Recognition of Rocks Lithology on the Images of Core Samples

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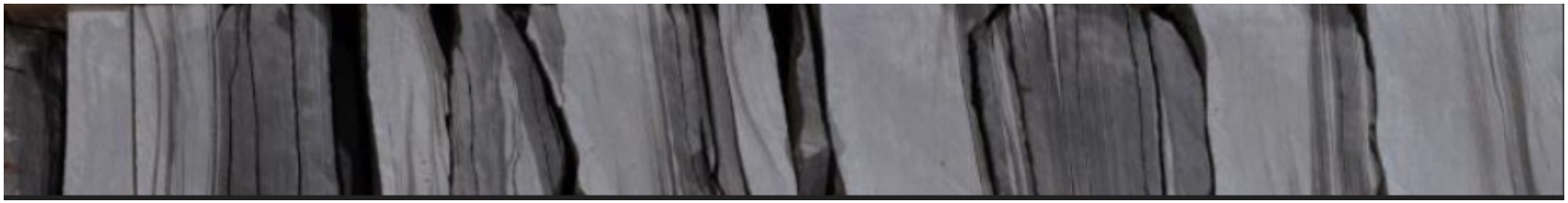
Overview

Problem

When an oil well is drilled, field engineers extract the samples of core to analyze it and build a geological model of the formation. Normally core samples are the most valuable source of data of the formation geology.

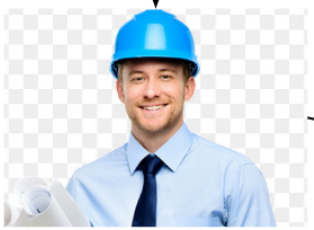


The Company "Digital Field Technologies" is aimed to automate several processes of analysis in a way of automatic recognition of core lithology based on the images of core samples.

Image Segmentation

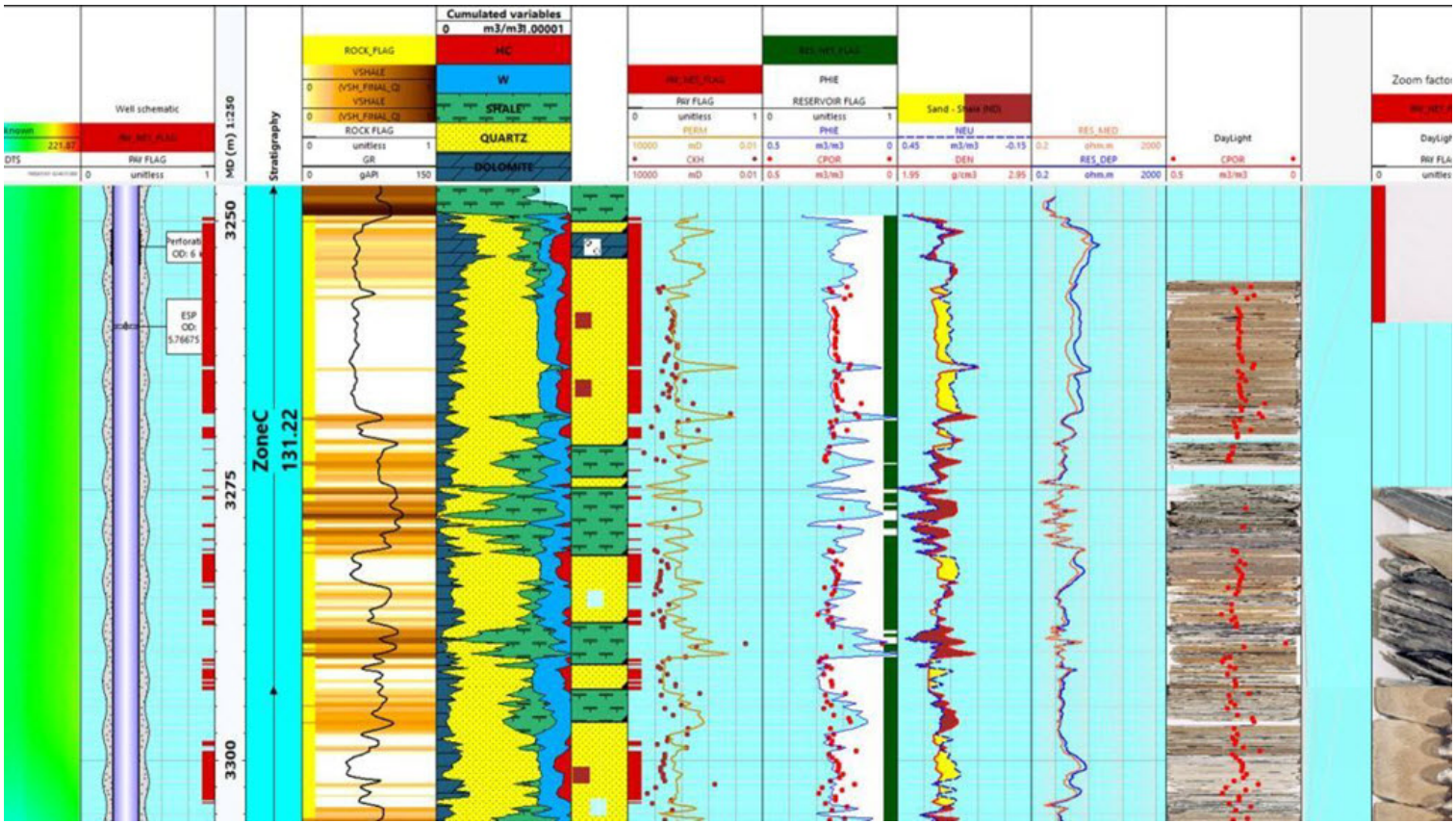
In computer vision, image segmentation is the process of partitioning a digital image into multiple segments.

Engineers by hand



18.10	18.10	100.00	2	0.10	2337.63	2339.19	ЮК0	Известняк органогенный	-	Конкреция - известняк органогенный с щебенчатой текстурой, с выпуклой бугристой поверхностью, с интенсивной вторичной литогенетической трещиноватостью. Трещины разнонаправленные, извилистые, мелкие, залеченные разнокристаллическим кальцитом.
18.10	18.10	100.00	3	2.95	2337.73	2339.29	ЮК0	Аргиллит	-	Аргиллит темно-серый с зеленоватым оттенком до черного, тонкогоризонтальнослоистый, битуминозный, послойно пиритизированный, трещиноватый. Интенсивность пиритизации уменьшается вниз по слою. Трещины разнонаправленные, тонкие, полые. Отмечаются карбонатные прослои и конкреции (размером больше диаметра керна х 3 см) в разной степени окремненные, различной формы (в основном линзовидные, вытянутые по напластованию), с массивной текстурой, некоторые трещиноватые (залечены белым кальцитом). Встречены единичные битуминозные крючки (однохитс). Контакт с нижележащим слоем отчетливый (по карбонатизации).

Schlumberger Techlog



An interactive image segmentation method for lithological boundary detection: A rapid mapping tool for geologists(2017)

Datarock 2020

DATAROCK

Figure: Example rock segmentation and measurement used to produce rock quality designation RQD from core photographs. The model is trained to predict the boundaries of rock fragments and measure them (e.g. 4.7, 10.4 = 4.7 cm high and 10.4 cm long). Yellow colours represent rock fragments larger than 10 cm long, blue segments are less than 10 cm long.

Datarock 2020

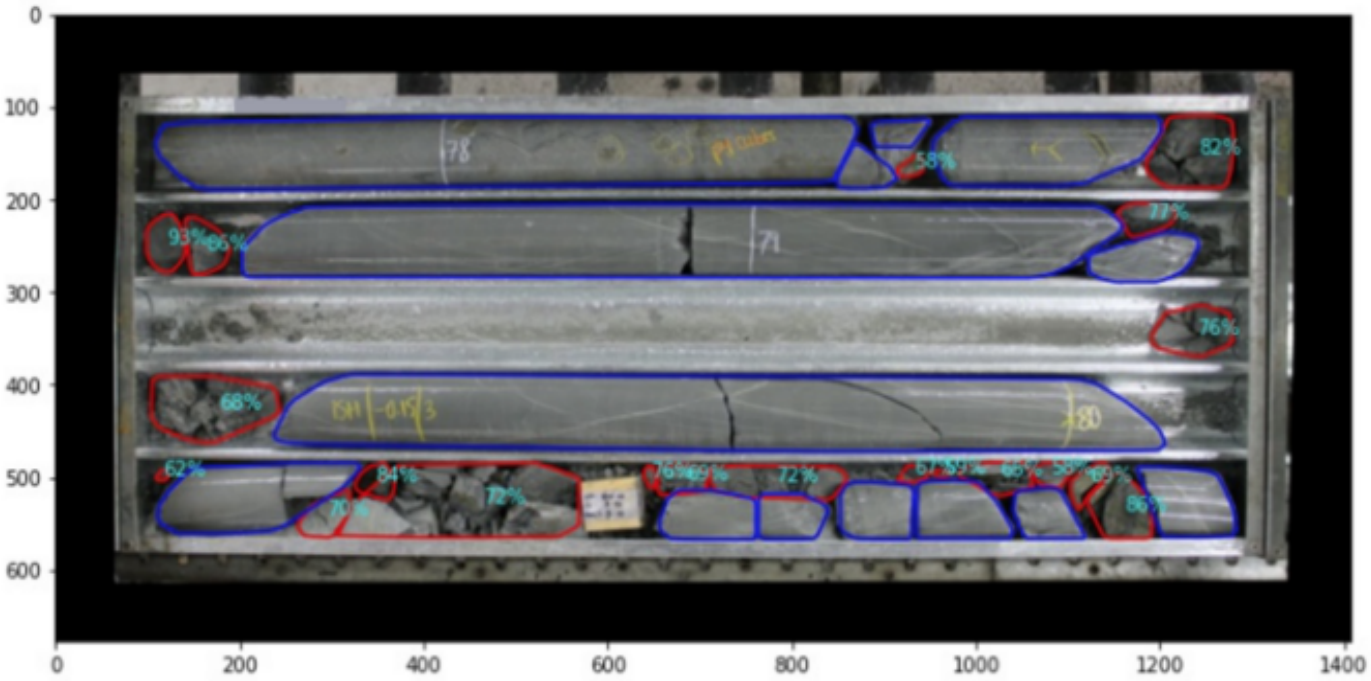


Figure: Datarock Example

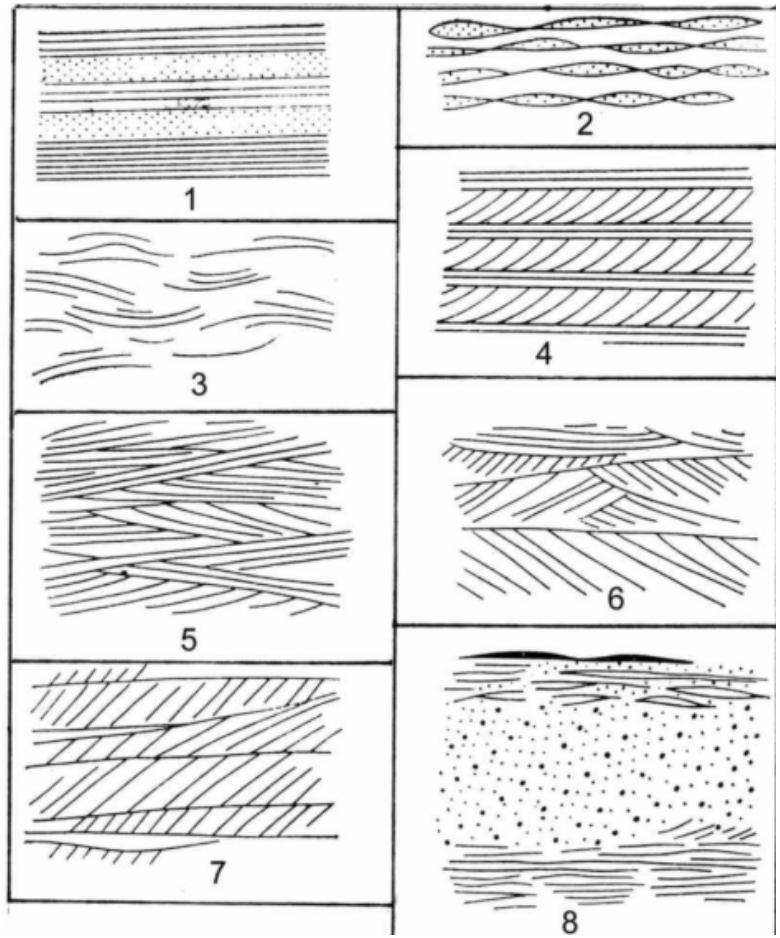
The task

The task is to segment the image of the Kern into:

1. Structural type of layering
2. Rock material

Structural Type of Layering

1. Horizontal
2. Lenticular
3. Wavy
4. Slanting
5. etc.



Rock Material

~ 2400 m ↓

Alevrolit	Sandstone	Siltstone	Coal




Example

Here we see:

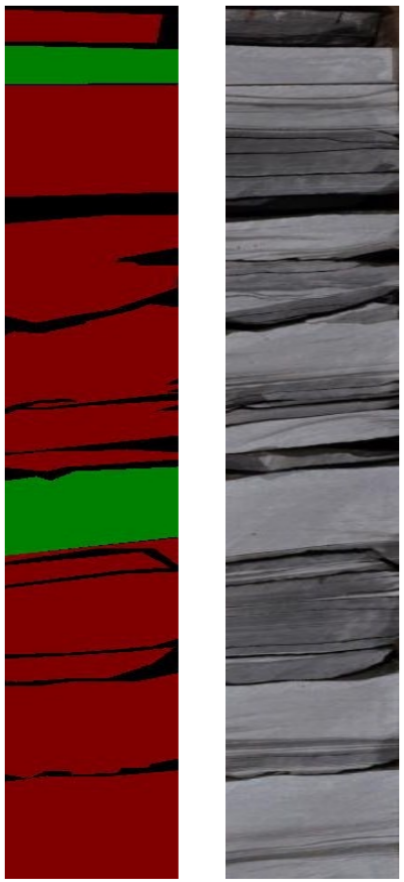
- Sandstone - rock material
- Small Wavy - type of layering

Example

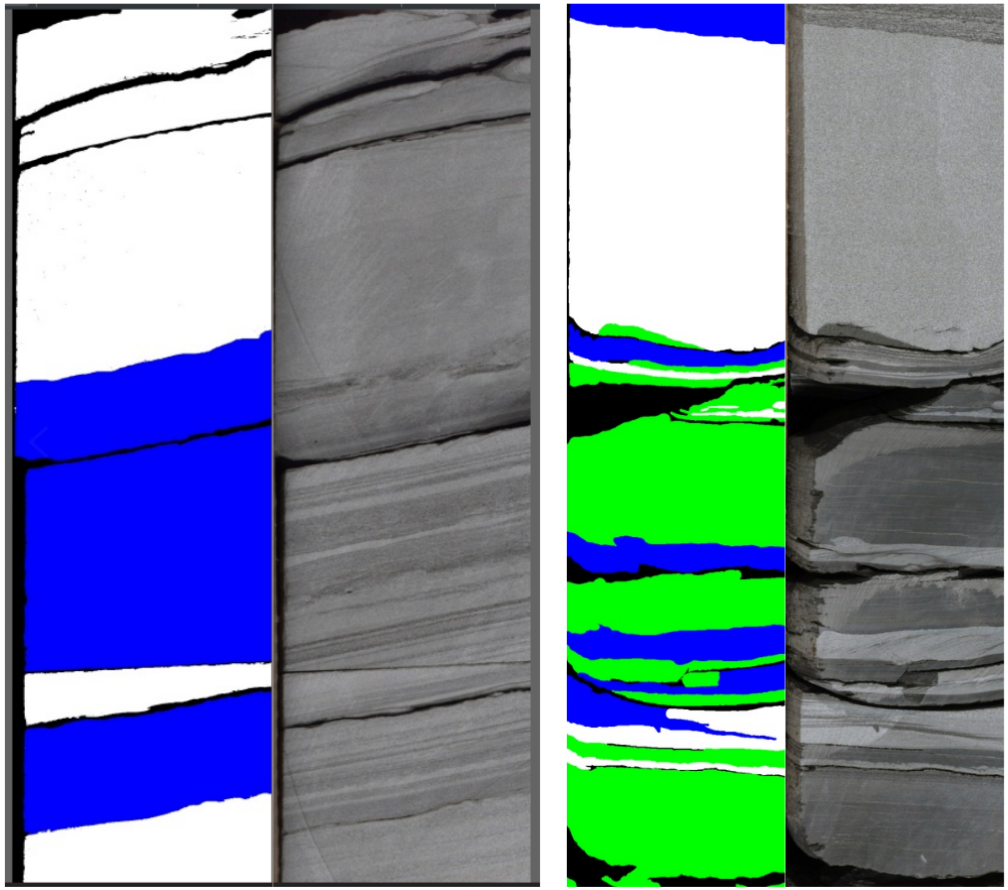
- Red - Black Coal, Fissured
- Blue - Argillite dark gray, Silty

Dataset Evolution

First try

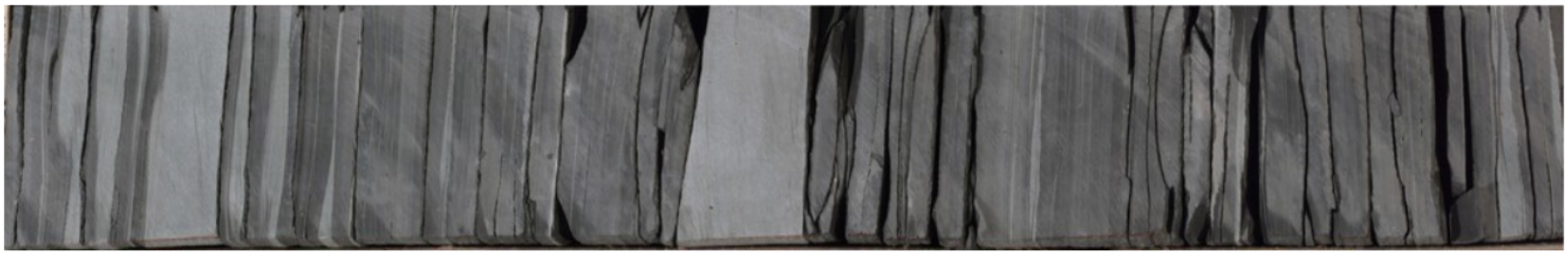


Second Try



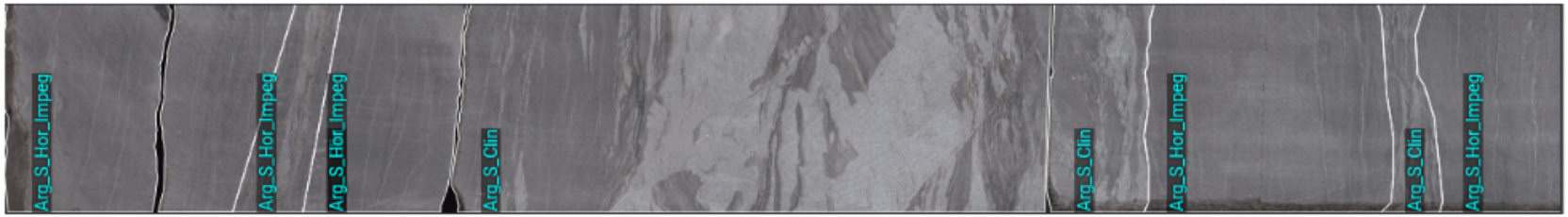
Dataset Evolution: 1-2

Third Try

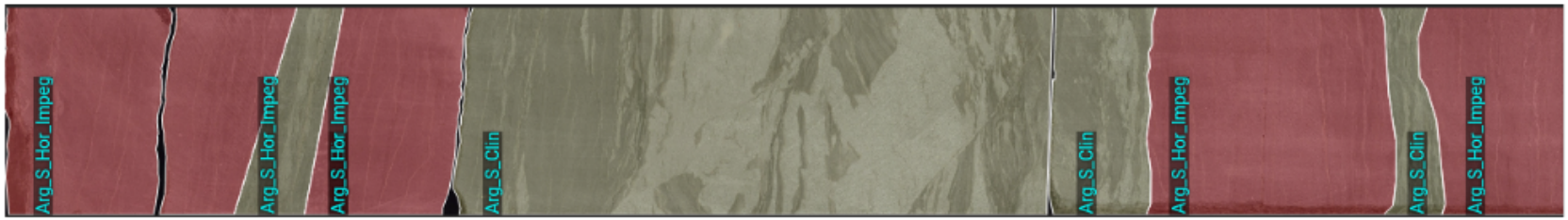


Dataset Evolution: 4

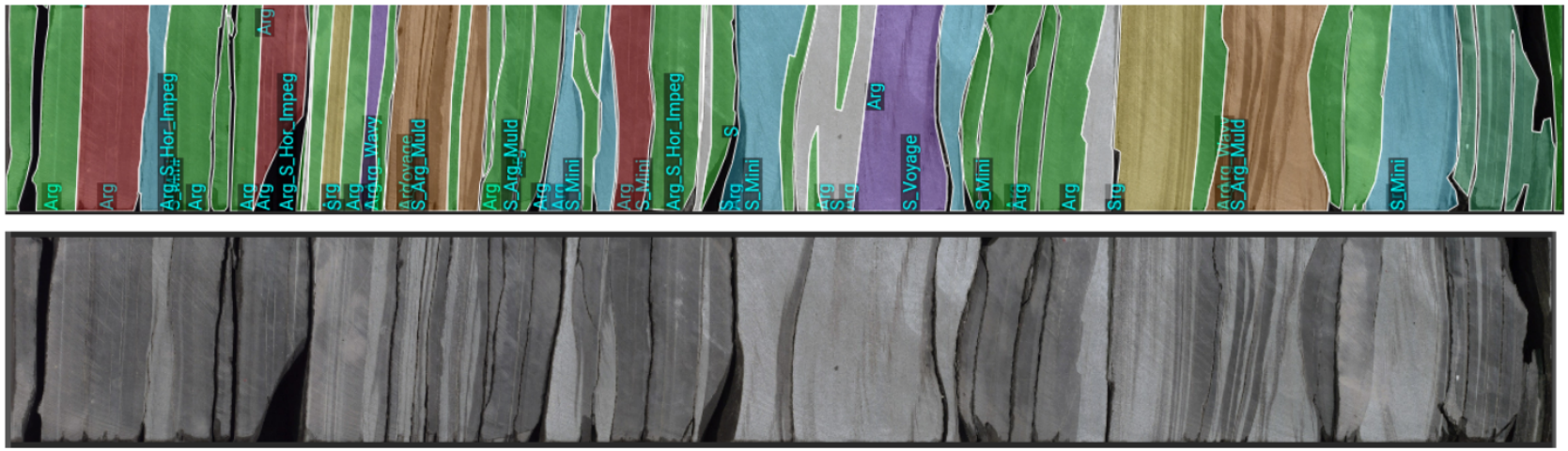
Original



Annotated



Dataset Evolution: 4



Classes before

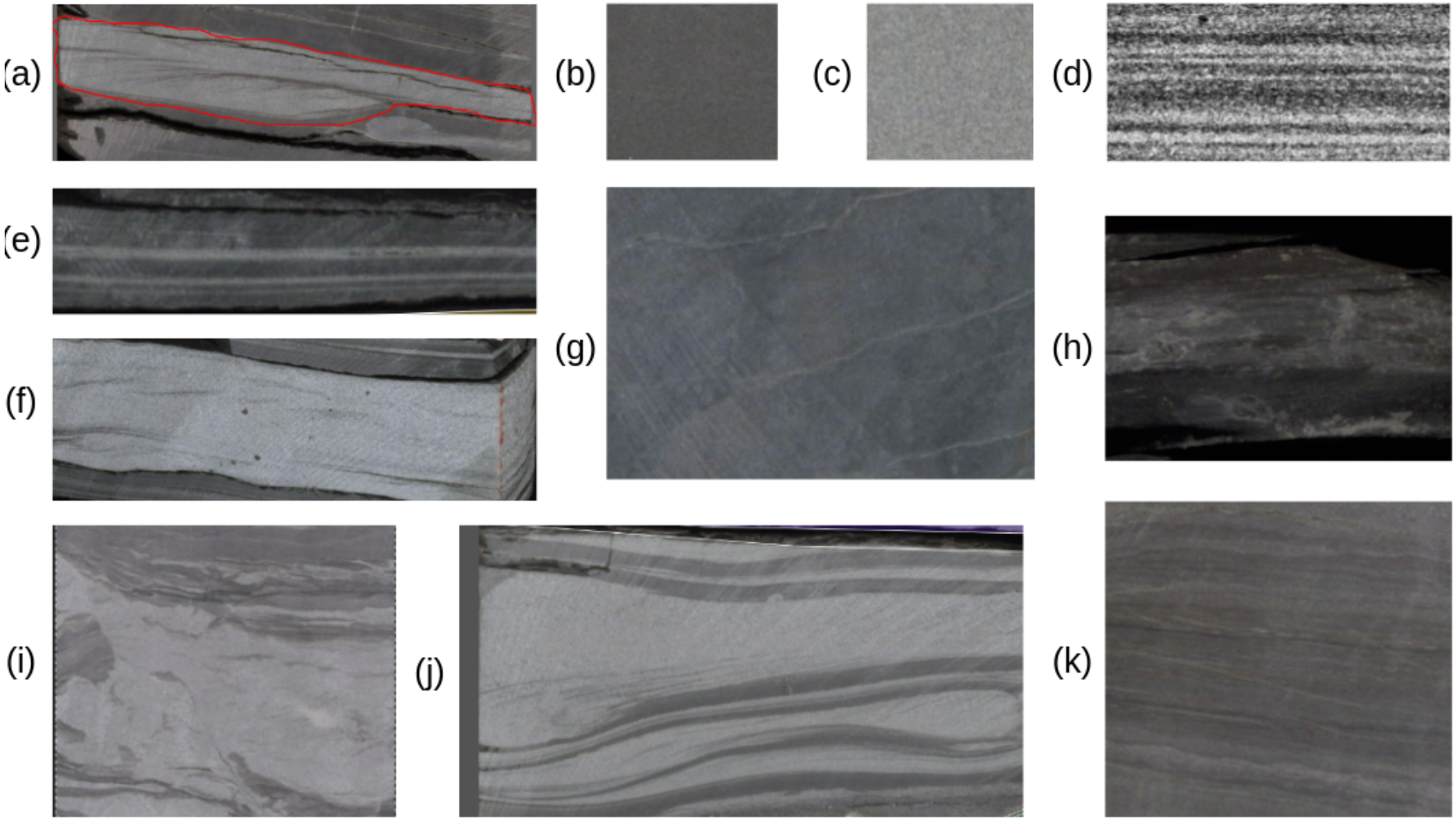
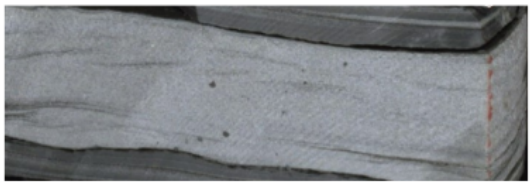


Figure: 11 different classes of the dataset: (a) S-Mini, (b) Arg, (c) S, (d)Arg-S-Noise, (e) S-Arg-P, (f) S-Voyage, (g) Arg-S-Hor-Impeg, (h) Def,

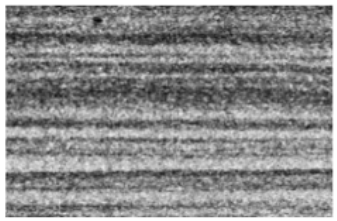
Classes after

S_Voyage



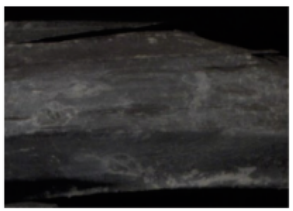
Arg_S_Clin

Arg_S_Noise



S_Arg_Muld

Def



Arg

S

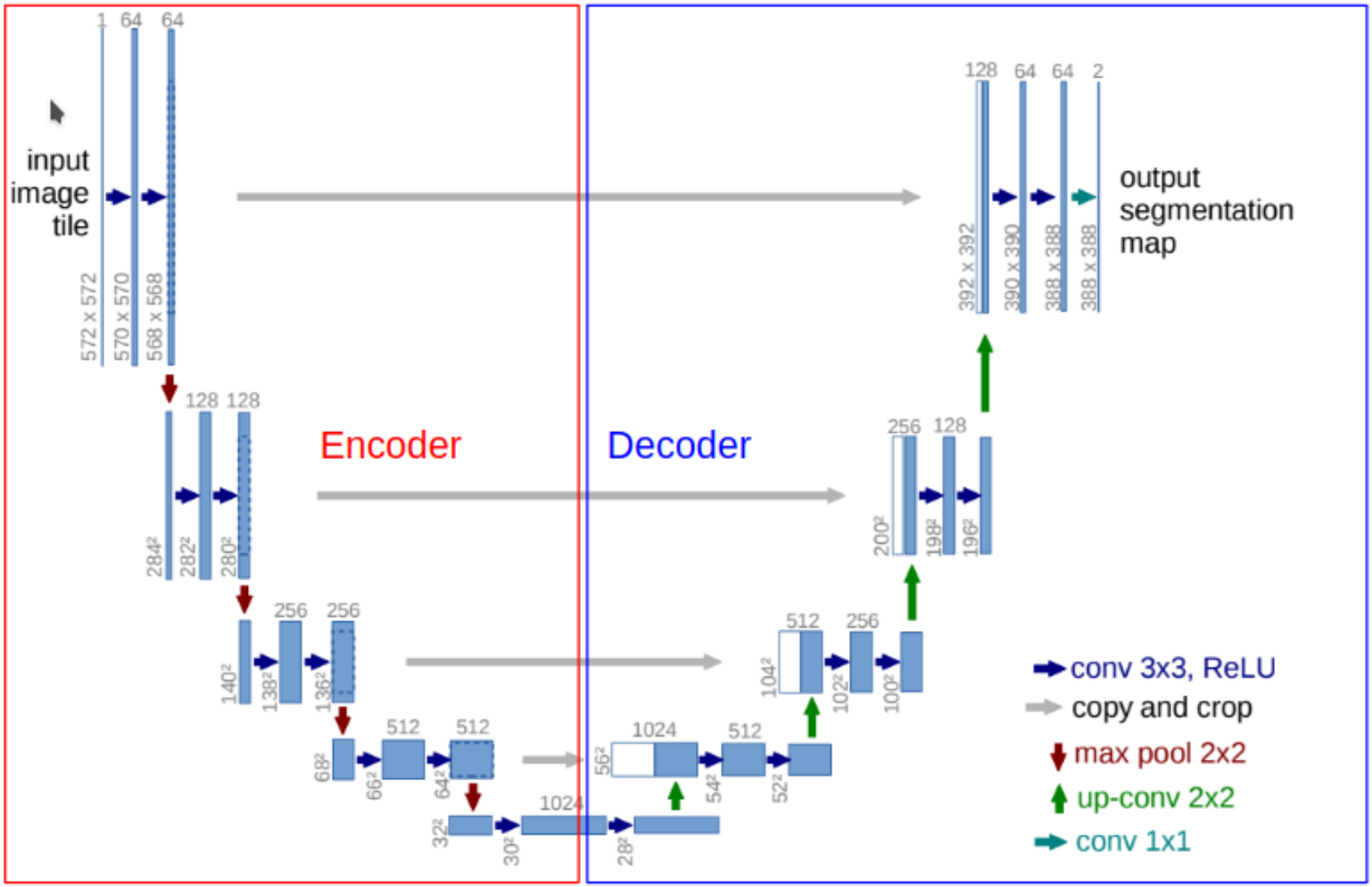
First Try: U-Net (2015)

U-Net: Convolutional Networks for Biomedical Image Segmentation

Olaf Ronneberger, Philipp Fischer, and Thomas Brox

Computer Science Department and BIOSS Centre for Biological Signalling Studies,
University of Freiburg, Germany
ronneber@informatik.uni-freiburg.de,
WWW home page: http://lmb.informatik.uni-freiburg.de/

U-Net (2015)


input image tile
572 x 572
570 x 570
568 x 568
1 64 64
128 128
284²
282²
280²
256 256
140²
138²
136²
512 512
68²
66²
64²
32²
1024
30²
28²
Encoder
Decoder
1024
56²
512
54²
512
52²
512 256
104²
102²
100²
256 128
200²
198²
196²
128 64 64 2
392 x 392
390 x 390
388 x 388
388 x 388
output segmentation map
conv 3x3, ReLU
copy and crop
max pool 2x2
up-conv 2x2
conv 1x1

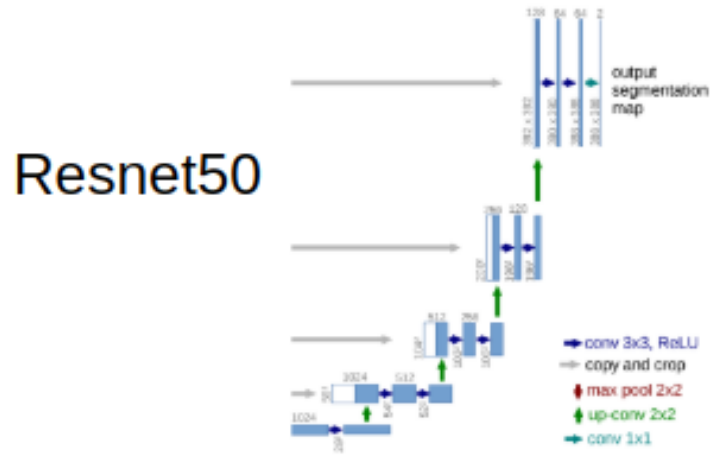
Initial Solution

For the start It is assumed that the pretrained segmentation network will be used and then fine-tuned.

So U-Net was used with the pretrained Resnet50 backbone (encoder).

3 classes are considered in the initial solution:

1. noise
2. smooth
3. unsmooth



Mean Intersection-Over-Union - is a common evaluation metric for image segmentation

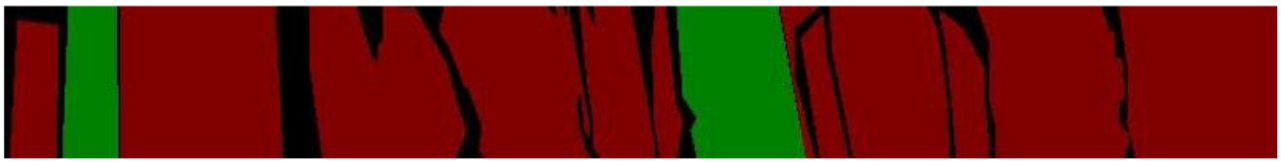
First Try: U-Net + Resnet50 Backbone

Input

Original Image

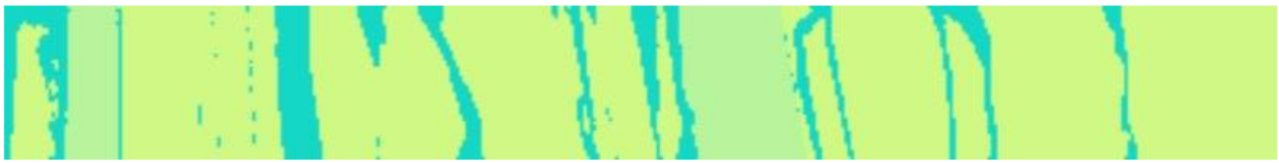
Ground Truth Mask

Black- noise
Red- unsmooth
Green- smooth

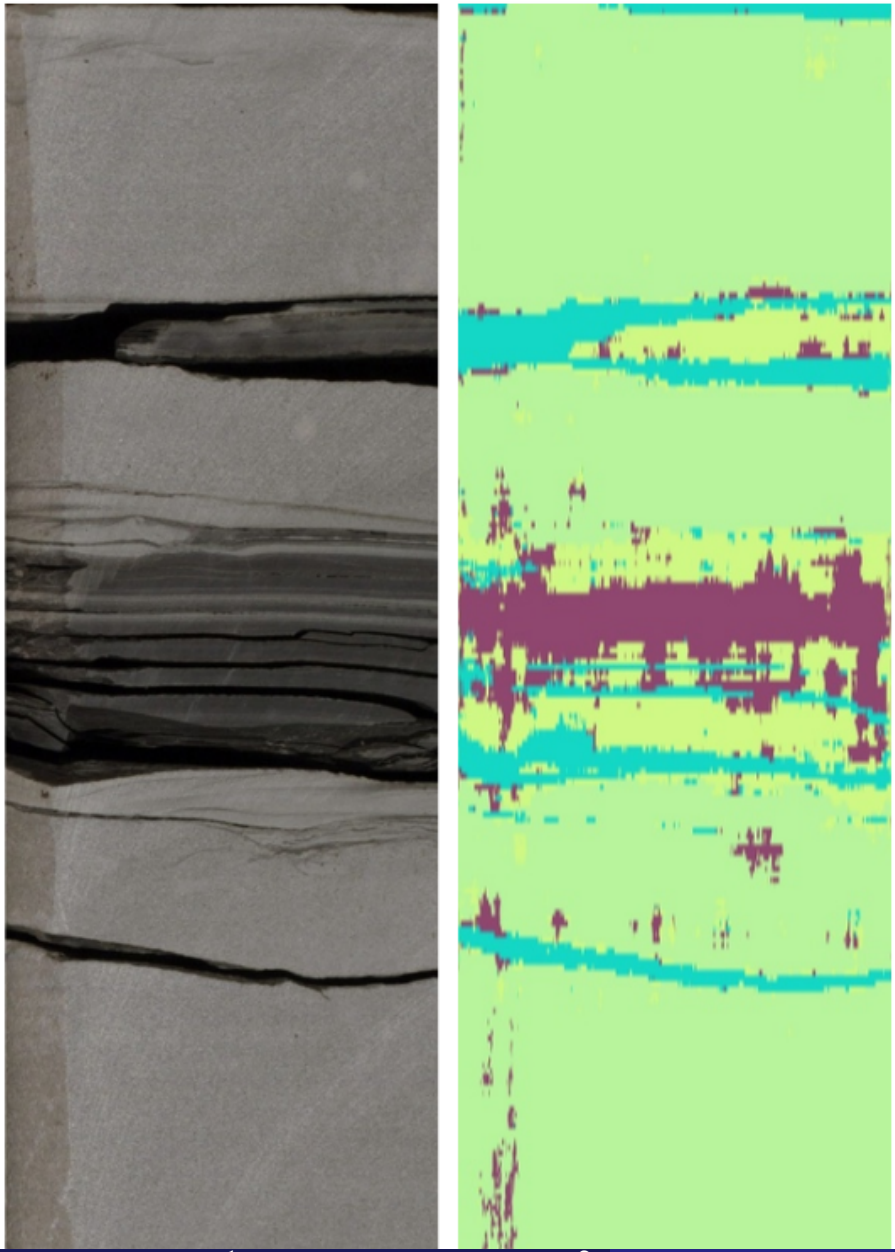


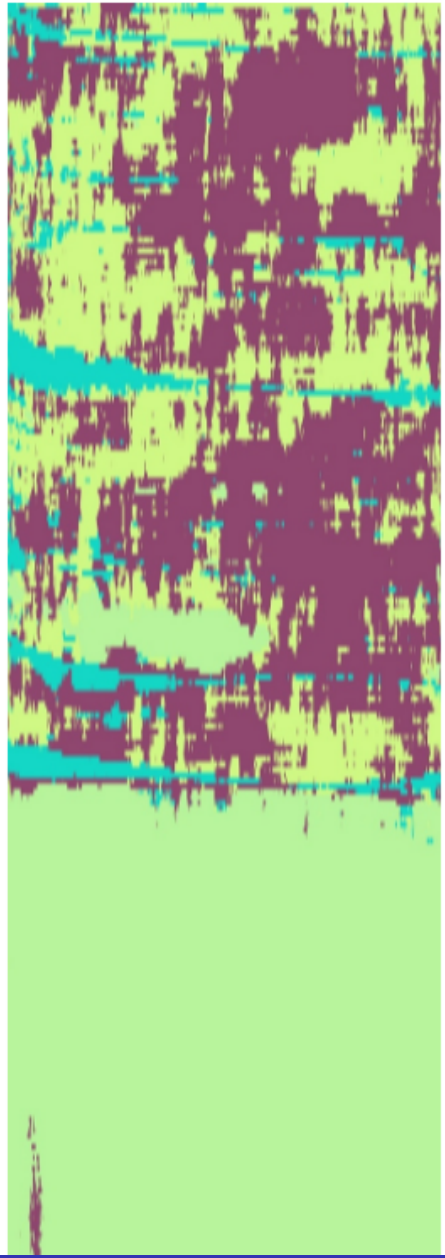
Output

Segmented Image

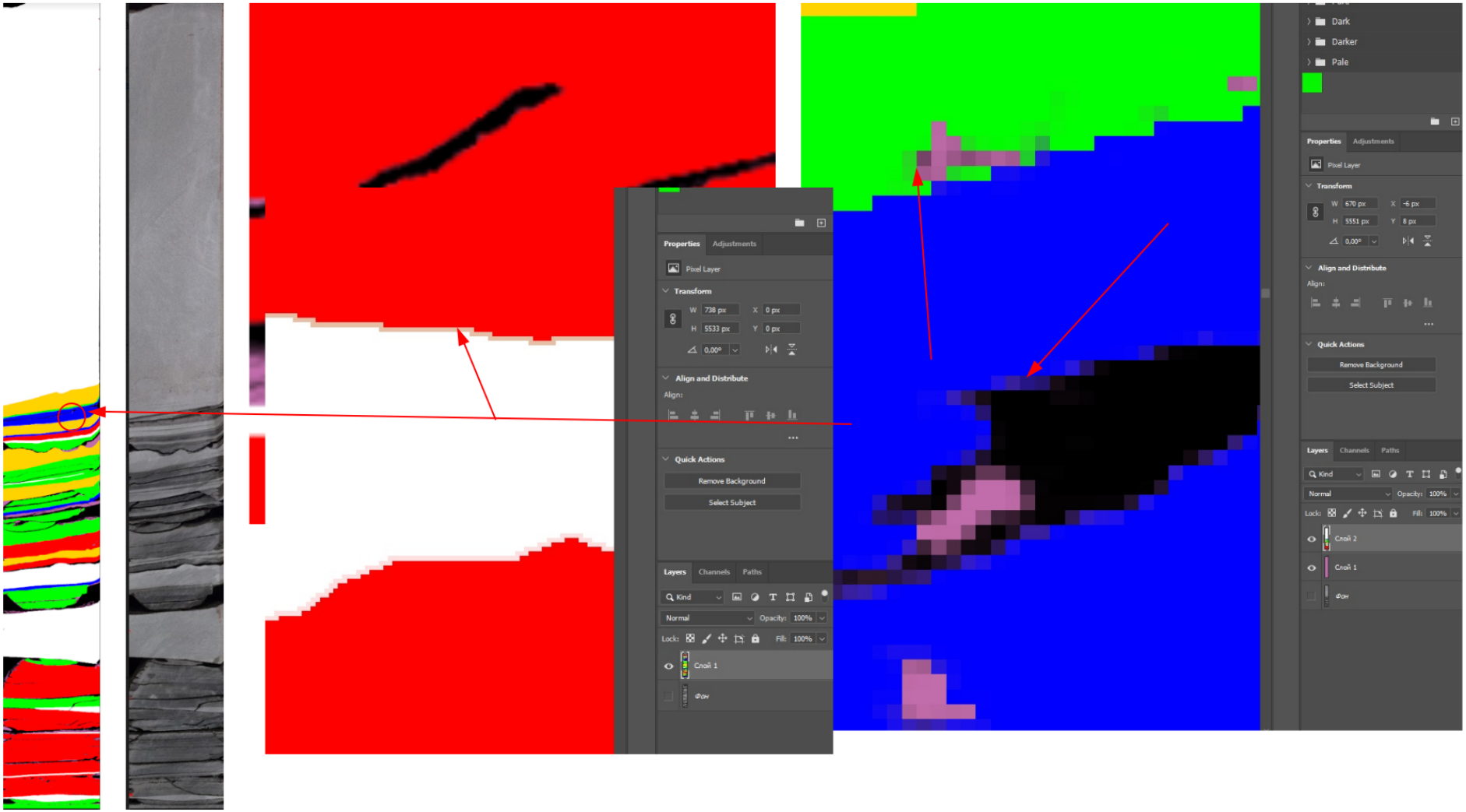


Second Try: U-Net + Resnet50 Backbone



Third Try: Failed dataset



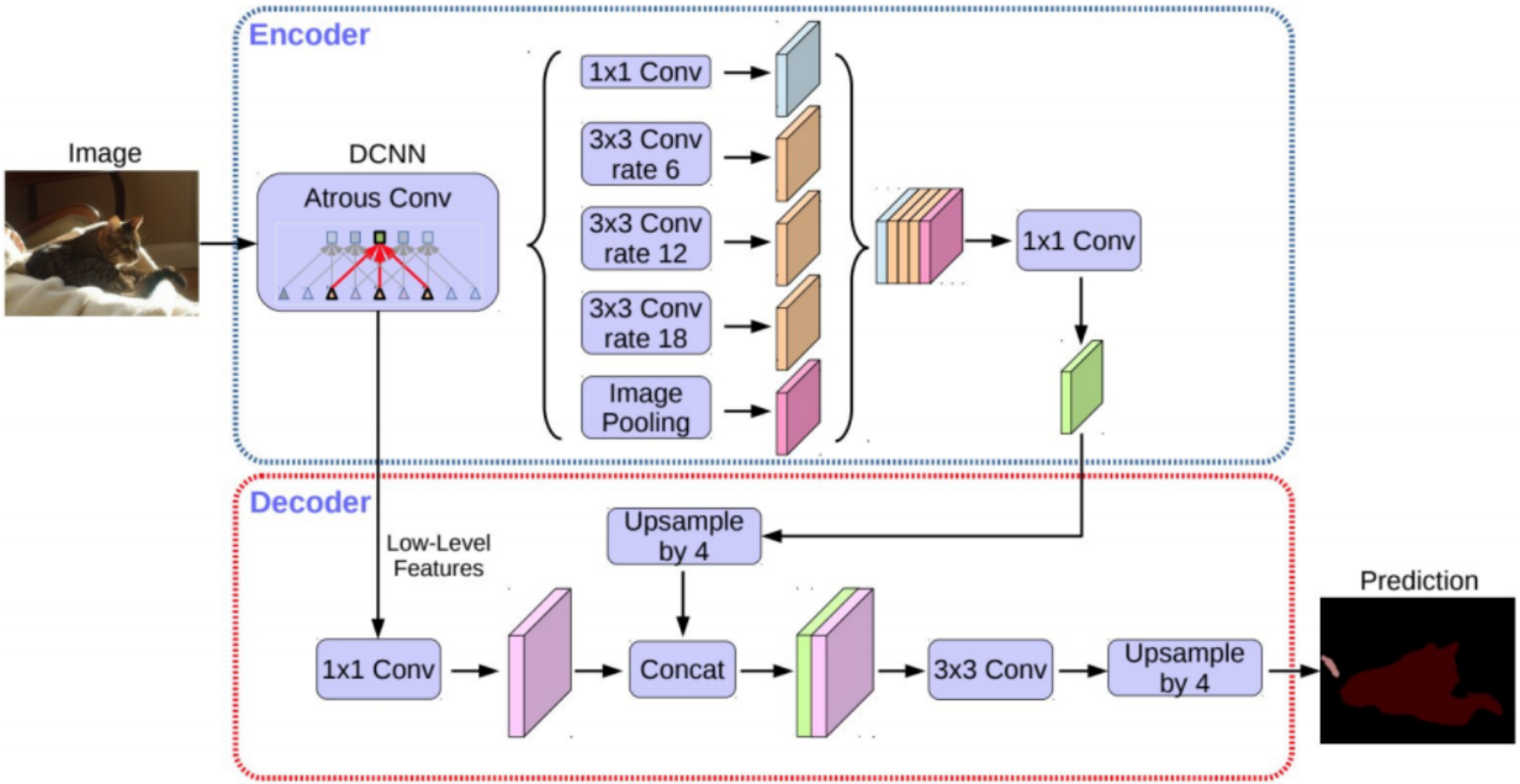
DeepLabV3+ (2018)

Encoder-Decoder with Atrous Separable Convolution for Semantic Image Segmentation

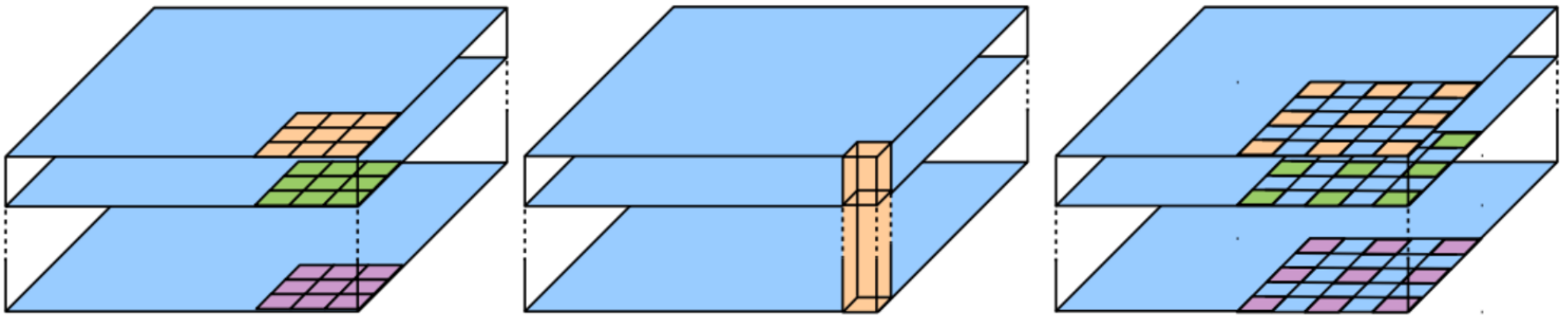
Liang-Chieh Chen, Yukun Zhu, George Papandreou, Florian Schroff, and Hartwig Adam

Google Inc.
{lcchen, yukun, gpapan, fschroff, hadam}@google.com

DeepLabV3+


Encoder
Image
DCNN
Atrous Conv
1x1 Conv
3x3 Conv rate 6
3x3 Conv rate 12
3x3 Conv rate 18
Image Pooling
1x1 Conv
Decoder
Low-Level Features
Upsample by 4
1x1 Conv
Concat
3x3 Conv
Upsample by 4
Prediction

Atrous Separable Convolution



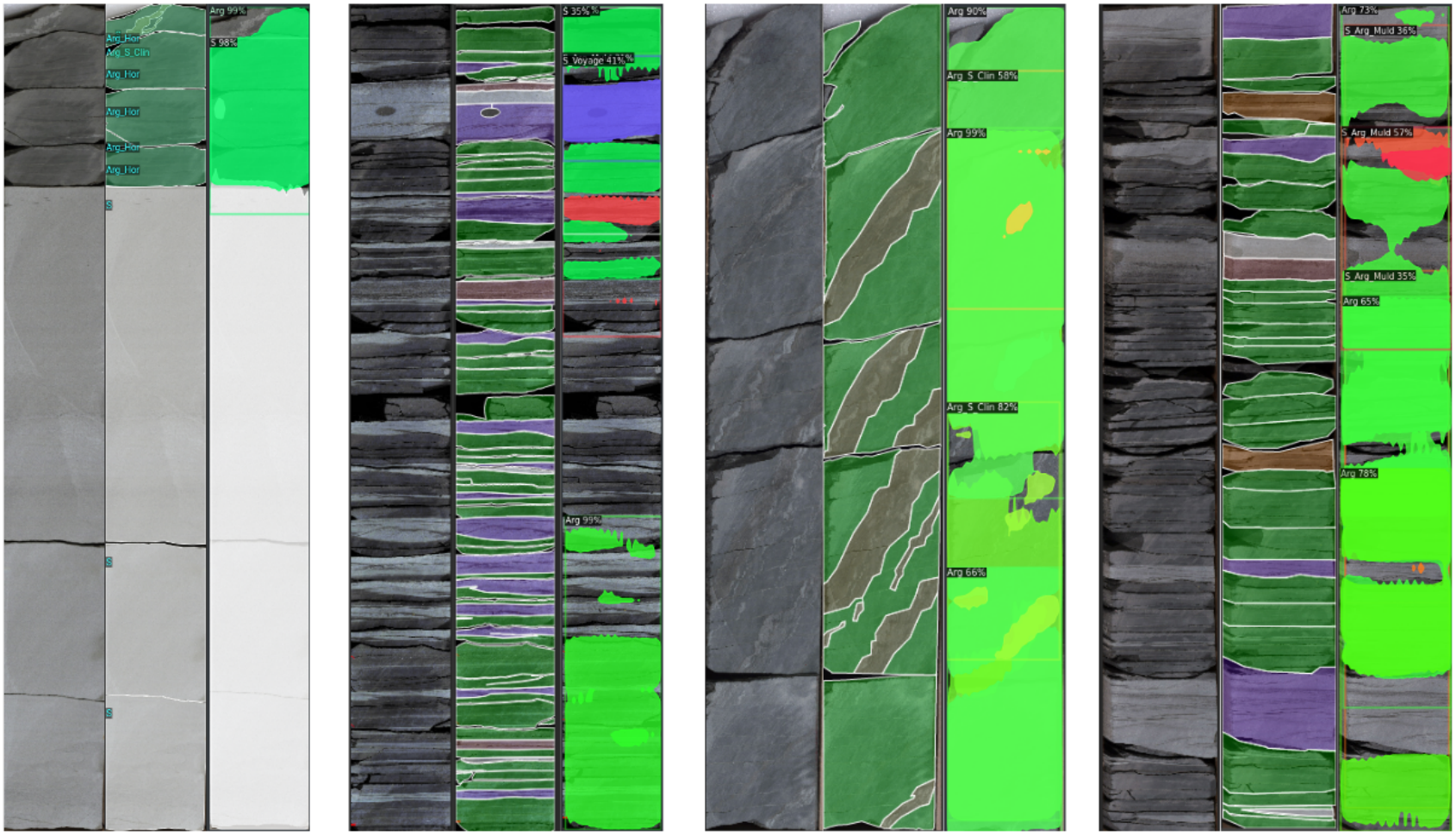
(a) Depthwise conv. (b) Pointwise conv. (c) Atrous depthwise conv.

$$y[i] = \sum_k x[i + rk]w[k] \tag{1}$$

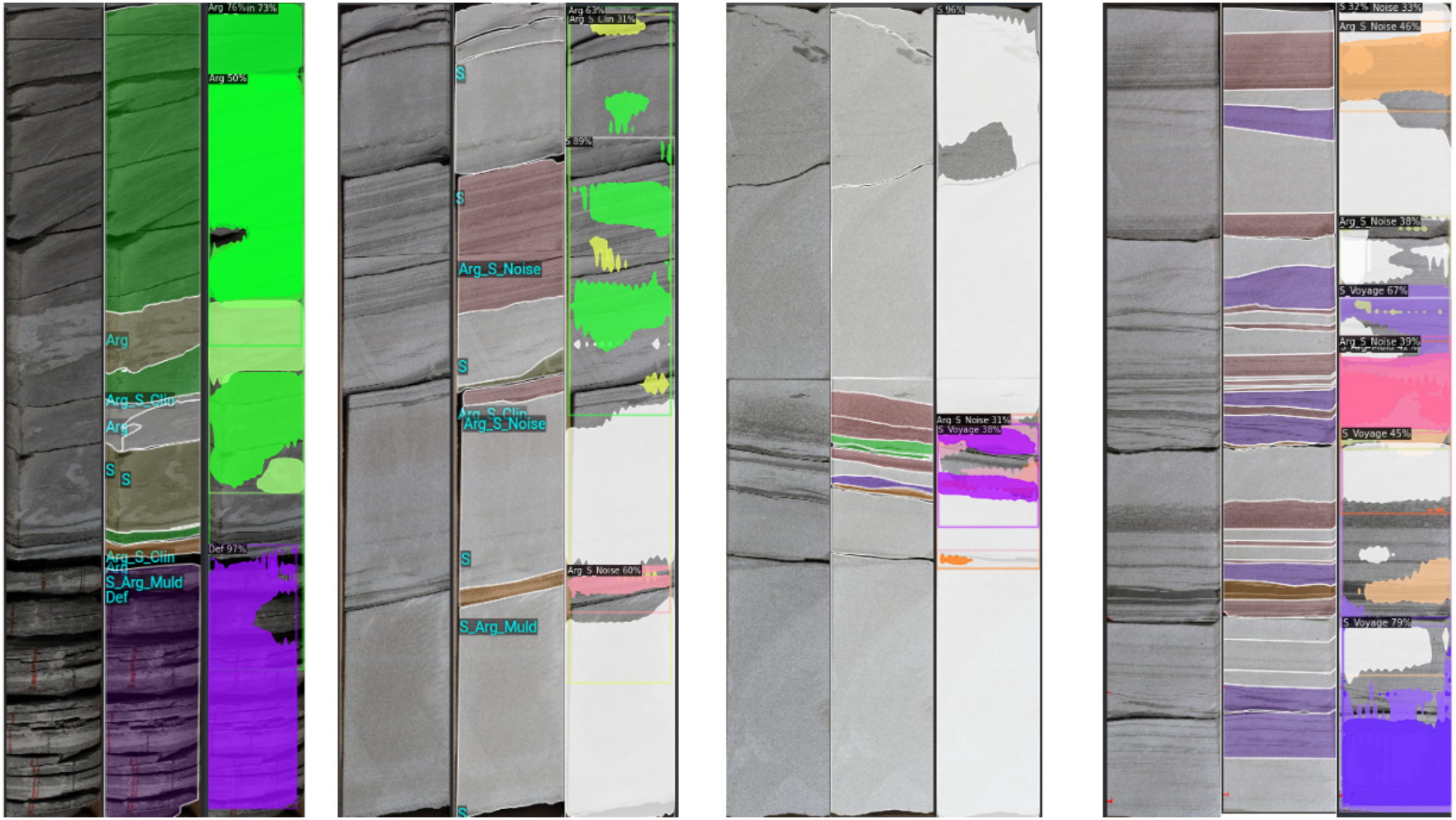
Detectron2

Figure: Detectron2 is Facebook AI Research's next generation software system that implements state-of-the-art object detection algorithms. It is a ground-up rewrite of the previous version, Detectron, and it originates from maskrcnn-benchmark.

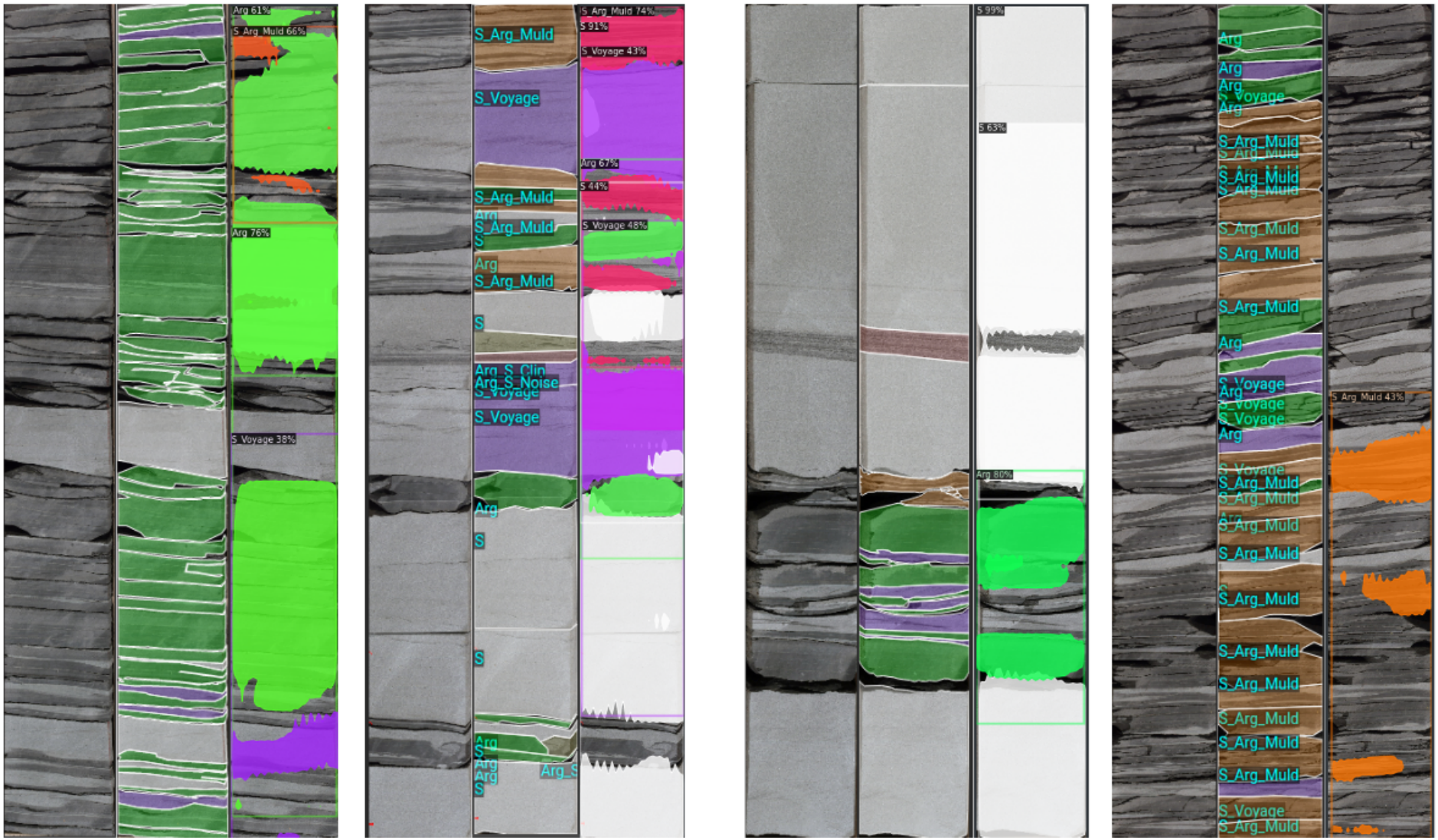
Detectron Results: R-CNN-100-FPN



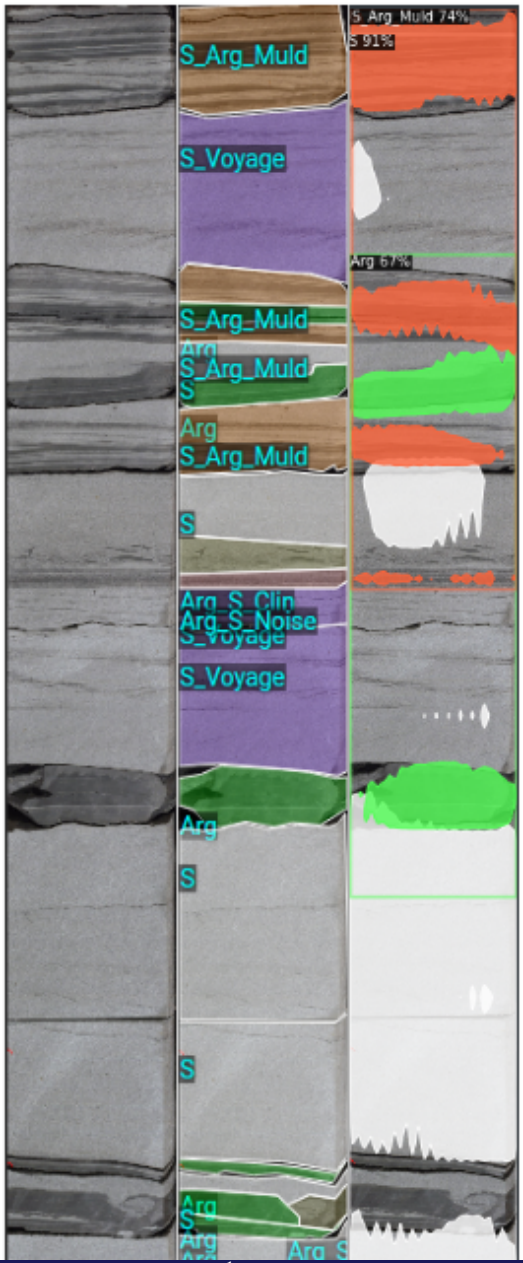
Detectron Results: R-CNN-100-FPN



Detectron Results: R-CNN-100-FPN



Detectron Results: R-CNN-100-FPN



Tasks

1. Try to clean dataset and achieve better results
2. Tune Detectron2 and DeepLabV3
3. Research other models
4. Write Diploma

Results

Easy	Name	AP
Detectron2	MaskRCNN101FPN	14.398
	MaskRCNN50FPN	12.629
DeepLabV3+	MaskRCNN101FPN	13.423
	MaskRCNN50FPN	11.423

Figure: Numerical Results. AP - average Precision.

Thanks

Would like to say thanks for helping to label the Dataset:

1. Vladislav Potapov
2. ALIX)
3. Mohammed Sajjadji
4. Aaron Zhang
5. Alexander Donets
6. Sergey Pnev
7. Rishabh Tiwari
8. Mikhail Liz
9. Alexander Rusnak

The End