Towards robots with geologist eyes?

Computer Vision and Deep Learning approaches to field samples analysis

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PITCH SLIDE

Photography encouraged

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Lithology recognition

1. Deep Learning classification model

input : photo of rock

output : lithology + confidence score

Likelihood

Basalt - 93 %
Shale - 2 %
Sandstone – 1 %

2. First application

Transfer Learning approach

12 litho classes

Training on 2700 public images

90 % accuracy

3. Background removal

Object detection model

4. Geological knowledge embedding

Recognize petro features

Predict litho from features and decision tree

Origin CNN classifier: Intrusive-looking (99%)

⇩

Chemistry CNN classifier: Felsic-looking (99%)

⇩

Banding CNN classifier: Visible (94%)

⇩

Litho-type decision tree: It may be an orthogneiss

Element extraction

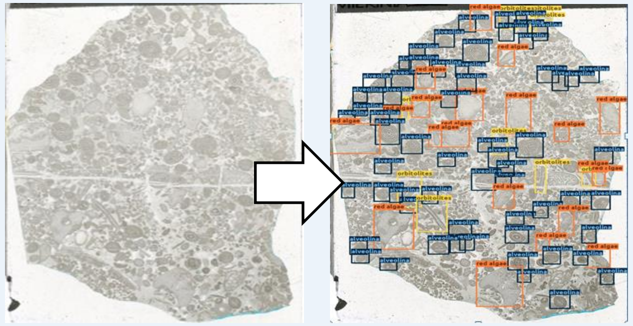
Ex: paleofauna on thin sections

Cascade R-CNN neural architecture

12 seconds by section

Categorization in 9 species

Results validated by experts



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FULL PRESENTATION

CONTEXT

Computer vision?

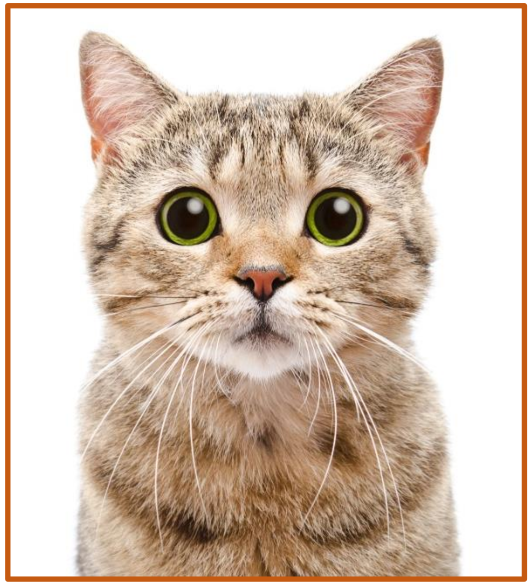
- Subfield of **Artificial Intelligence**
- Dedicated to **automated image interpretation**
- Technological leaps thanks to the **Deep Learning** boom
- **Applications:** medical diagnosis, facial recognition, self-driving cars…

CONTEXT

Three main families of algorithms

- Image classification

DOG

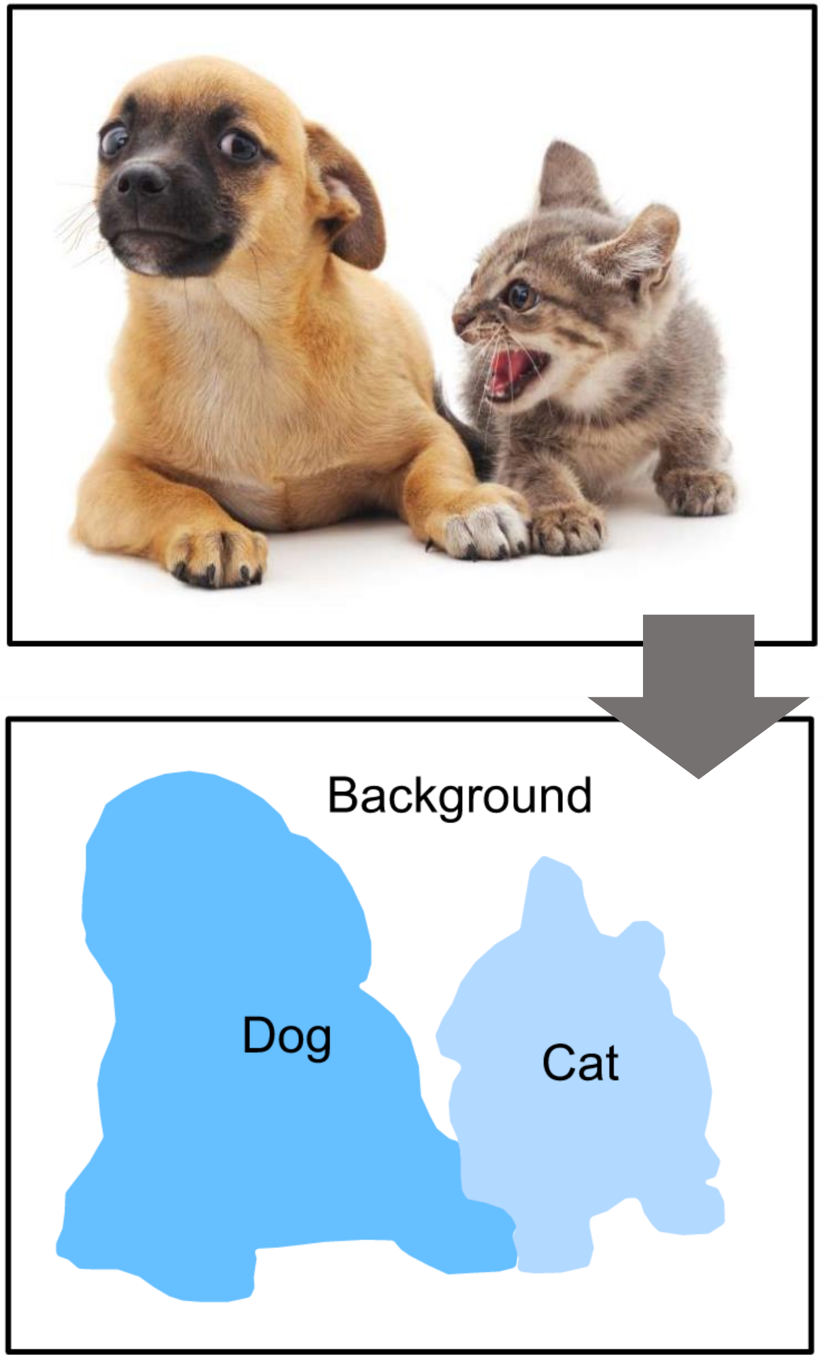


CAT

CONTEXT

Three main families of algorithms

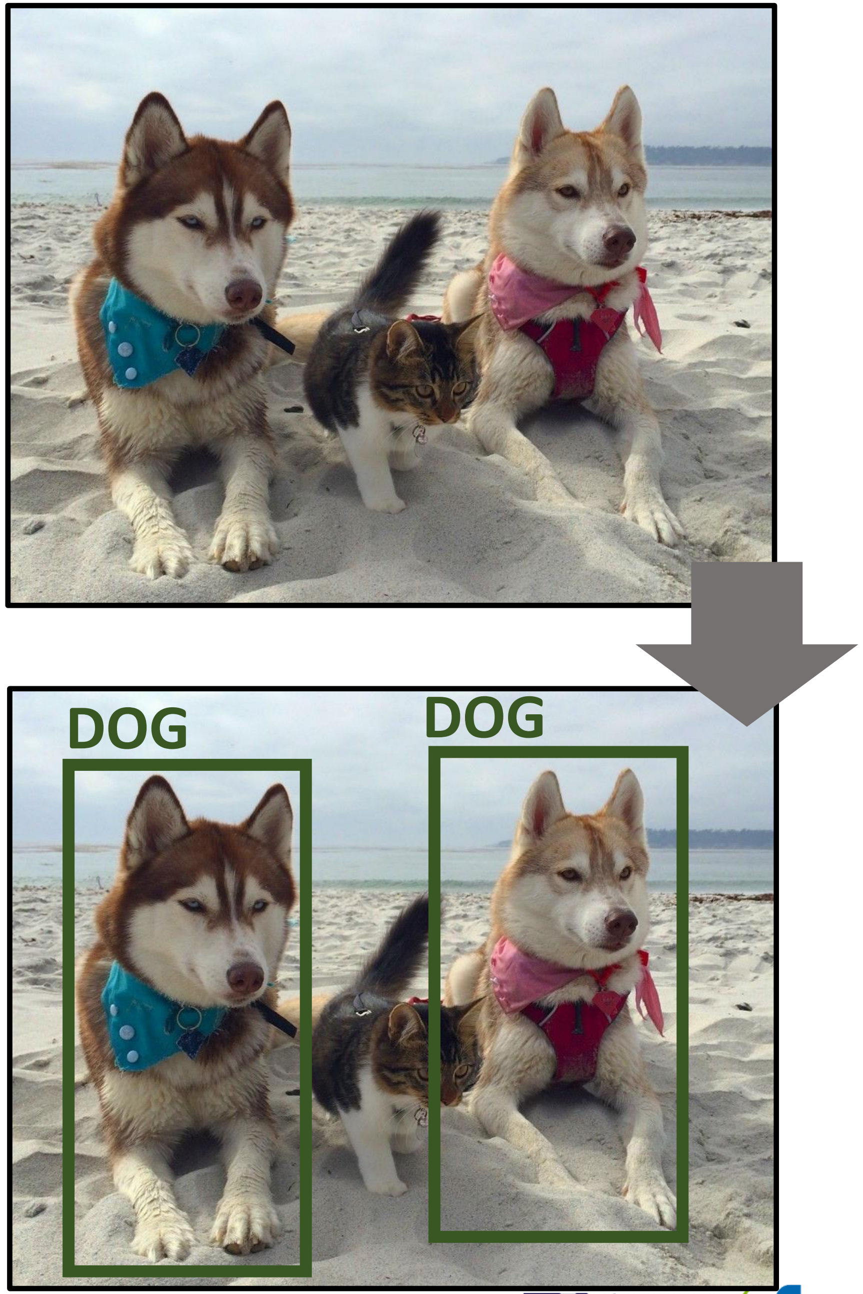
- Image classification
- Image segmentation



CONTEXT

Three main families of algorithms

- Image classification
- Image segmentation
- Object detection



CONTEXT

Computer vision for rock images?

- Multiple applications

- May be key for mining automation

- But rocks are complex objects

- Exciting research area

OUTLINE

Use case 1: Lithology recognition

Use case 2: Element detection

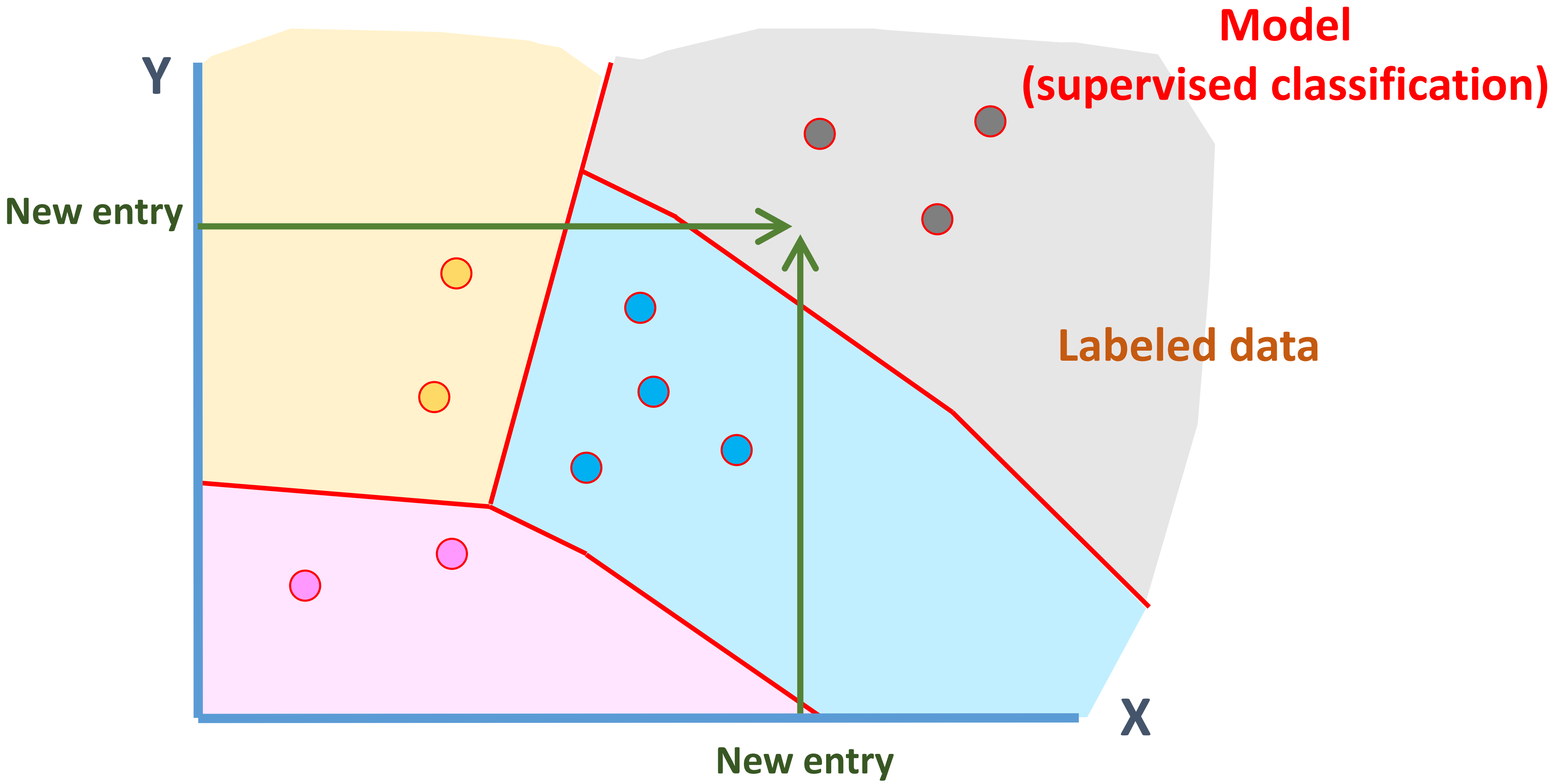
LITHOLOGY RECOGNITION

Feasibility study

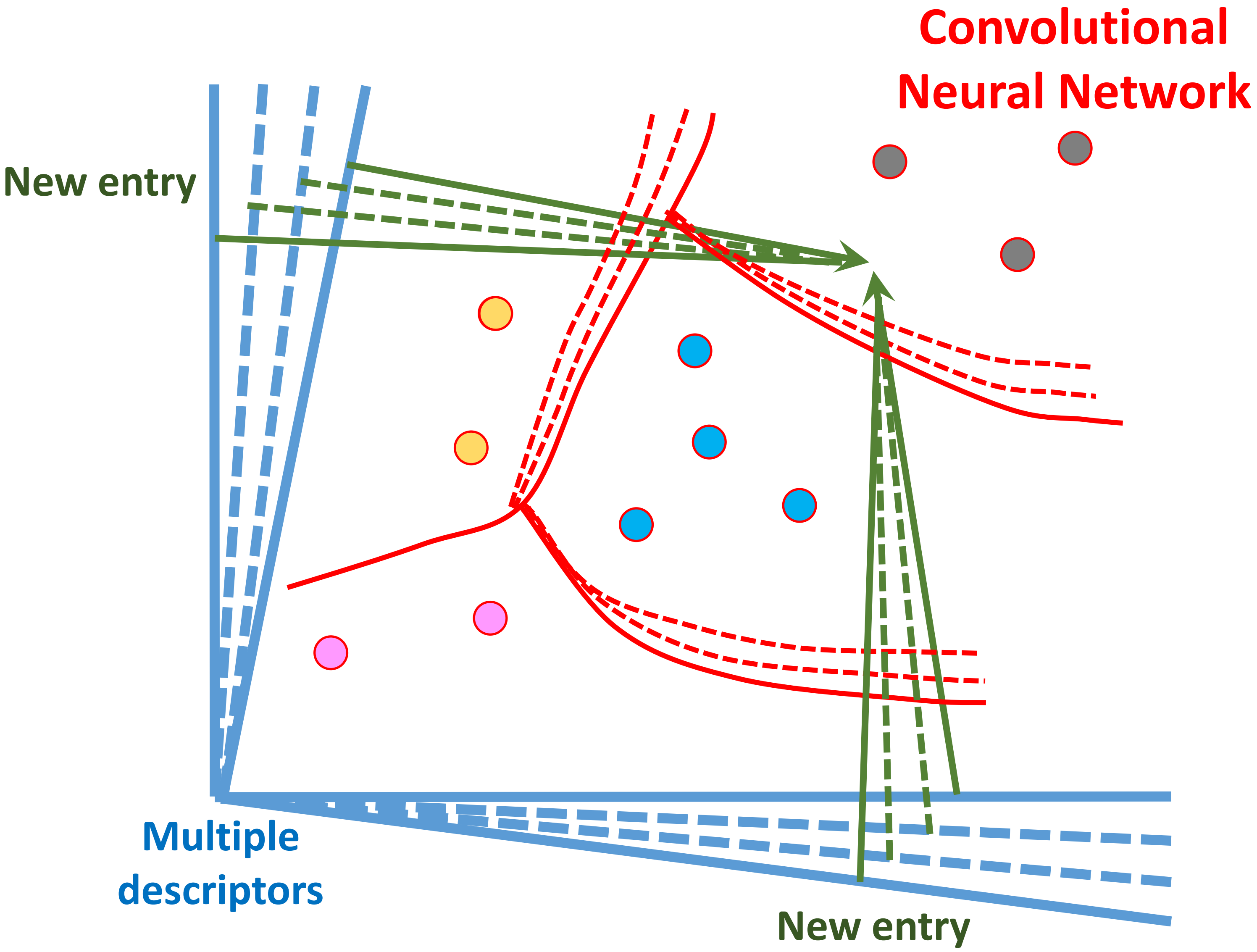
- Pluri-centimetric field samples
- 12 lithological classes

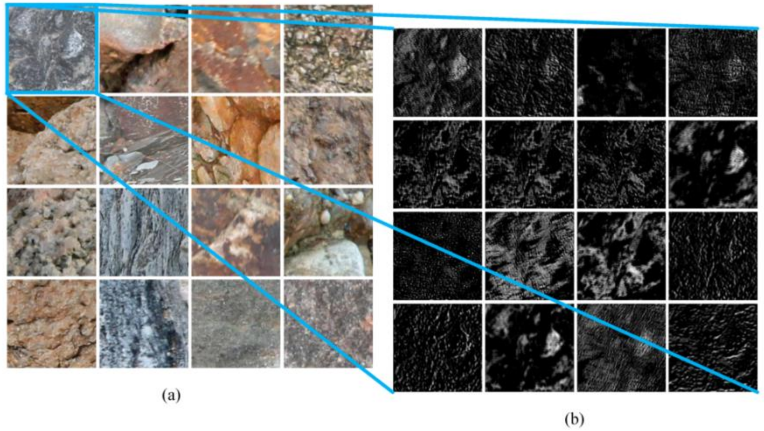
- **Sandstone**
- **Conglomerate**
- **Shale**
- **Limestone**
- **Flint**
- **Evaporite**
- **Orthogneiss**
- **Micaschist**
- **Granite**
- **Basalt**
- **Gabbro**
- **Dunite**

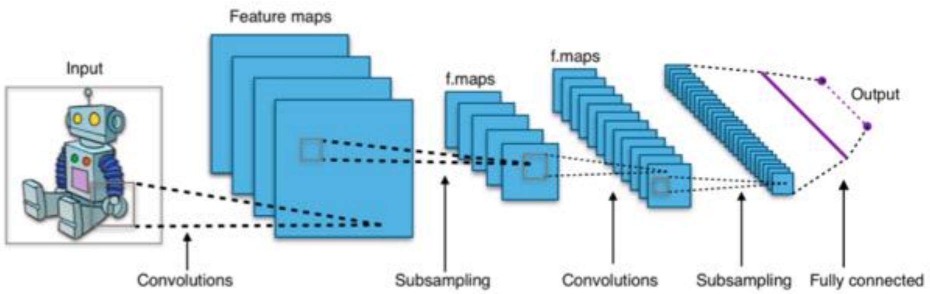
LITHOLOGY RECOGNITION

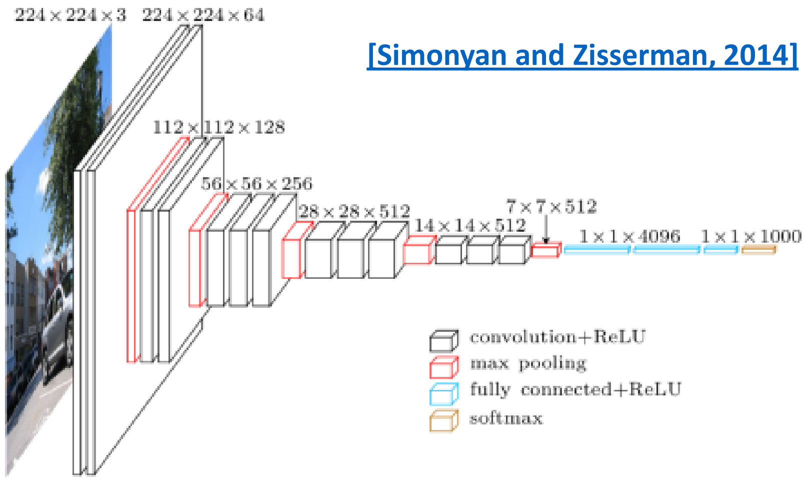


LITHOLOGY RECOGNITION









[Simonyan and Zisserman, 2014]

 |

LITHOLOGY RECOGNITION

➢ DIRECT APPROACH

Model architecture

- **Input:** a rock sample picture
- **Output:** probabilities of belonging to the 12 classes
- VGG convolutional neural network

Data set

- 2700 labelled images - 80% used for training
- Standard data augmentation (rotate, flip…)

Results

- Most probable class is correct for 90% of test pictures
- Photo quality is an impactful factor

Basalt 93%
Shale 2%
Sandstone 1%

Sandstone 99%
Dunite < 1%
Limestone < 1%

Conglomerate 98%
Flint 1%
Mica schist < 1%

Mudrock 87%
Flint 11%
Mica schist < 1%

Limestone 37%
Sandstone 32%
Mudrock 26%

LITHOLOGY RECOGNITION

[Bouziat *et al.* 2020]

➢ WITH PRIOR GEOLOGICAL KNOWLEDGE

Challenge

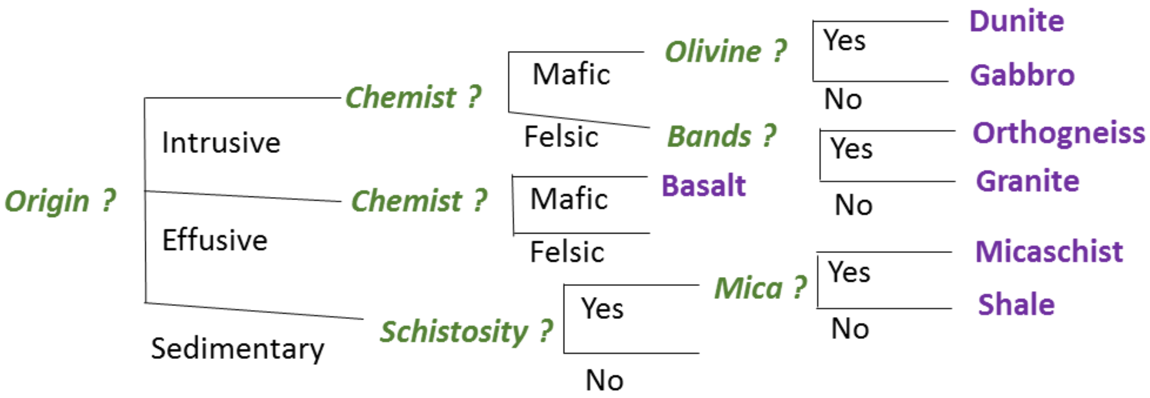
- Embed prior geological knowledge in the model

Proposal

- Train CNNs to recognize petrological features
- Combine them in a naturalist decision tree

Assets

- Split the question in a series of simpler ones
- More data per class from the same images set
- Integrate more geological control in the model



Origin CNN classifier: Intrusive-looking (99%)

⇩

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⇩

Banding CNN classifier: Visible (94%)

⇩

Litho-type decision tree: It may be an orthogneiss

LITHOLOGY RECOGNITION

➢ WITH OBJECT DETECTION

Objective

- Reduce sensibility to photo framing

Model architecture

- Mask-RCNN network
- Detectron2 implementation

Data set

- 800 images manually annotated

OUTLINE

Use case 1: Lithology recognition

Use case 2: Element detection

Photography encouraged

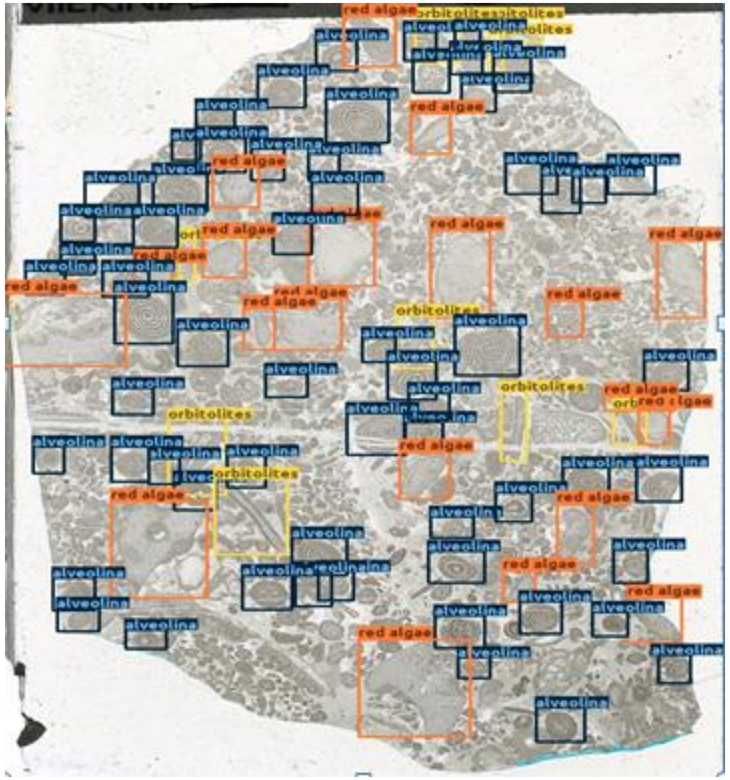
ELEMENT DETECTION

Feasability study

- Automatic detection and categorization of microfossils in thin section images

- Maybe extended to other use cases
  (ex: detection of ore nuggets)

Input image

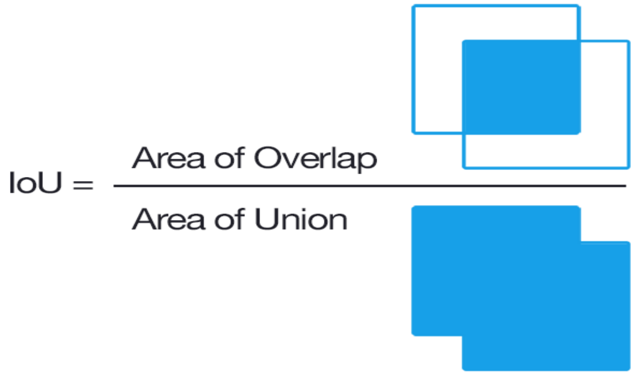


Automated interpretation

ELEMENT DETECTION

[Padilla *et al.* 2020]

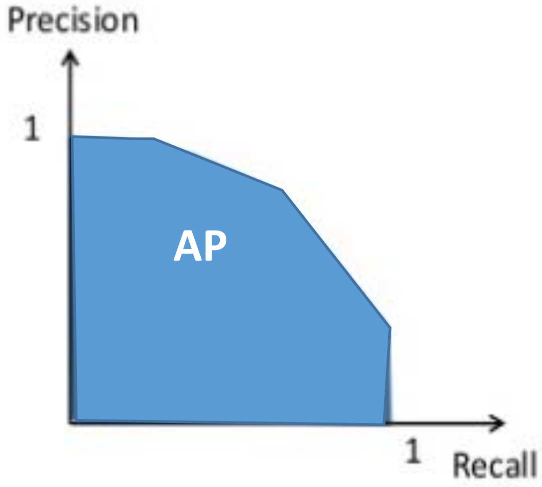
Metric used for evaluation of detection algorithms: Average Precision (AP)



- Intersection Over Union (IOU) (between 0 and 1)

- True Positive (TP): correct detection (IOU>threshold)
- False Positive (FP): wrong detection (IOU<threshold)
- False Negative (FN): ground truth non detected

- $\text{precision} = \frac{TP}{TP+FP}$
- $\text{recall} = \frac{TP}{TP+FN}$
- curve $precision\ vs\ recall\ r \mapsto p(r)$
- $AP = \int_0^1 p(r)dr$



The threshold is usually set to 0.5, 0.75 or 0.95

ELEMENT DETECTION

[Zhao *et al.* 2019]

Two groups of Deep-Learning-based detection algorithms

- **One-stage** detectors: less precise but faster

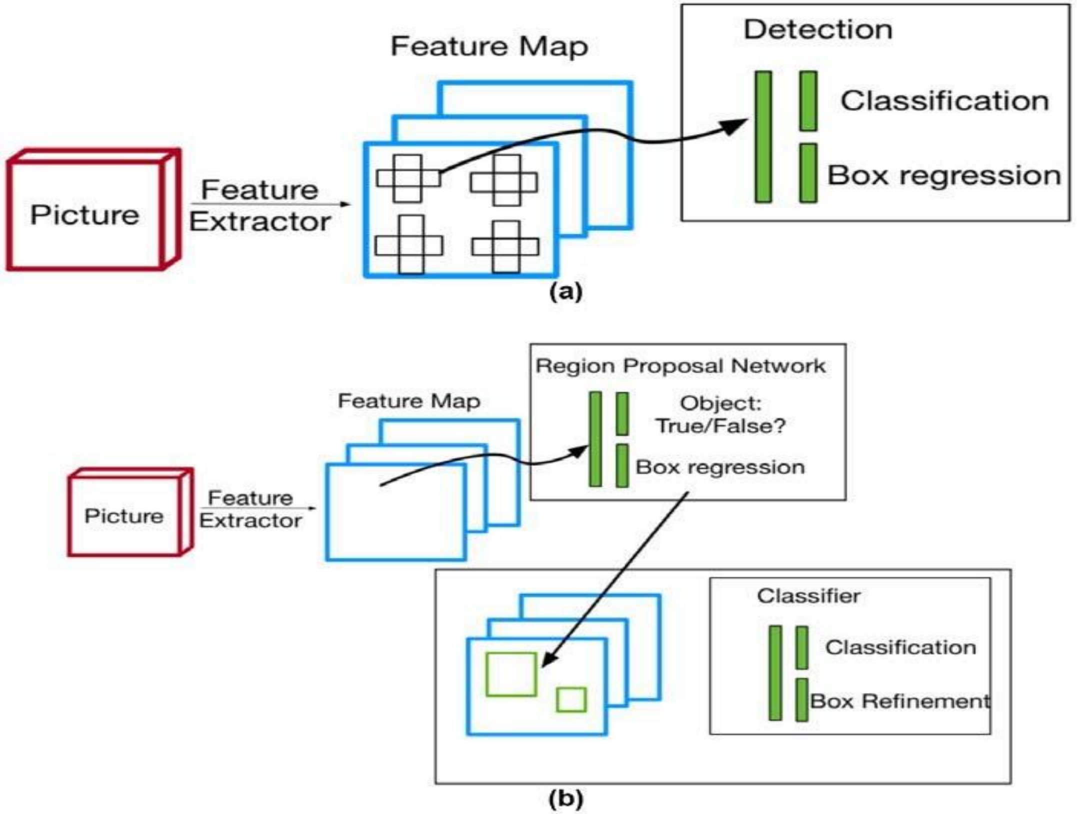
- **Two-stage** detectors: more precise but slower

Most popular one-stage detectors:

- YOLO - SSD - RetinaNet

Most popular two-stage detectors:

- R-CNN - Fast R-CNN - Faster R-CNN
- Mask R-CNN - Cascade R-CNN



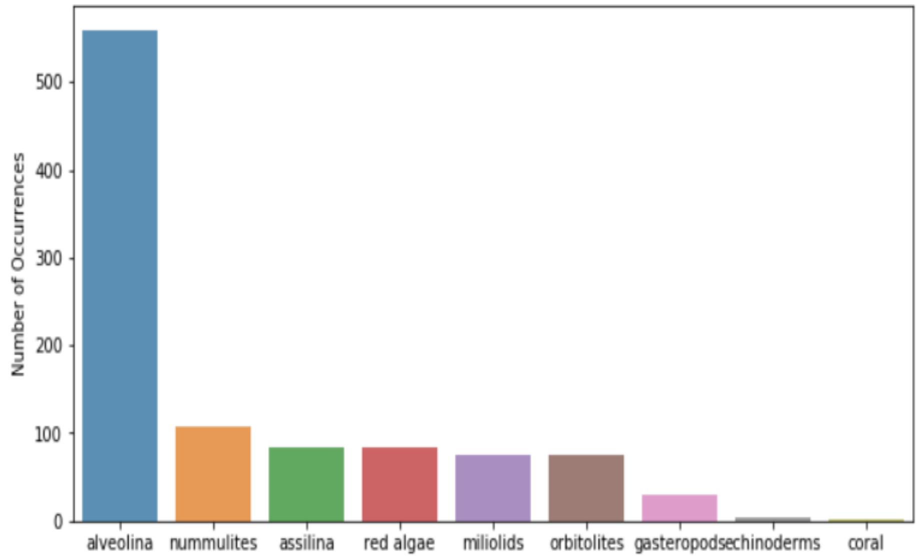
(a) one-stage detector

(b) two-stage detector

ELEMENT DETECTION

Data from carbonate samples

- **145** scanned sections - **9** microfossil families
- **15** annotated (with Microsoft VoTT https://github.com/microsoft/VoTT)
- Highly imbalanced classes
- Use of data augmentation techniques



Four models trained with the annotated sections

- RetinaNet - Faster R-CNN - Mask R-CNN - Cascade R-CNN

Assessment of inference

- **Quantitative on training set:** Average Precision metric
- **Qualitative on test set:** professional geologists
- Average inference time measured for each model

Frameworks: - Detectron2 - Pytorch

https://github.com/facebookresearch/detectron2

https://pytorch.org/

ELEMENT DETECTION

[Koroko *et al.* 2021]

Promising results of Deep Learning models on our business case

Microfossils with high number of occurences in the training set tend to be correctly detected and identified.

One-stage detectors less accurate but faster than two-stage ones

- **Best AP50 model:** Mask R-CNN
- **Best AP75 model:** Cascade R-CNN
- **Slowest model:** Cascade R-CNN
- **Fastest model:** RetinaNet
- **Least accurate model on average:** RetinaNet

Speed differences not so significant in our use case

=> The most accurate models even if slower are recommended

Results to be confirmed on larger datasets

Detector	Precision (AP50)	Precision (AP75)	Inference time (on CPU)
RetinaNet	88.095	87.73	7.10 s / img
Faster R-CNN	94.087	93.07	11 s / img
Mask R-CNN	96.36	86.74	12.43 s / img
Cascade R-CNN	95.60	94.96	12.45 s / img

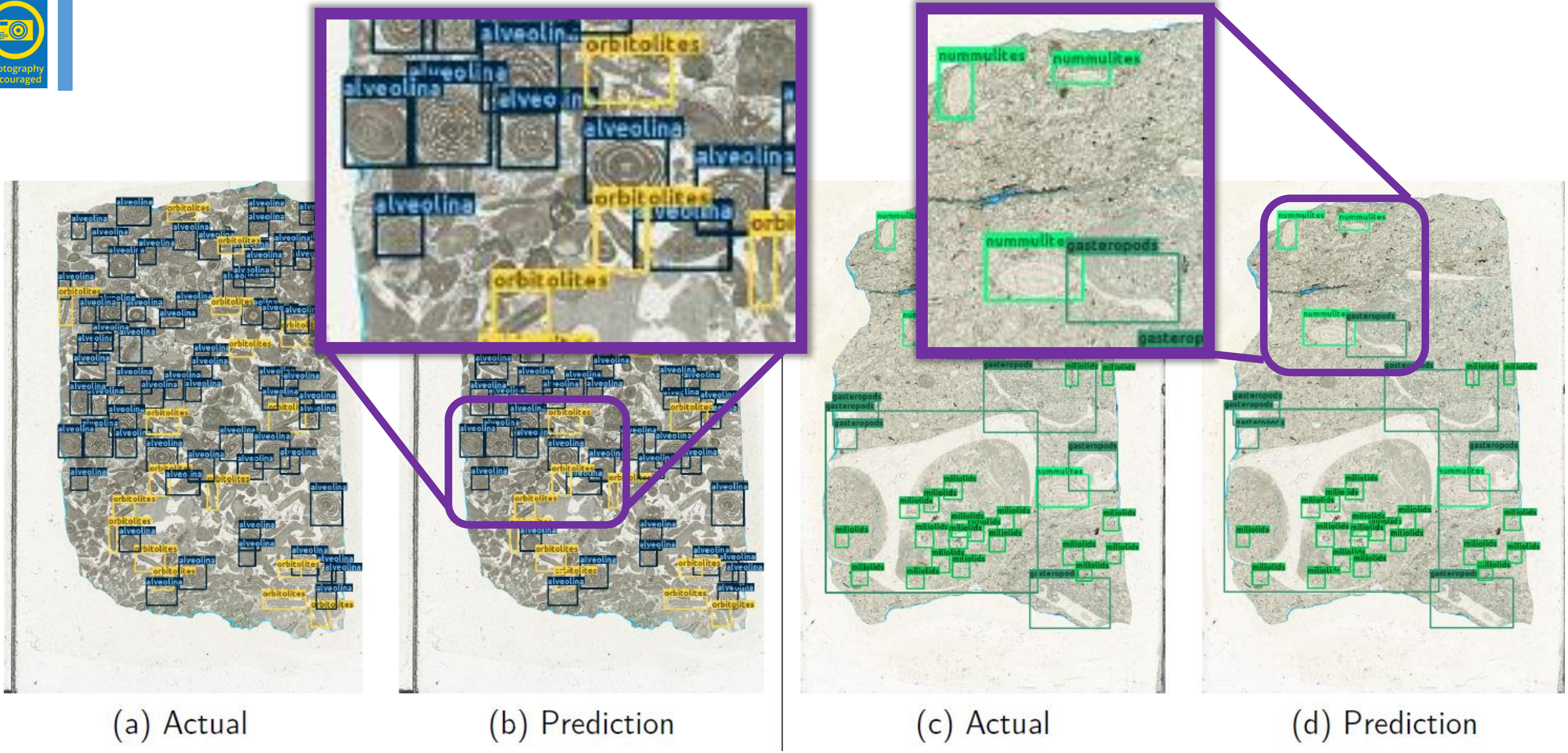
Results of quantitative evaluation of the models on the training data

ELEMENT DETECTION

(a) Actual (b) Prediction (c) Actual (d) Prediction

Some detections from training images with Mask R-CNN

Photography encouraged

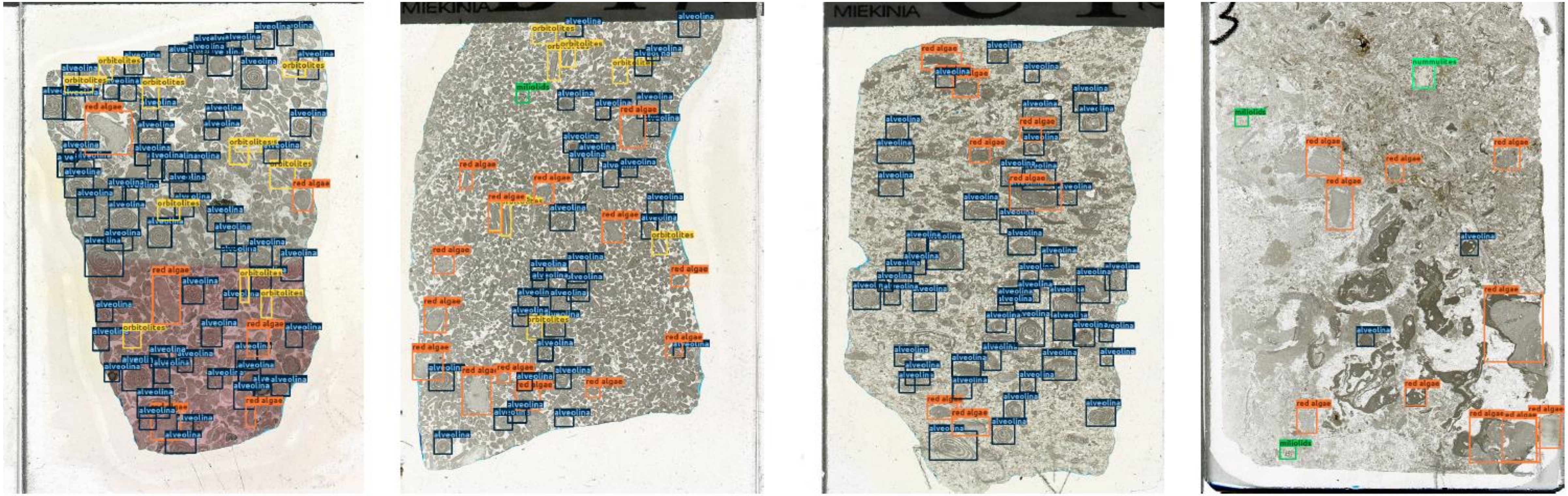


Some detections from training images with Mask R-CNN

Photography encouraged

ELEMENT DETECTION

For all detection models, the results on the test data were evaluated as very satisfactory by geologists



(a) (b) (c) (d)

Some detections from test images with Mask R-CNN

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ELEMENT DETECTION

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(a) (b) (c) (d)

Some detections from test images with Mask R-CNN

CONCLUSIONS & PERSPECTIVES

Promising results using Deep Learning for rock images analysis

Close collaboration between geologists and data scientists

Technologies yet to be integrated in **operational mining processes**

- Stimulating R&D opportunities
- Interest in industrial and academic partnerships
- TELLUS consortium

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Thanks for your attention!

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