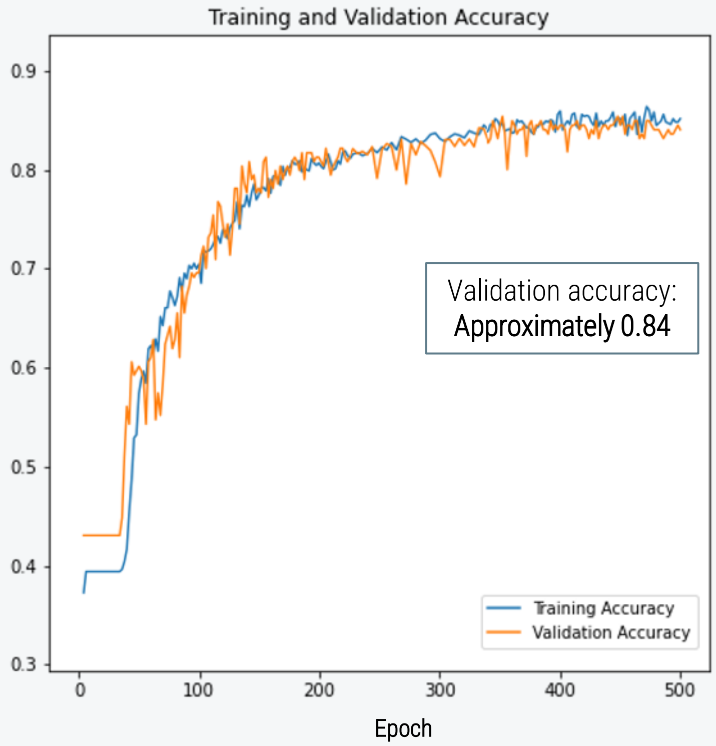
Network Architecture	Image Dataset	Training Accuracy	Validation Accuracy
Untrained ResNext50	10,000 (2,000 each)	0.78	0.77
	25,000 (5,000 each)	0.85	0.84

Network Architecture	Image Dataset	Training Accuracy	Validation Accuracy
Tuned ResNext50	10,000 (2,000 each)	0.83	0.81
	25,000 (5,000 each)	0.93	0.90

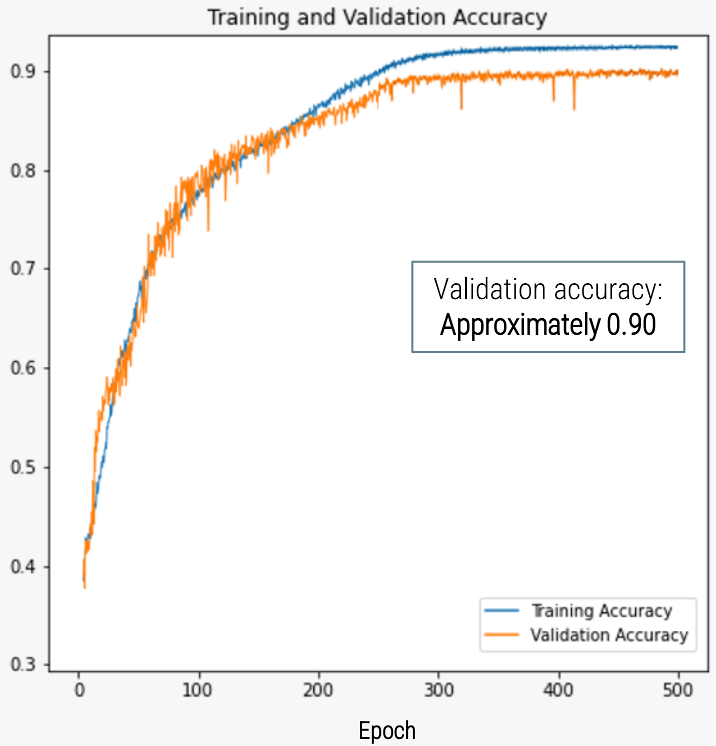
Stylolite Training and Validation Accuracy

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

Untrained ResNext-50



Tuned ResNext-50



Results

Classification of all classes in Confusion Matrix

Predicted Label

True Label	Stylolite	Crack	Intact Rock	H-Plug	V-Plug
Stylolite	907	37	4	1	1
Crack	79	948	0	4	2
Intact Rock	12	1	996	0	0
H-Plug	2	5	0	994	0
V-Plug	0	8	0	1	997

- 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 tunned ResNext50 was more convenient.
- Future studies:
  - Finalize Net. tunning , dataset size, sensitivity on hyperparameters
  - Implementing other architectures
  - Stylolite type classifications

References

1. Rolland, A., et al., *Modeling the growth of stylolites in sedimentary rocks.* Journal of Geophysical Research: Solid Earth, 2012. **117**(B6).

2. Toussaint, R., et al., *Stylolites: A review.* Journal of Structural Geology, 2018. **114**: p. 163-195.

3. Koehn, D., et al., *A new stylolite classification scheme to estimate compaction and local permeability variations.* Sedimentary Geology, 2016. **346**: p. 60-71.

4. Alzubaidi, F., et al., *Automatic fracture detection and characterization from unwrapped drill-core images using mask R−CNN.* Journal of Petroleum Science and Engineering, 2022. **208**: p. 109471.

5. Alzubaidi, F., et al., *Automated lithology classification from drill core images using convolutional neural networks.* Journal of Petroleum Science and Engineering, 2021. **197**: p. 107933.

6. Baraboshkin, E.E., et al., *Deep convolutions for in-depth automated rock typing.* Computers & Geosciences, 2020. **135**: p. 104330.

7. de Lima, R.P., et al., *Petrographic microfacies classification with deep convolutional neural networks.* Computers & Geosciences, 2020. **142**: p. 104481.

8. Zhang, H., et al., *Permeability prediction of low-resolution porous media images using autoencoder-based convolutional neural network.* Journal of Petroleum Science and Engineering, 2022. **208**: p. 109589.

9. Bruna, P.-O., et al., *Are stylolites fluid-flow efficient features?* Journal of Structural Geology, 2019. **125**: p. 270-277.

Thank you!

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