Deep learning methods for analyzing the mineral composition of reservoir rocks according to energy contrast µCT

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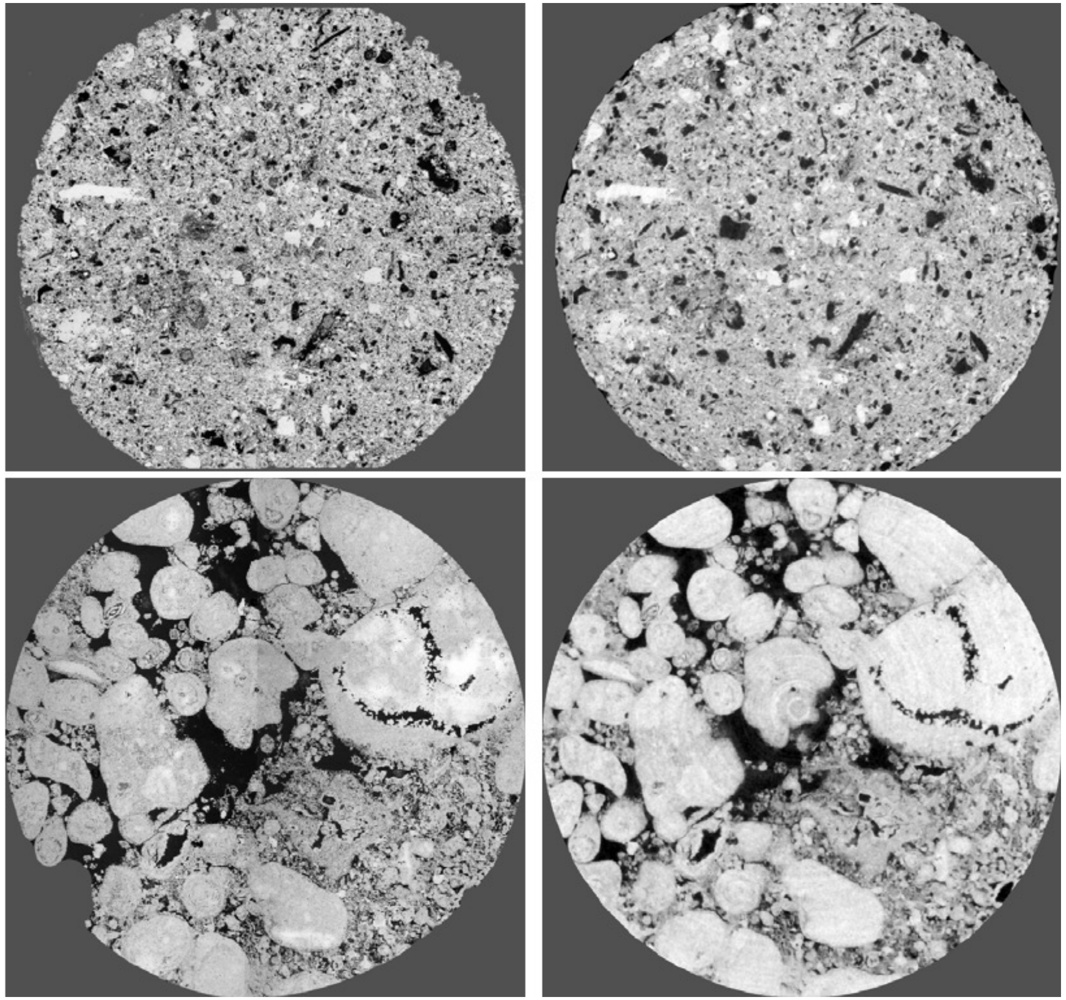
Part I. Current progress

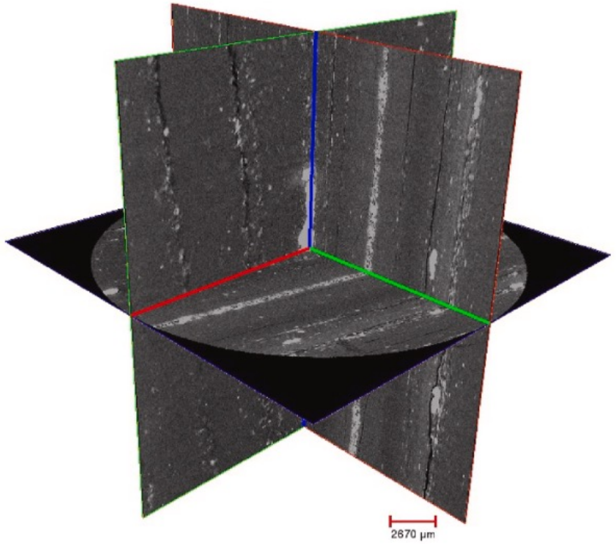
Purposes:

1. Investigation of the applicability of μCT images obtained at two different tomograph energies as input data of a deep learning model for solving the problem of mineral mapping.
2. Compare the results of predicting a model trained on two images obtained at two different energies of the tomograph with the results of predicting a model trained only on images obtained at one energy of the tomograph.

Computer tomography (CT)

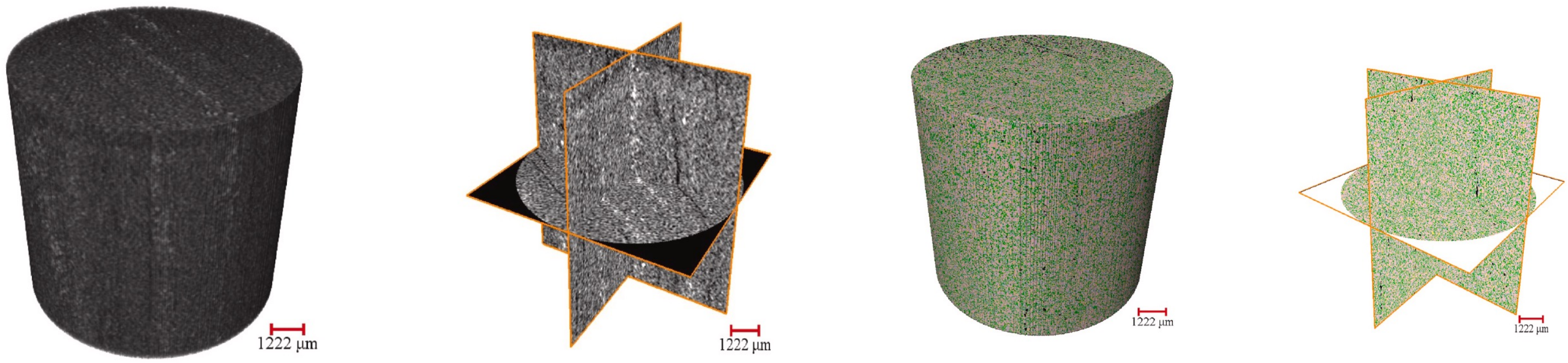


X–ray tomography is an innovative and promising direction in the study of the properties of rocks. Core analysis on a special tomograph is based on the analysis of differences in rock density, mineral inclusions, cracks and voids, reservoir fluids.



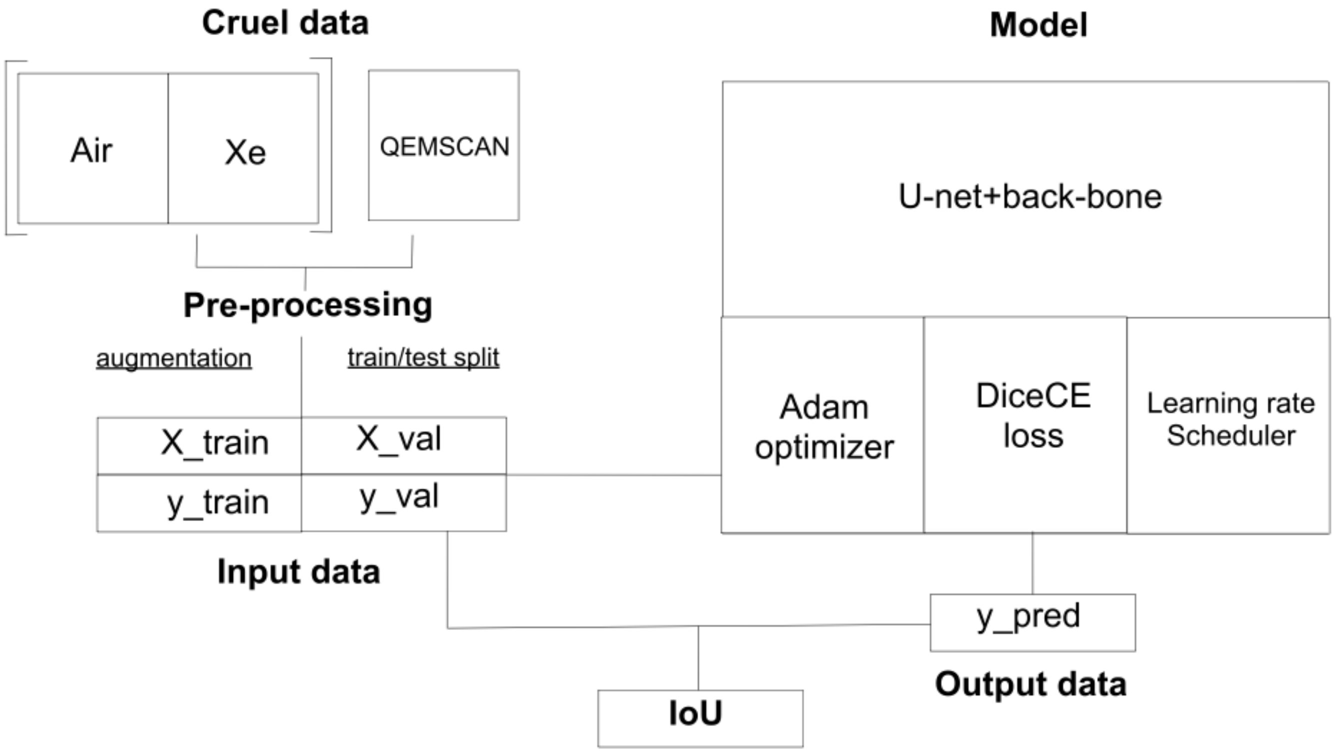
Bingke Li, X U-Net model for multi-component digital rock modeling of shales based on CT and QEMSCAN images
https://doi.org/10.1016/j.petrol.2022.110734.

QEMSCAN technology



QEMSCAN allows you to automatically identify minerals and the desired mineral phases by comparing the information obtained from secondary X-rays with an extensive library of minerals.

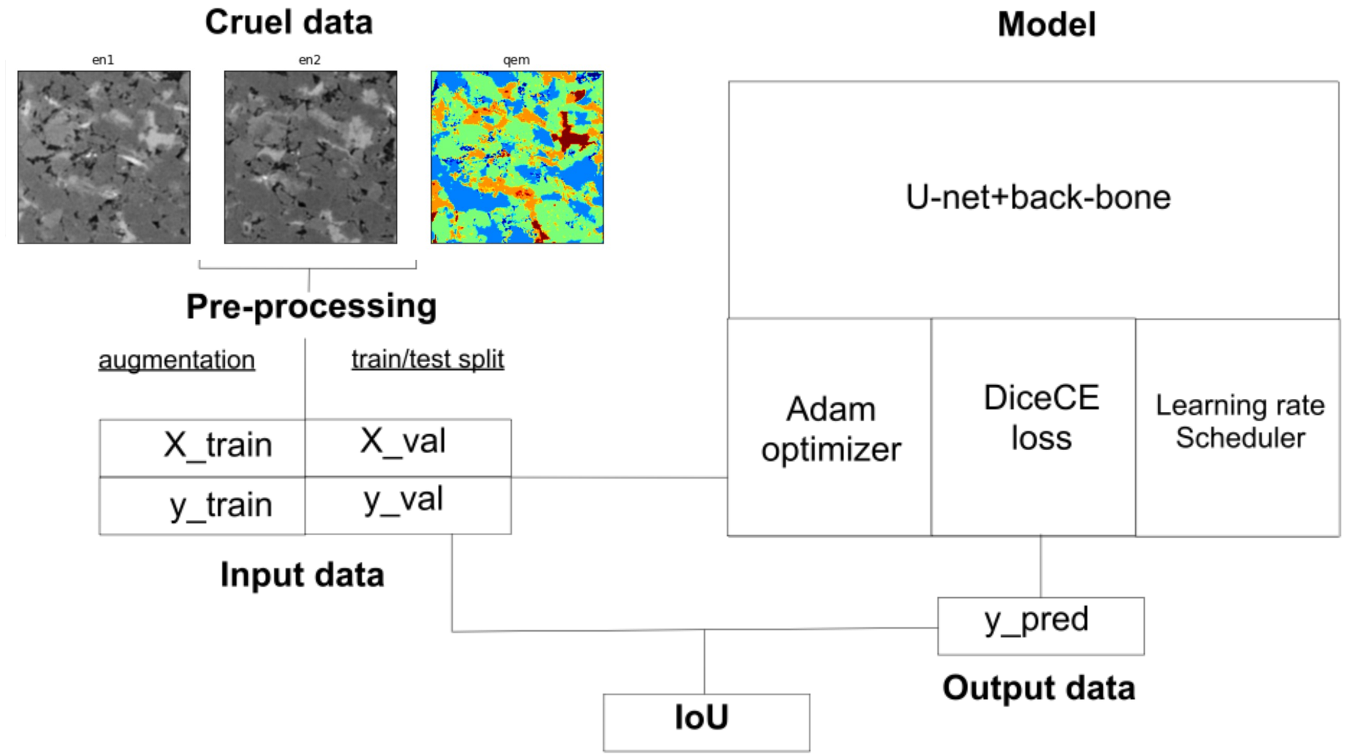
U-net for mapping air and xenon minerals



The results on mapping minerals using U-net

Model	Pores	Quartz	Albilite	Clay
Unet+inceptionv3	0.63	0.58	0.45	0.44

U-net for mapping minerals of two energies



Models:

- ResNet-50;
- ResNet-18;
- Inception-v4.
- Efficient-b4;
- Efficient-b0;

Model components:

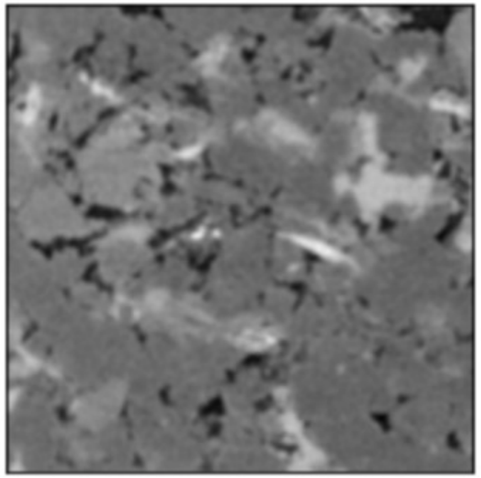
- Adam (optimizer)
- FocalDice – loss function;
- Cosine Annealing Learning Rate

Input data

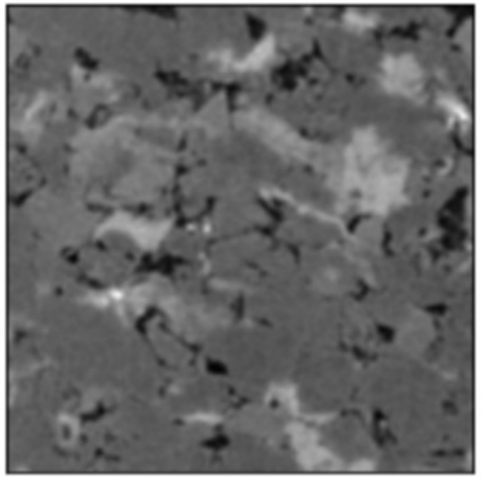
Two different mKT images with different values of the energy of the µCT scanner are used as initial data: 120 kV and 80 kV.

For our purposes, we use cultures with a size of 256×256 pixels from a single slice of the Achimov sandstone deposits of 3mkm MKKT-shooting and after the separation operation there are :

en1



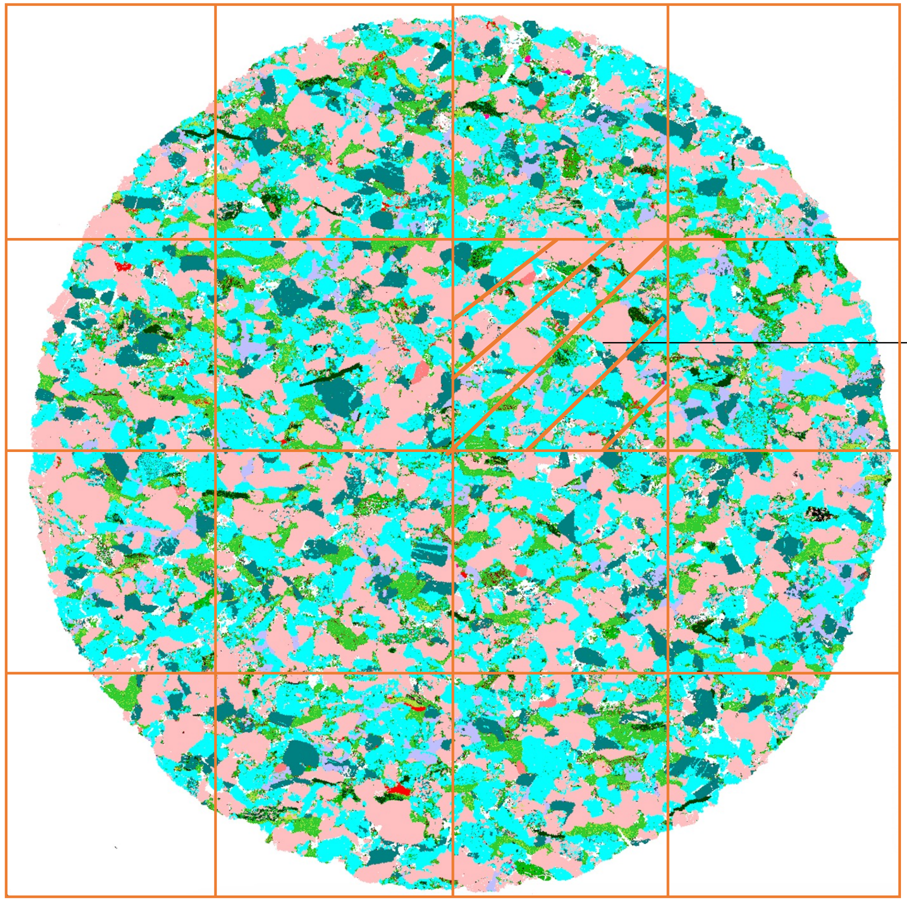
en2

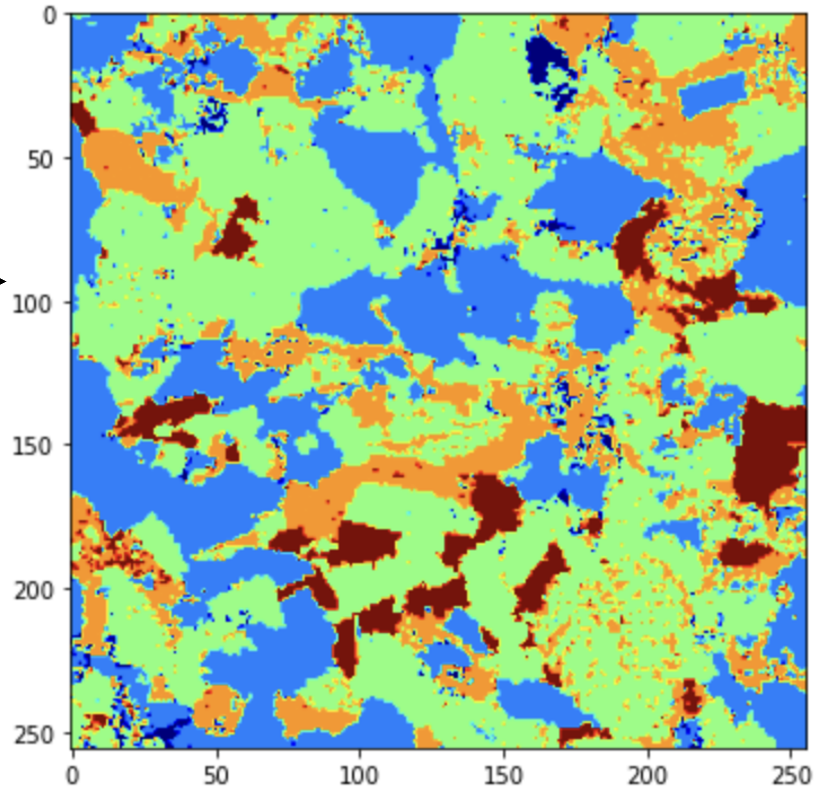


- 21 samples for training;

- 9 samples for validation.

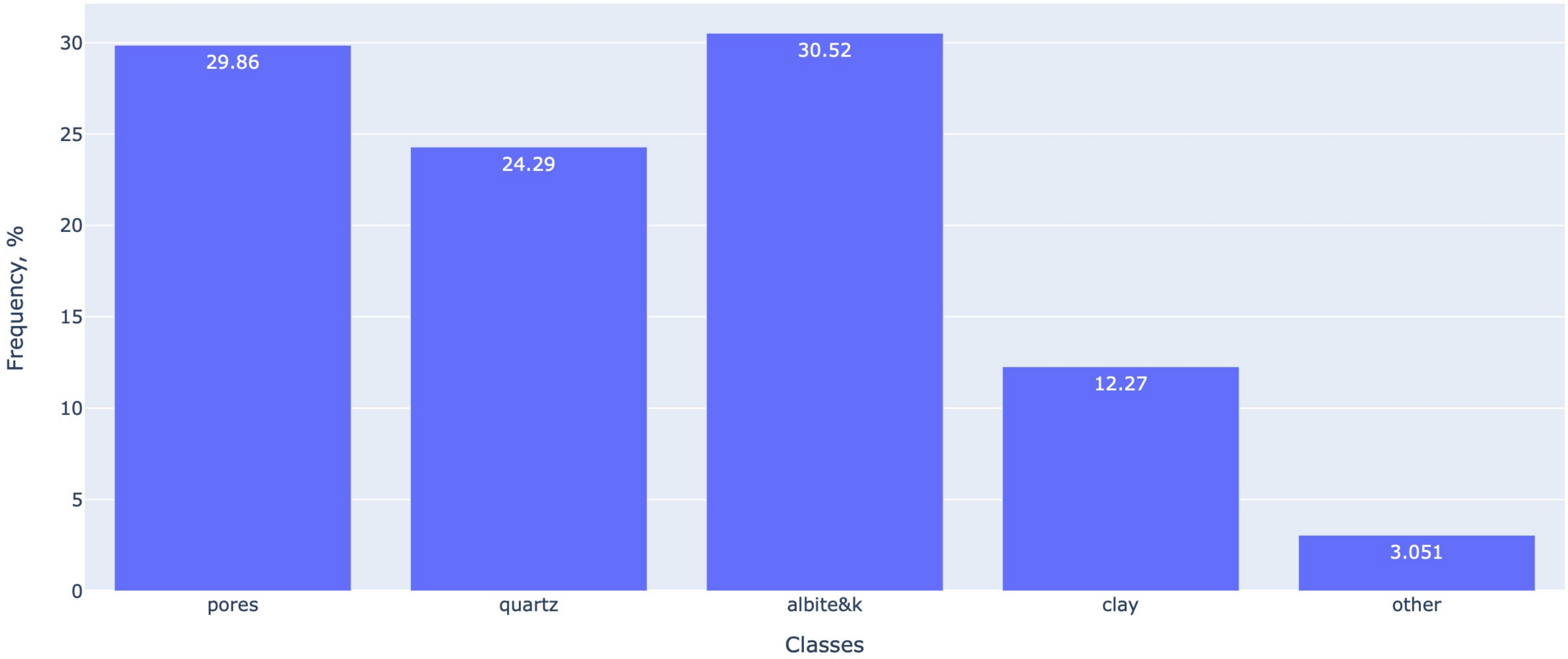
Targets for NN model





indigo – pores, blue – quartz, green – albilite , orange – clay, red – other.

Class distribution in the source data according to QEMSCAN data



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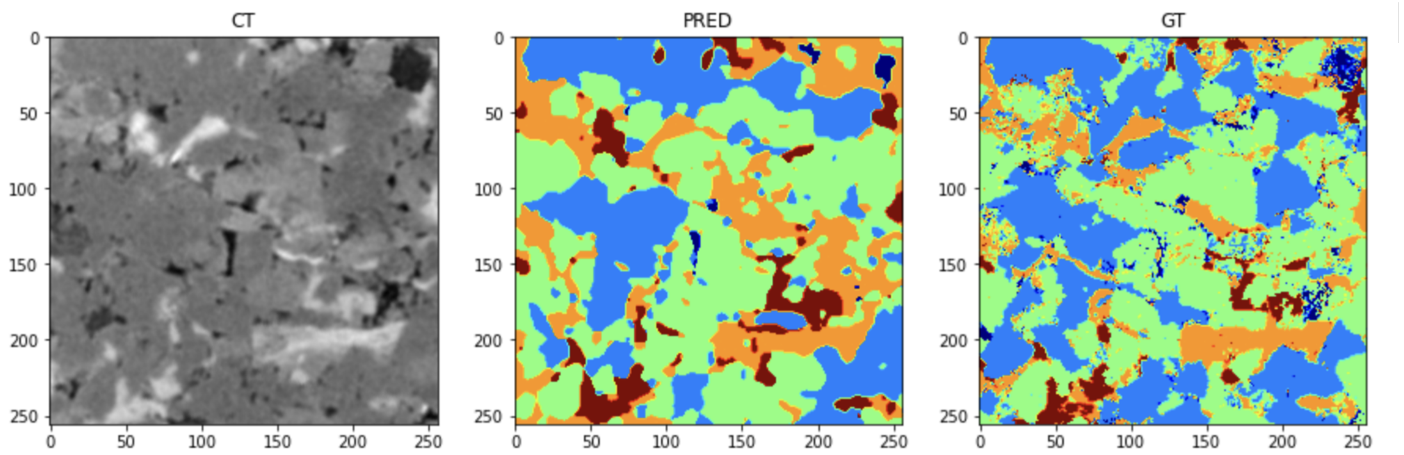
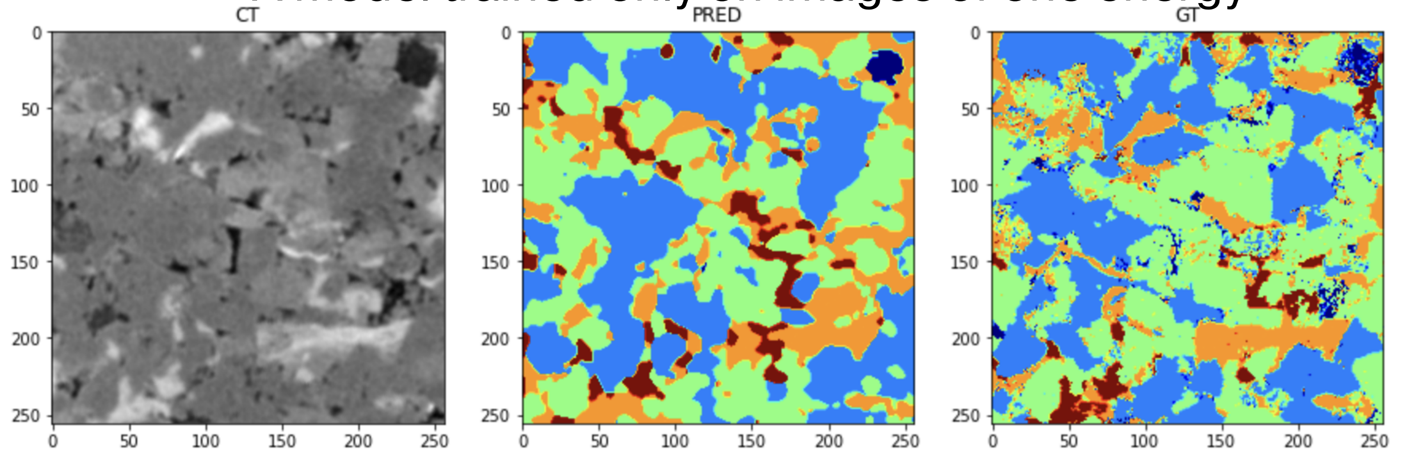
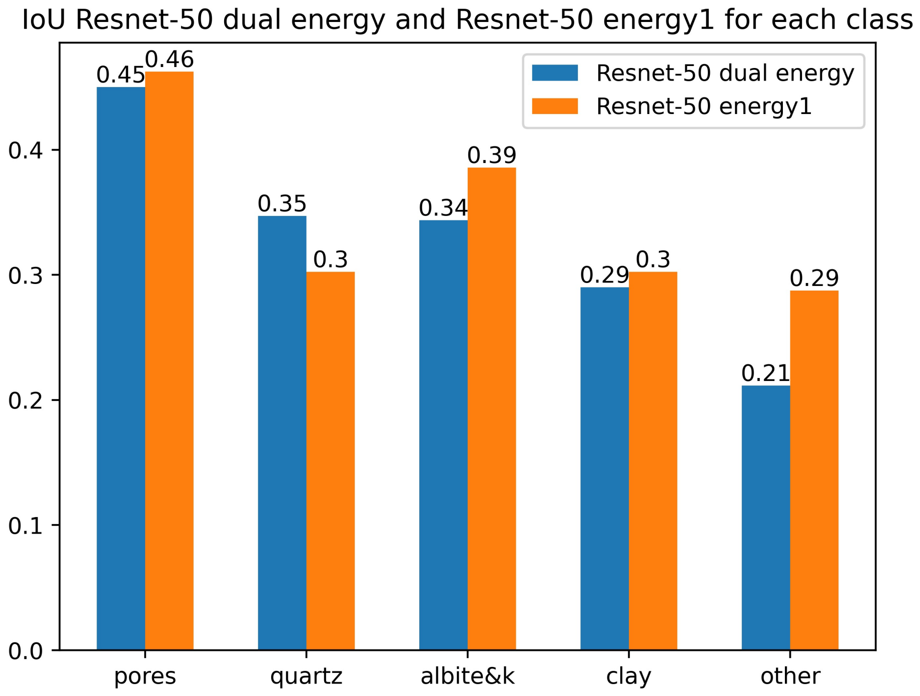
Unet+ResNet-50



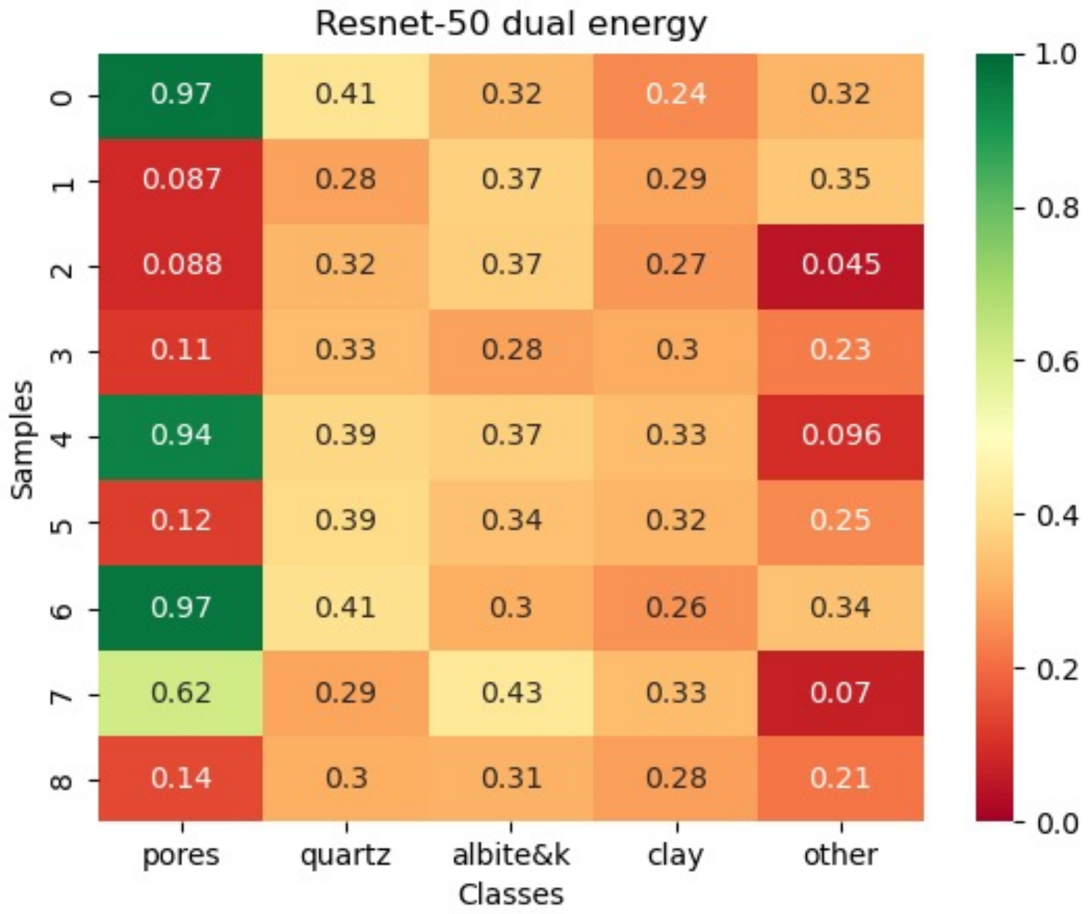
A model trained only on images of one energy

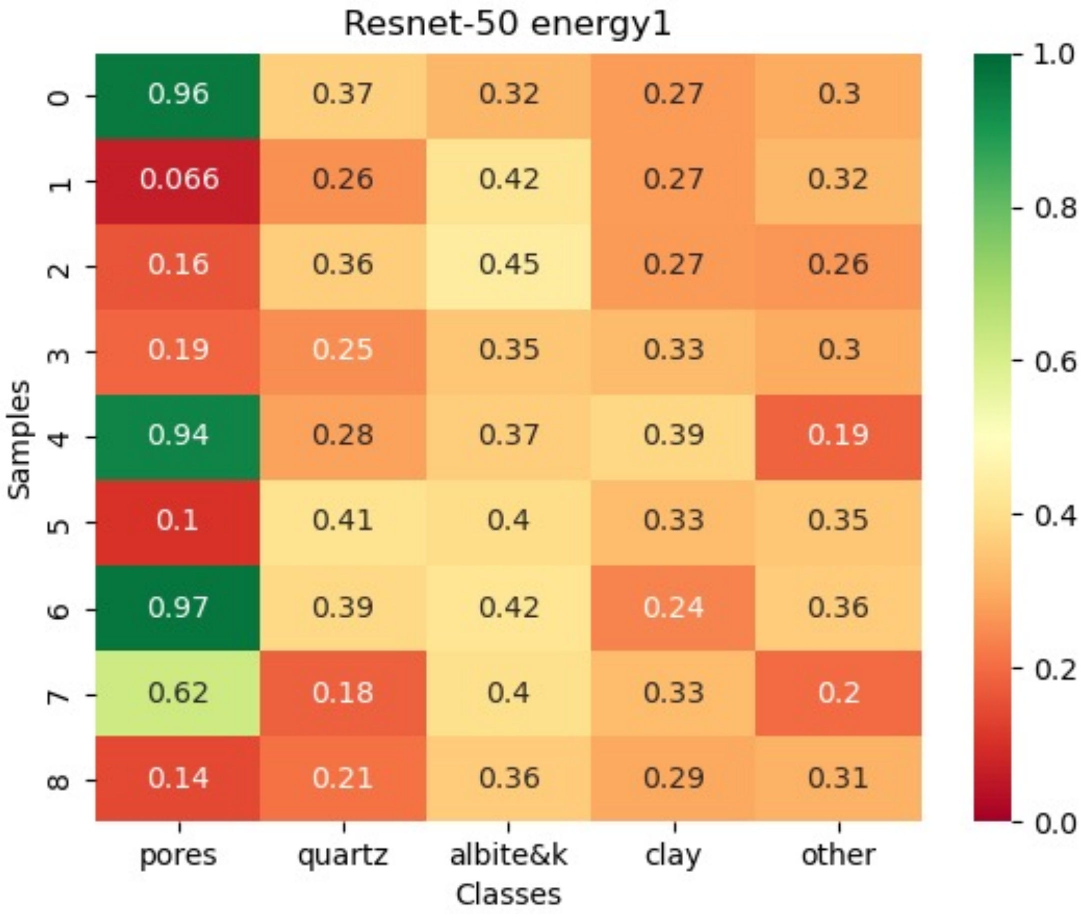


A model trained on images of two energies

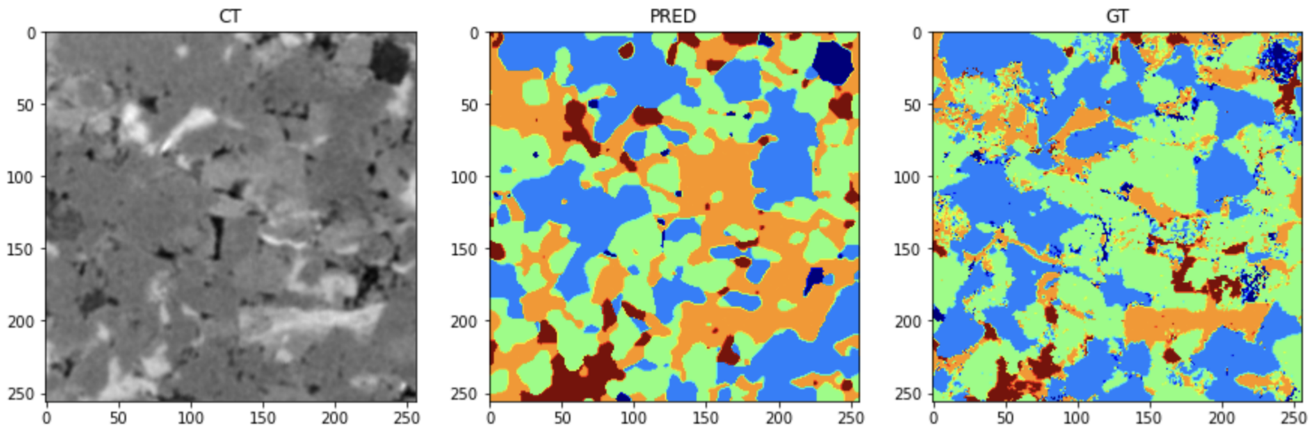


Unet+ResNet-50

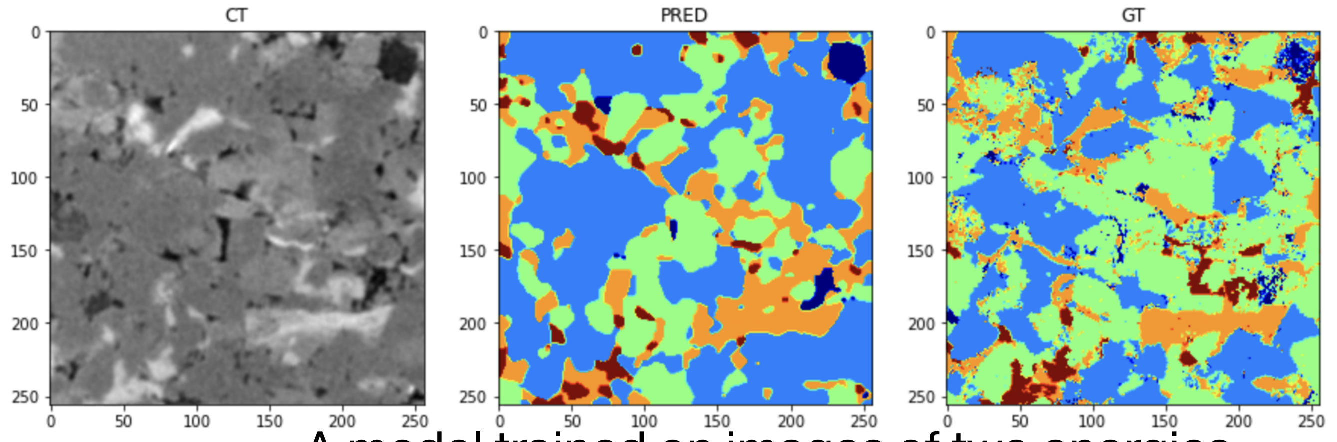




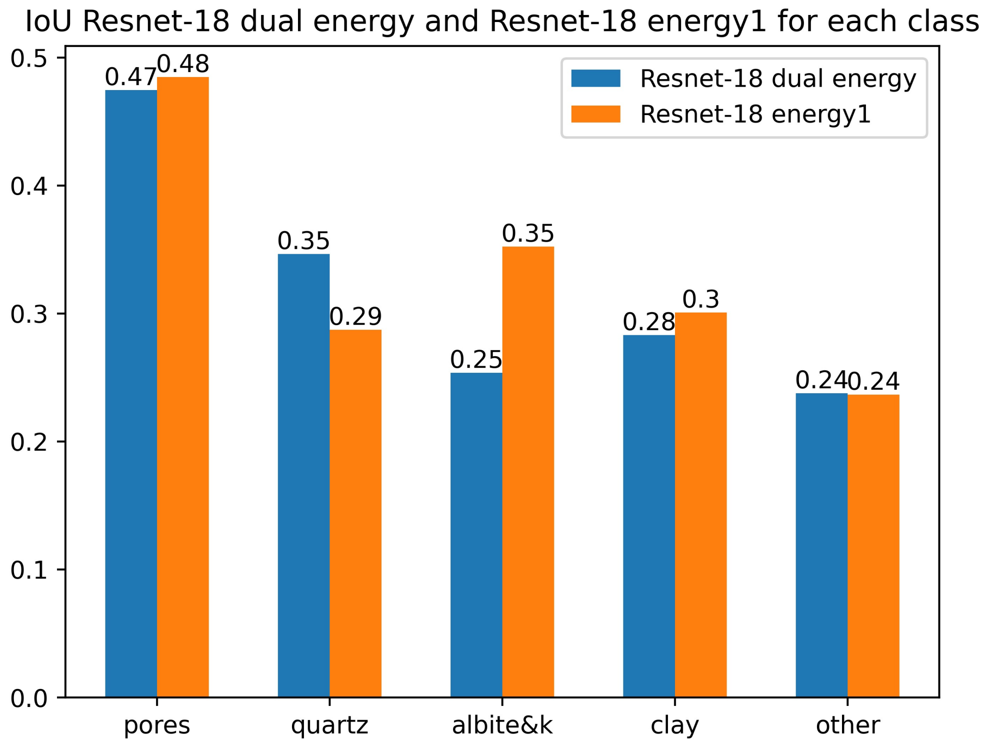
Unet+ResNet-18



A model trained only on images of one energy



A model trained on images of two energies



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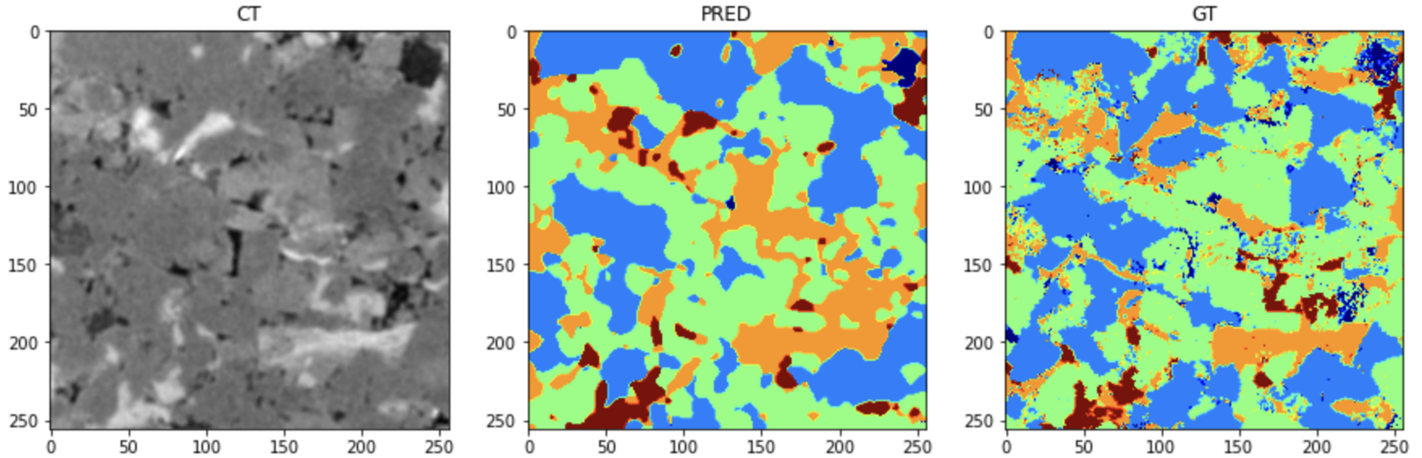
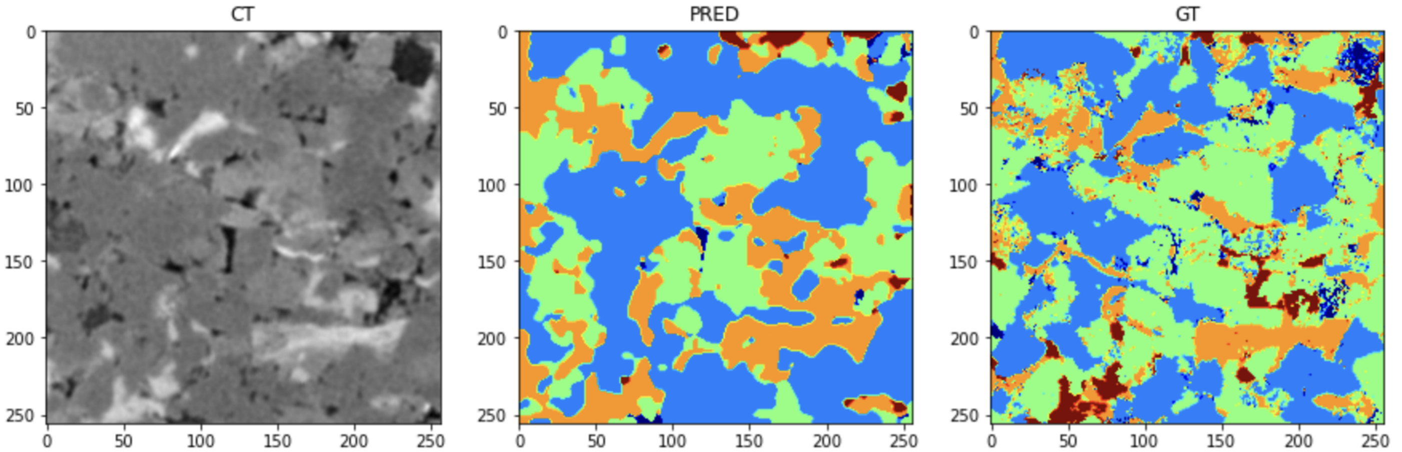
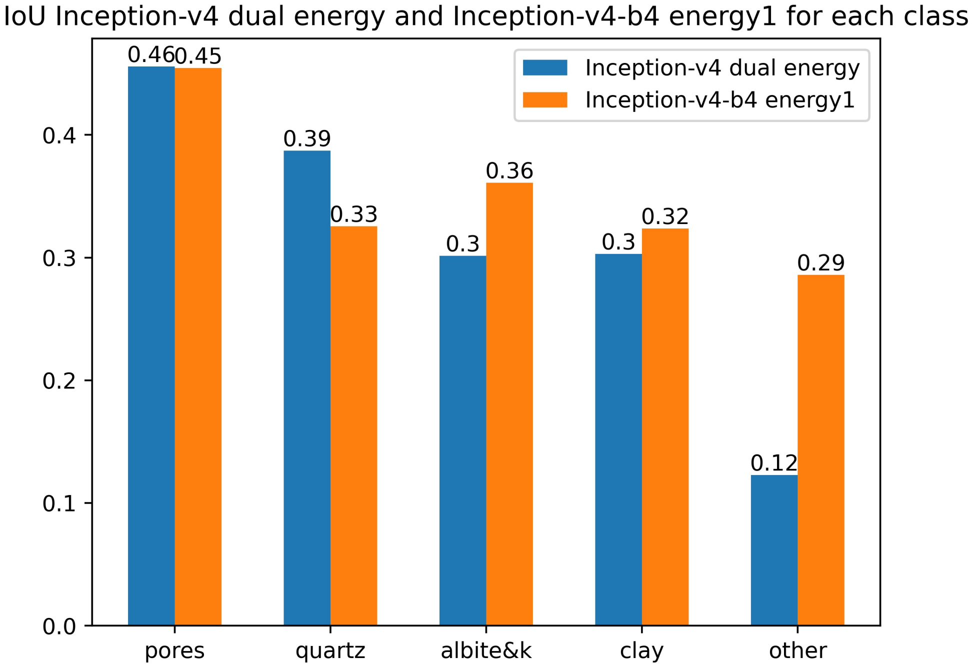
Unet + Inception-v4



A model trained only on images of one energy



A model trained on images of two energies



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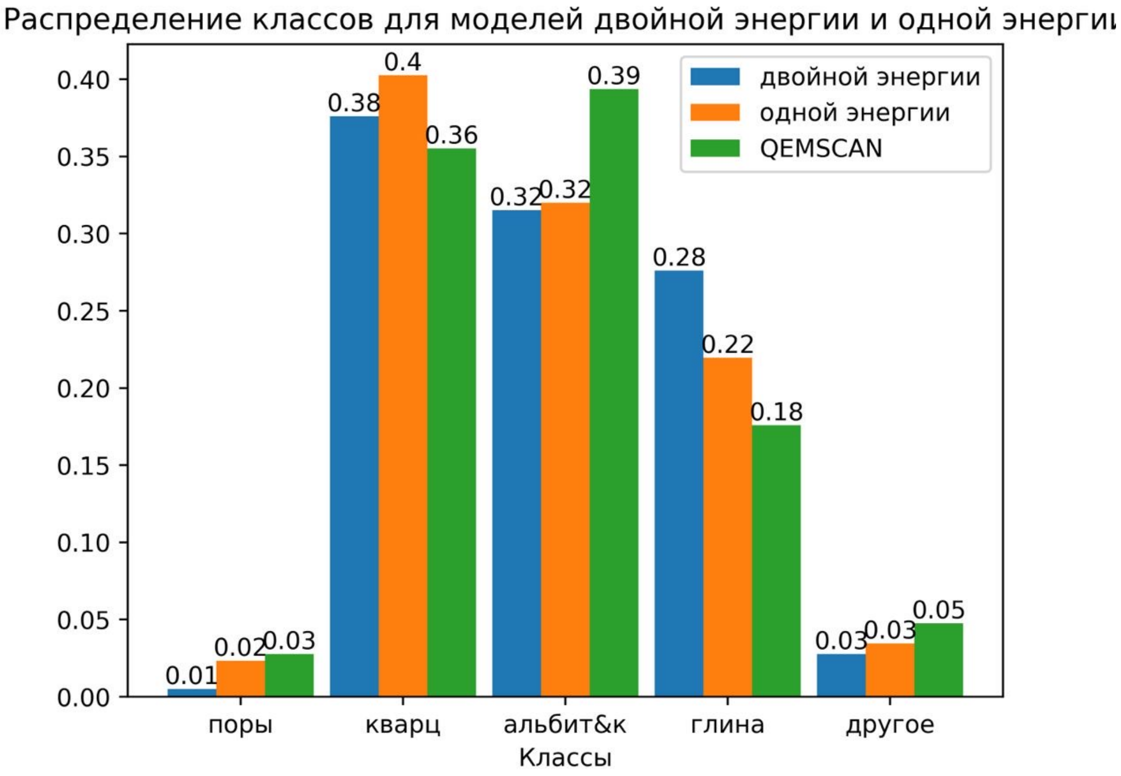
Summary table of different results and class distribution for predictions of double and single energy models

Model	Pores	Quartz	Albilite	Clay	Other
ResNet-50	0,45	0,35	0,34	0,29	0,21
ResNet-50	**0,46**	**0,3**	**0,39**	**0,3**	**0,29**
ResNet-18	0,47	0,35	0,25	0,28	0,24
ResNet-18	0,48	0,29	0,35	0,3	0,24
EfficientNet-b0	0,4	0,32	0,36	0,27	0,23
EfficientNet-b0	0,43	0,33	0,36	0,27	0,34
EfficientNet-b4	0,44	0,36	0,33	0,31	0,17
EfficientNet-b4	**0,5**	**0,35**	**0,34**	**0,32**	**0,2**
Inception-v4	0,46	**0,39**	0,3	0,3	0,12
Inception-v4	0,45	0,33	0,36	0,32	0,29



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Conclusions

1. The problem of image segmentation with the help of µCT images obtained at two radiation energies of the tomograph was investigated.
2. Ten neural networks were trained on different inputs and on different back-bone models.
3. It was found that in the case of pattern recognition, not all models increase their result when switching from a more complex model to a simpler one (for ResNet with two energies, the result increases, for EfficientNet it decreases).
4. In all cases, on a small set of training data from a single slice, a model trained on only one energy value recognizes classes better than a model trained on images obtained at two radiation energies of a tomograph.
5. Some minerals, such as quartz, were better recognized by a model trained on images obtained at two different radiation energies of the tomograph.
6. To confirm the hypothesis that double-energy models simply do not have enough data to determine the models of various minerals, further research is needed on a larger data set and a larger number of input images obtained at different radiation energies.

References

[1] V. V. Alekseev, D. M. Orlov, and D. A. Koroteev, “Multi-Mineral Segmentation of SEM Images Using Deep Learning Techniques,” in Day 3 Thu, October 14, 2021, Virtual, Oct. 2021, p. D031S017R004. doi: 10.2118/206526-MS.

[2] D. P. Kingma and J. Ba, “Adam: A Method for Stochastic Optimization,” 2014, doi: 10.48550/ARXIV.1412.6980.

[3] T.-Y. Lin, P. Goyal, R. Girshick, K. He, and P. Dollá r, “Focal Loss for Dense Object Detection,” 2017, doi: 10.48550/ARXIV.1708.02002.

[4] O. Ronneberger, P. Fischer, и T. Brox, «U-Net: Convolutional Networks for Biomedical Image Segmentation», 2015, doi: 10.48550/ARXIV.1505.04597.

[5] Knappett, C., Pirrie, D., Power, M.R., Nikolakopoulou, I., Hilditch, J., Rollinson, G.K. 2005. Mineralogical analysis and provenancing of ancient ce- ramics using automated SEM-EDS analysis (QEMSCAN): A pilot study on LB I pottery from Akrotiri, Thera. Journal of Archaeological Science, in press doi:10.1016/j.jas.2010.08.022

Part II. Next steps

Further research

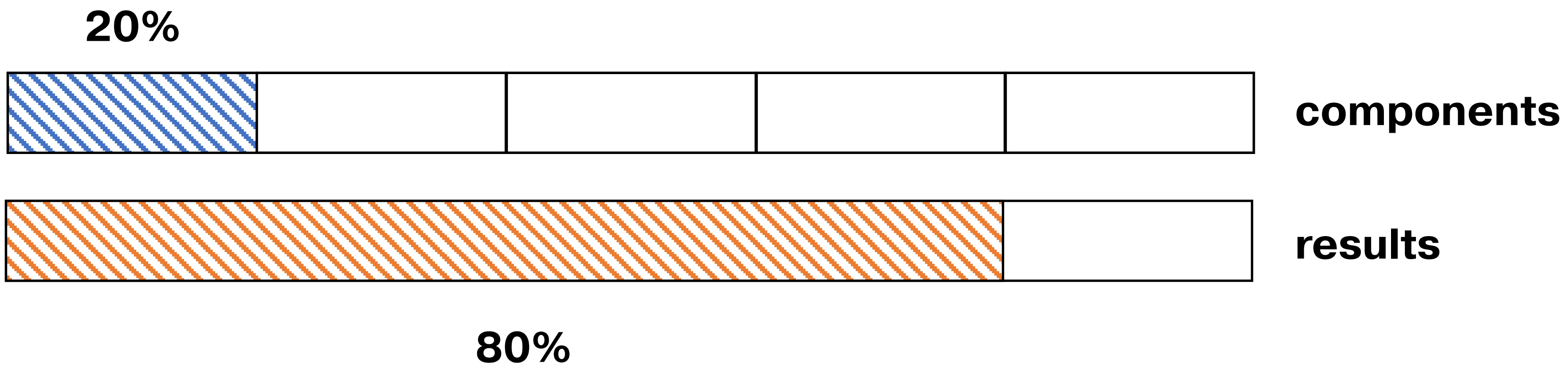
1. Increasing the data set by using more QEMSCAN samples per core.
2. Using more energy as input.
3. Using QEMSCAN data from other core samples.
4. Introduction of a physical informed loss function with a preliminary study of the physical model of the absorption of X-ray radiation by minerals.
5. Using a different neural network architecture, for example, generative-adversarial neural networks (GAN).

Conference feedback

1. Kolmogorov neural network (according to Priezhev I. articles).
2. Geochemical analysis.
3. Artificial model of the rock core.
4. Using non-neural network approach.

The most significant factor in this research is data

According to the Pareto rule:



data-factor

amount

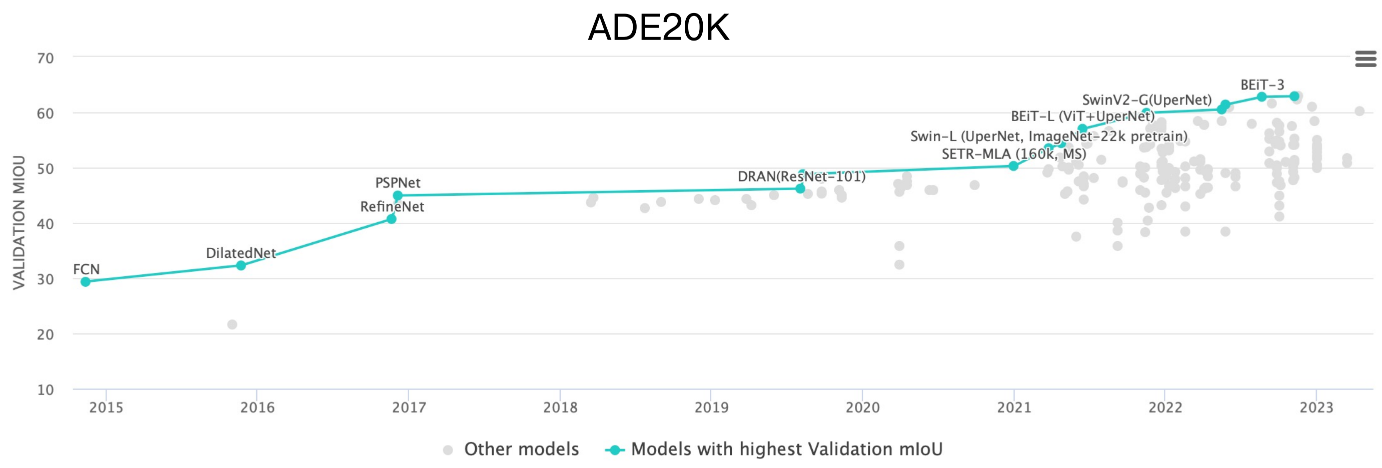
collection,
augmentation

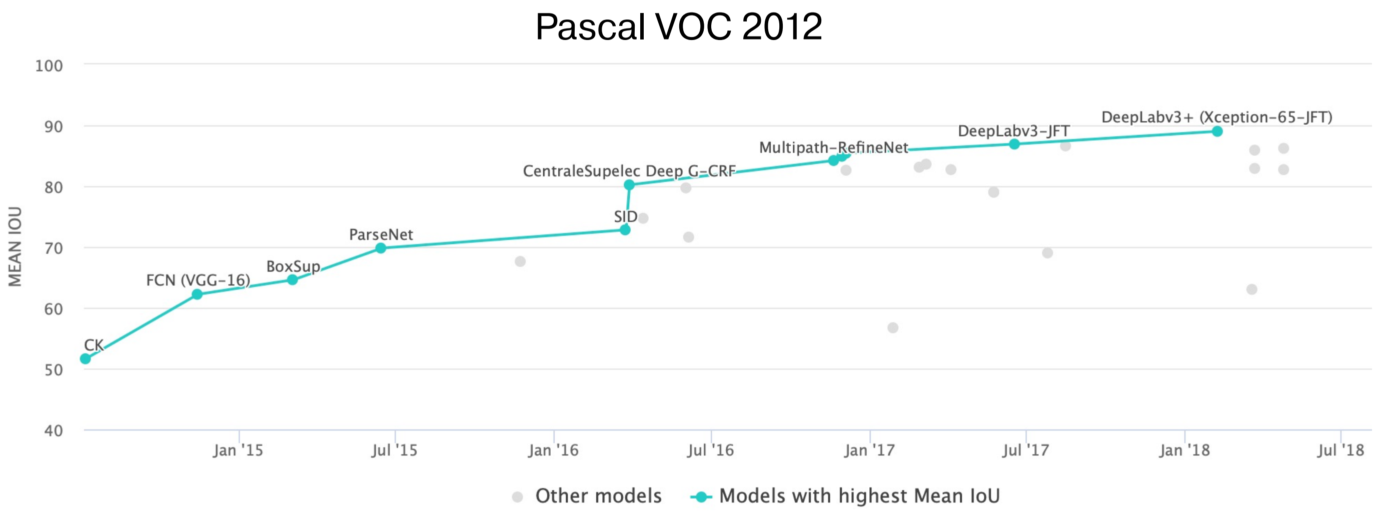
quality

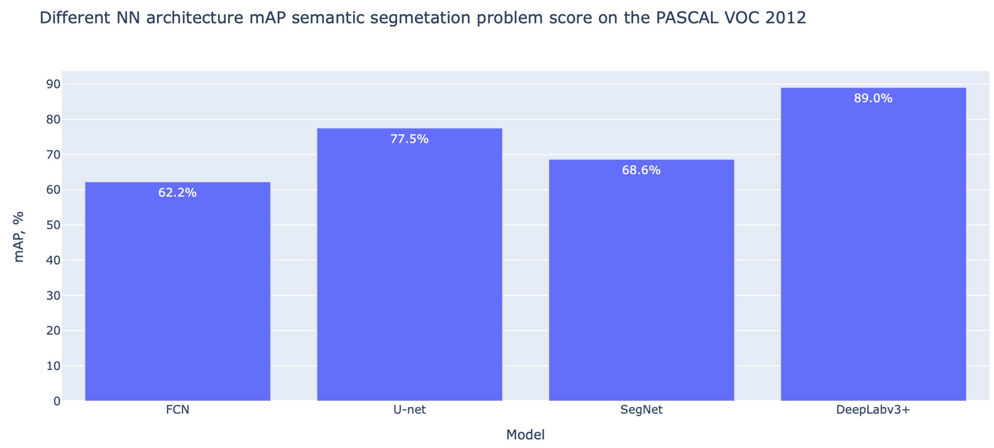
pre-processing,
registration

1. Increasing the data set by using more QEMSCAN samples per core.
2. Using more energy as input.
3. Using QEMSCAN data from other core samples.

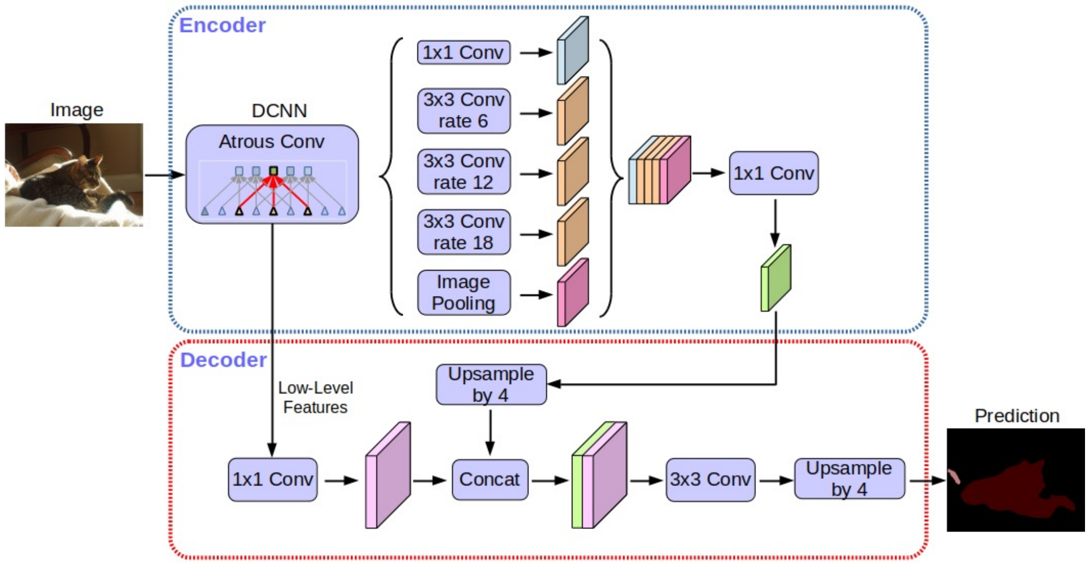
Neural network architecture







DeepLab v3+ architecture



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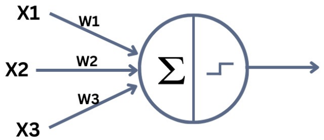
https://paperswithcode.com/task/semantic-segmentation

https://ai.googleblog.com/2018/03/semantic-image-segmentation-with.html

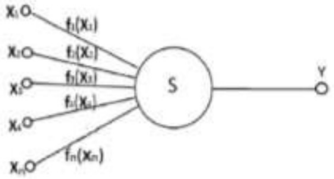
Kolmogorov neural network

Conventional neuron

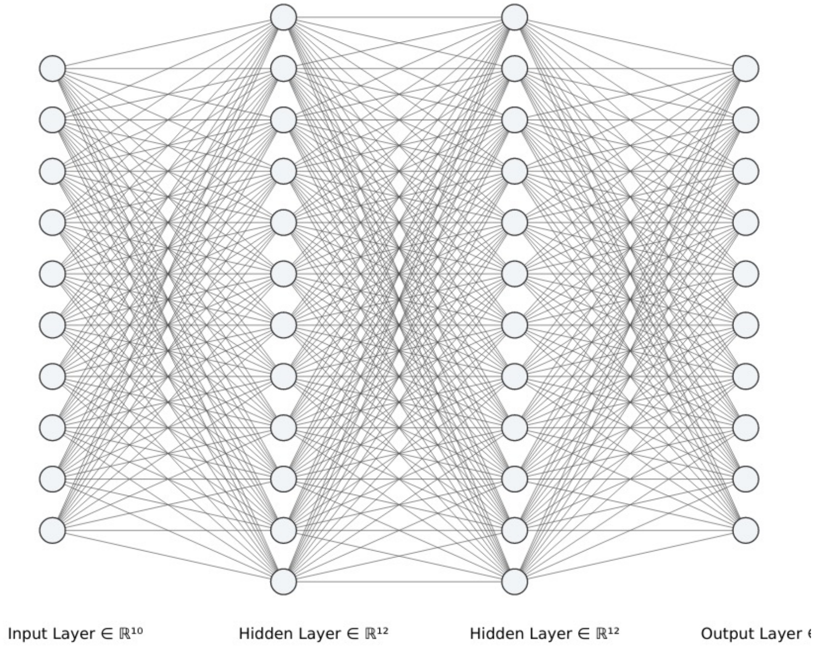


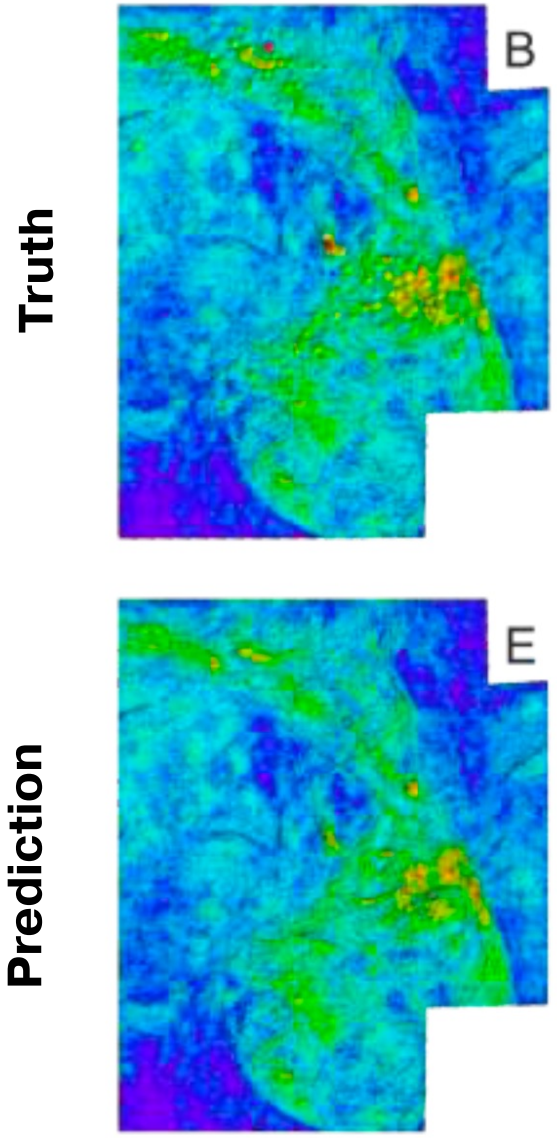
$$y = \sigma\left(\sum_{i=0}^{n} w_i x_i + b\right)$$

Kolmogorov neuron



$$y = \sum_{i=0}^{n} f_i(x_i)$$





The scheme of the tabular assignment of a function in a fully functional Kolmogorov neuron

x_1	x_2	x_3	x_4	x_5	...	x_n
y_1	y_2	y_3	y_4	y_5	...	y_n

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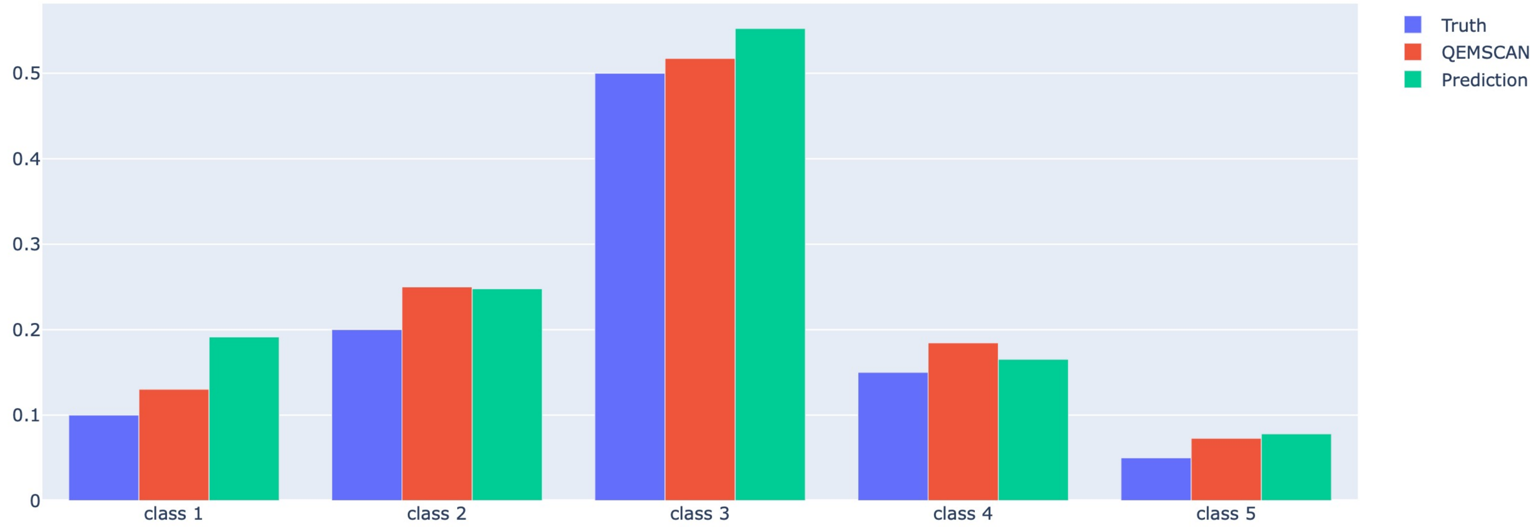
Geochemical analysis



Non-neural network approach

> *So, while you could potentially use CatBoost or XGBoost for semantic segmentation, it may not be the most efficient or effective solution. I would recommend exploring deep learning-based methods instead.*
>
> **ChatGPT**

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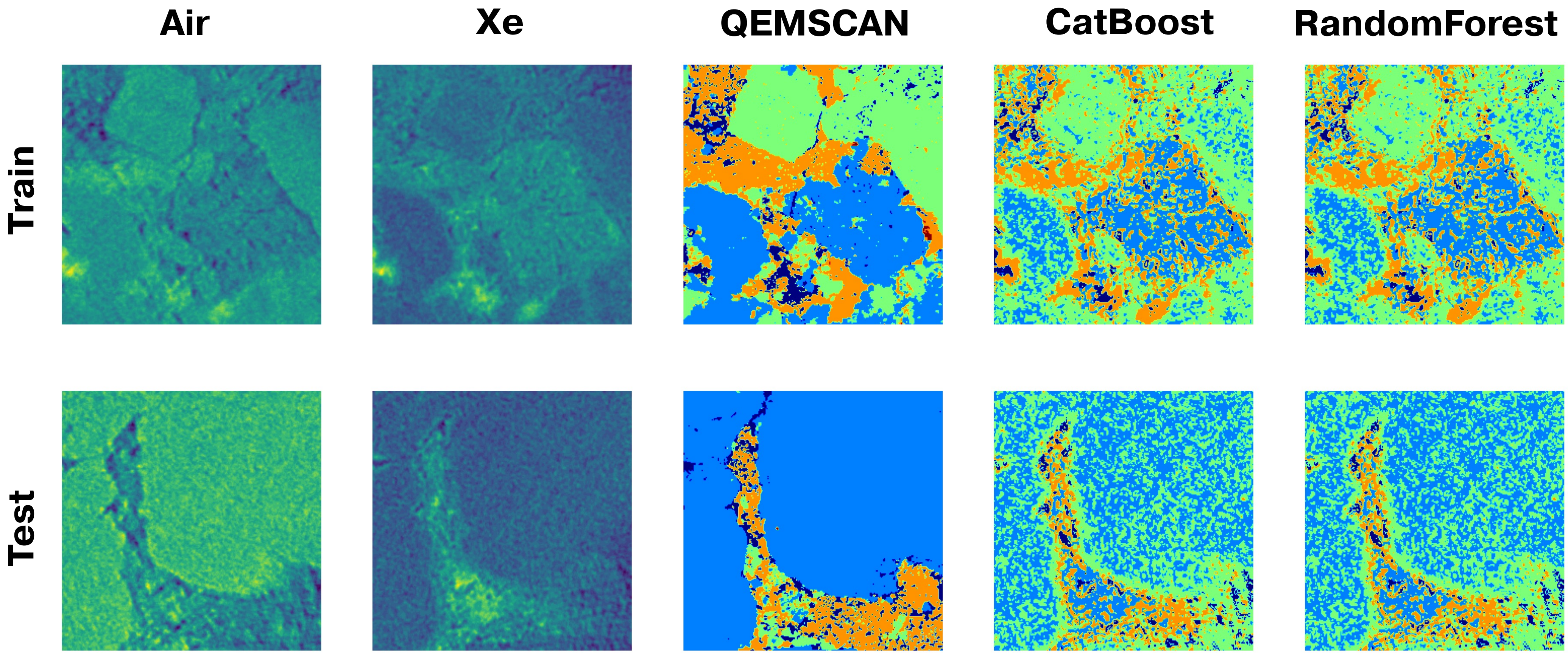
Non-neural network approach



Accuracy:
56.2% - train
48.5% - test

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56.2% - train
48.5% - test

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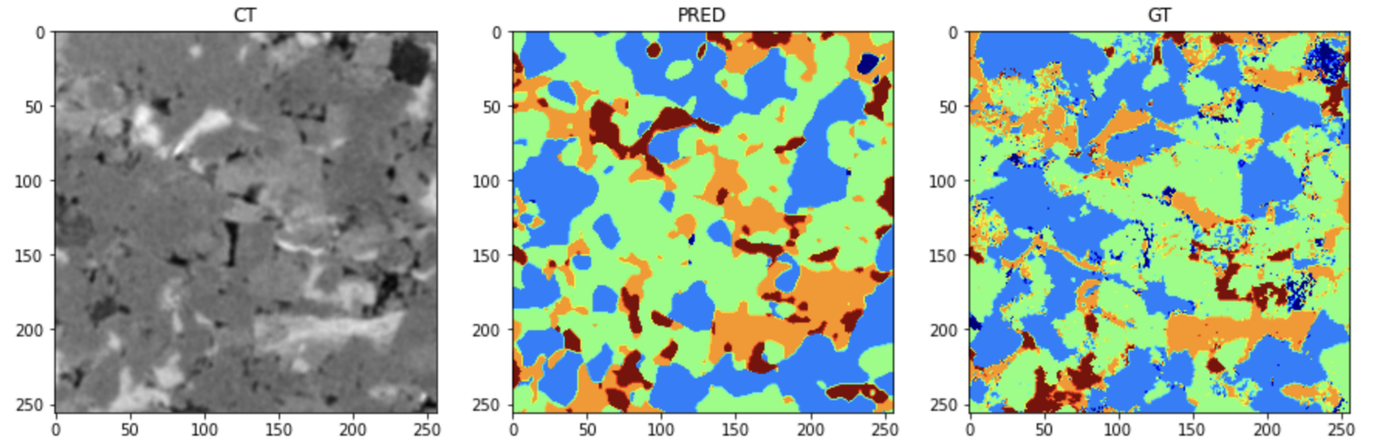
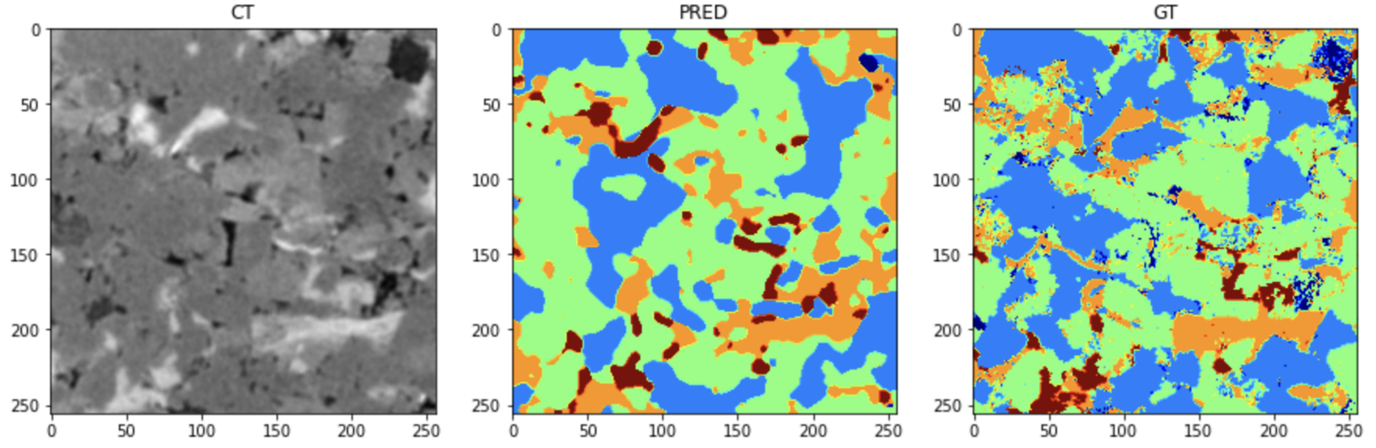
References

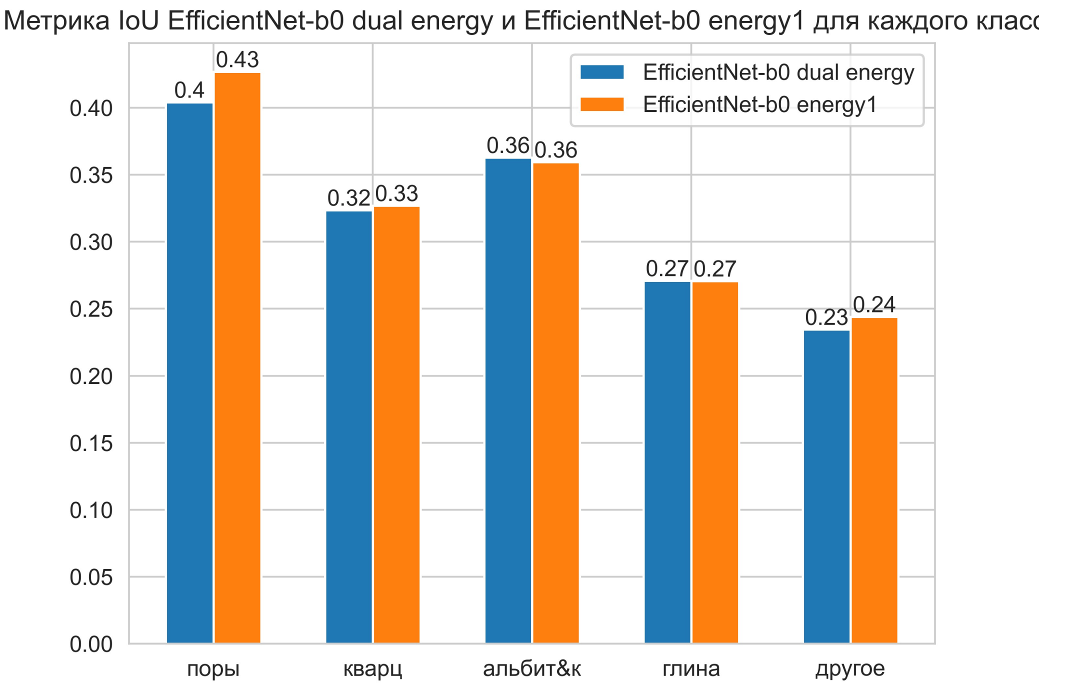
[1] Priezhev, I. I. Application of new generation neural networks based on fully functional Kolmogorov neurons for reservoir prediction / I. I. Priezhev, D. A. Danko // GeoEurasia-2021. Geological Exploration in Modern Realities : Proceedings of the IV International Geological and Geophysical Conference and Exhibition, Moscow, 02-04 March 2021 / GeoEurasia LLC. Volume II. – Tver: LLC"PoliPRESS", 2021. – pp. 168-172. – EDN CTFWOU.

Extra slides

Unet + EfficientNet-b0







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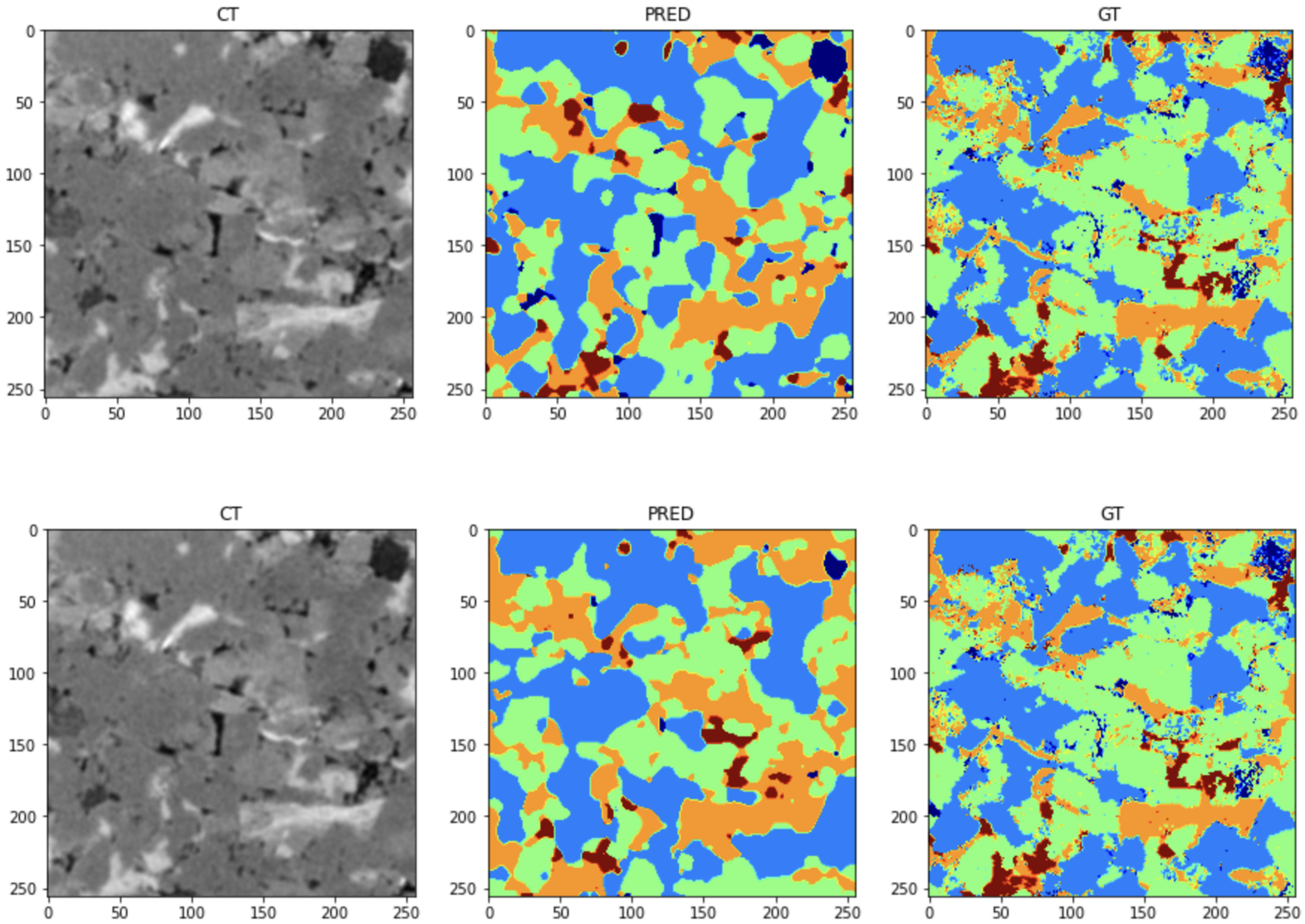
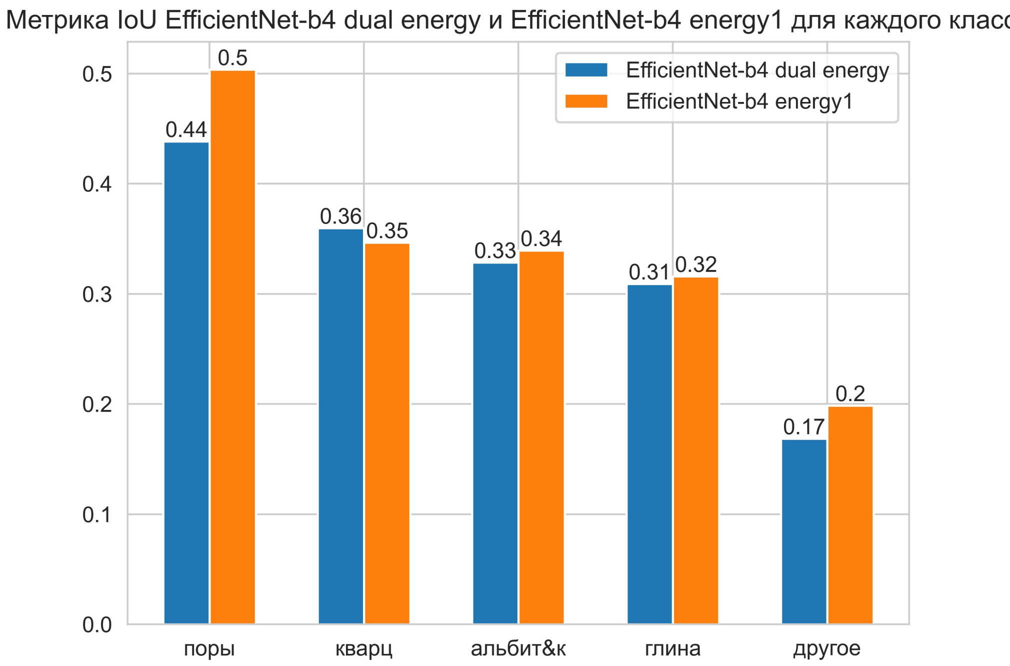
Unet + EfficientNet-b4





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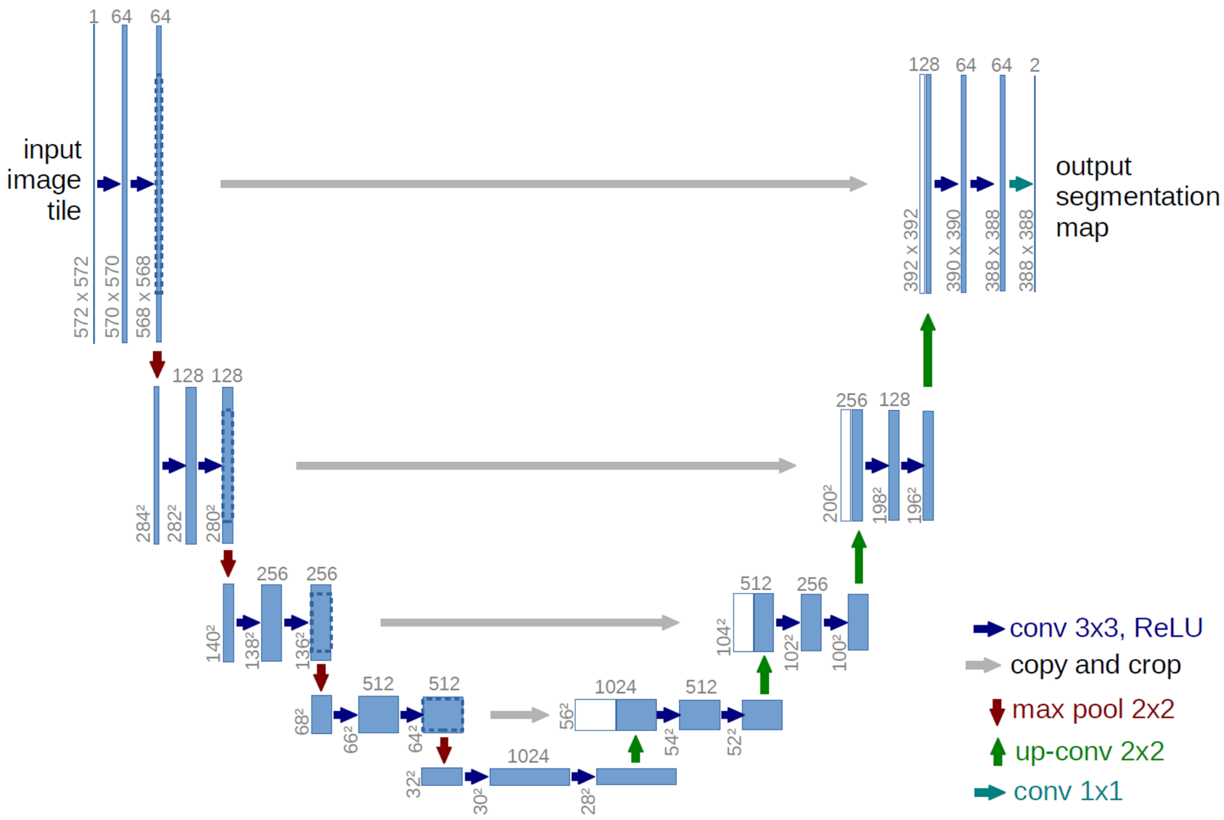
Basic terms

U-net is fully convolution neural network network using for image segmentation problem. It is combination of encoder network and followed by decoder network. Encoders if convolution with 3x3 kernel and ReLU-function. Technically, in this research U-net used such as convolution algorithm with black-bone ResNet-50.



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Basic terms

Augmentation is a method of increasing training data with modification original training data copies (horizontal flip, vertical flip, rotation by some small angle and others).

Adam optimizer is an optimization algorithm which combines the advantages of RMSProp and SGD with Momentum to adaptively adjust the learning rate. It is suitable for non-stationary objectives and problems that have noisy or sparse gradients. It's show himself well for segmentation image problem.

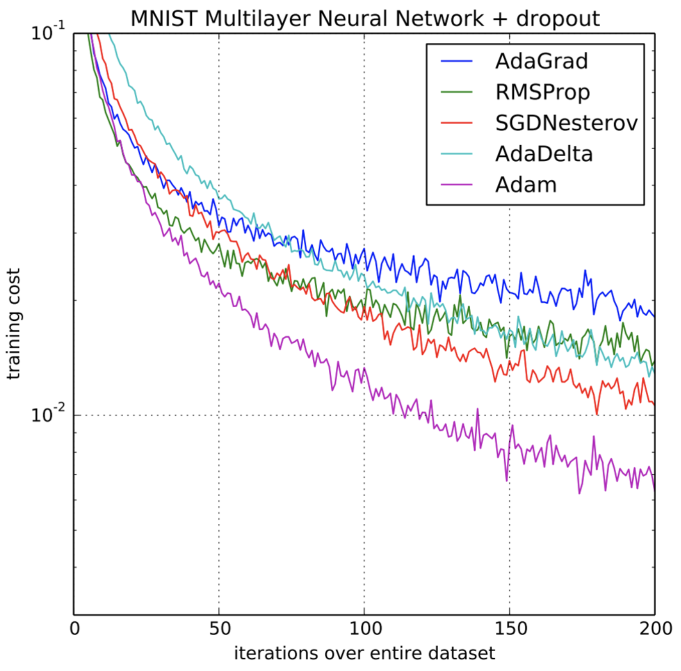
$$\theta_t = \theta_{t-1} - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}$$

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}$$

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t}$$

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t$$

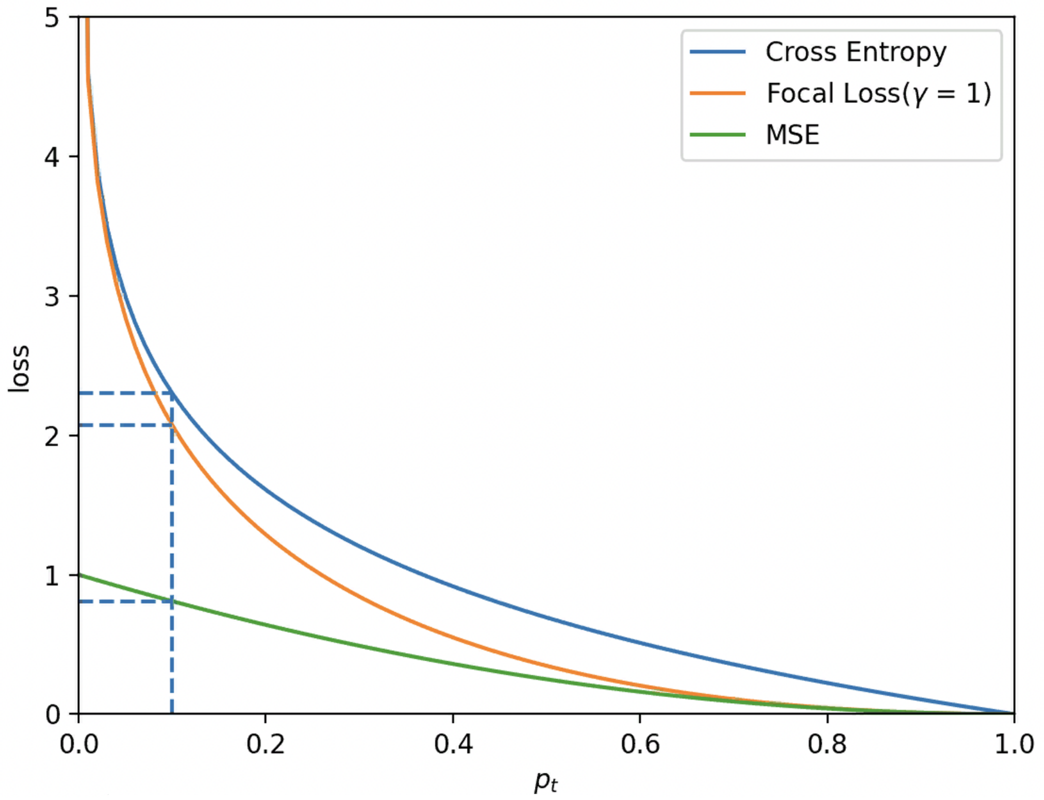


Basic terms

Cross-entropy loss, or **log loss,** measures the performance of a classification model whose output is a probability value between 0 and 1. Cross-entropy loss increases as the predicted probability diverges from the actual label. So predicting a probability of .012 when the actual observation label is 1 would be bad and result in a high loss value. A perfect model would have a log loss of 0.

Focal loss is a option of cross-entropy loss function modification, which can control value of penalty with γ-modulating parameter with tuning $\gamma \geqslant 0$. It used in Deep Learning, because in same points Cross-Entropy has bigger value of derivartion as compared to cross-entropy loss function

Loss function comparing



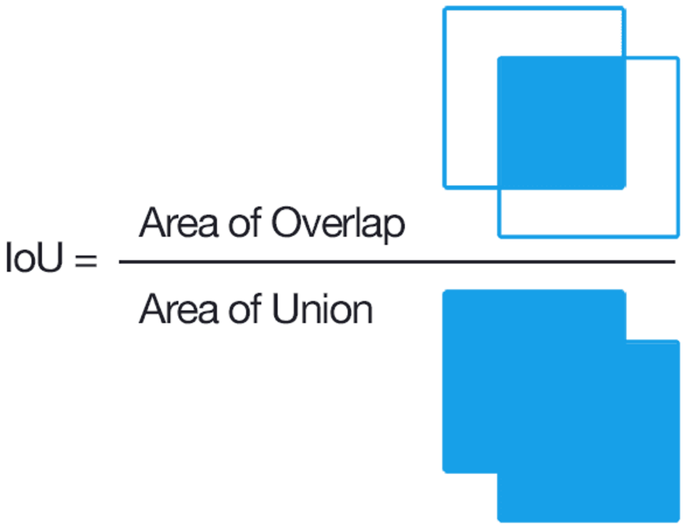
$$\mathrm{FL}(p_t) = -(1-p_t)^{\gamma}\log(p_t) \qquad \mathrm{CE}(p_t) = -\log(p_t)$$

Basic terms

The Intersection-Over-Union(Jaccard Index) is an evaluation metric used to measure the accuracy of an object detector on a particular dataset and it is relation between area of overlap labeled image and predicted image and area of union of these two.

$$\mathrm{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP} + \mathrm{FN}}$$

where TP - true positive, FP - false positive, FN - false negative.



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Augmentation

Augmentation included following operations:

- Horizontal flip with probabillity 0.5;
- Vertical flip with probabillity 0.5;
- Random rotate by 90 degrees with probabillity 0.5;
- Transpose with probabillity 0.5;
- Rotation by some angle(limit=30 degress) with probabillity 0.3.