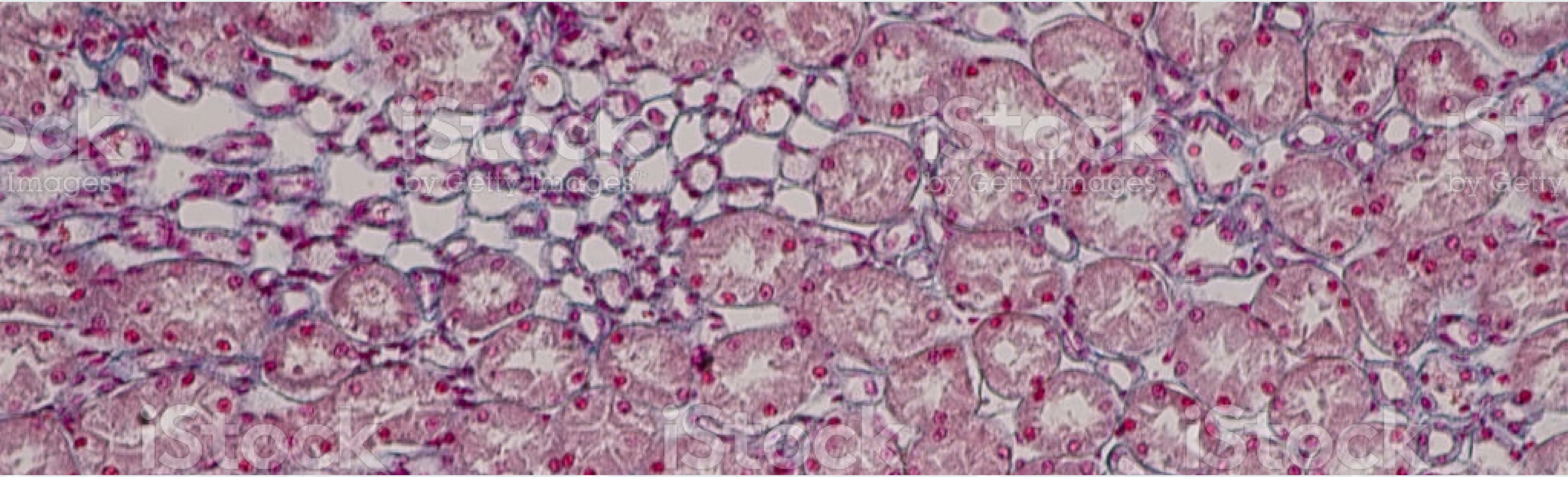
SEGMENTATION AND CLASSIFICATION ON HUMAN RENAL TISSUE



Bioinformatics
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QUESTIONS

What transformations are the most useful?

What backbone is the most useful?

Does resizing images helps?

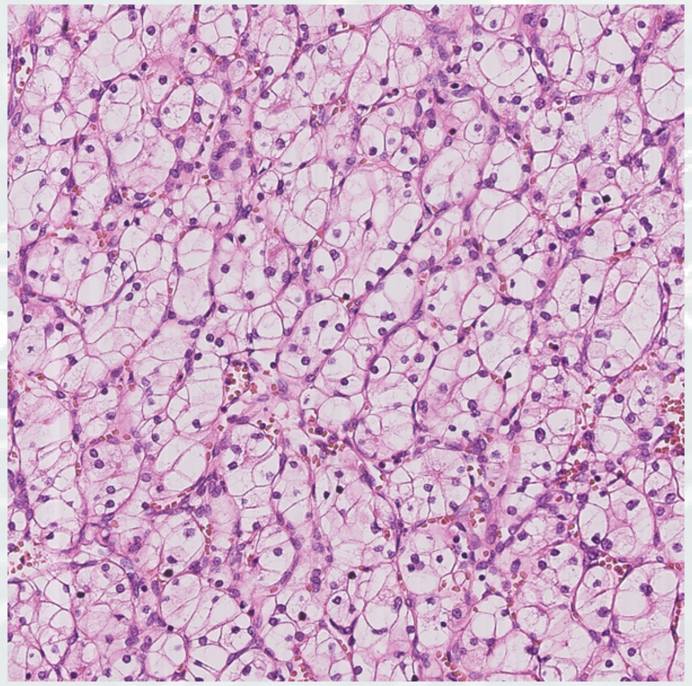
What segmentation model performs best?

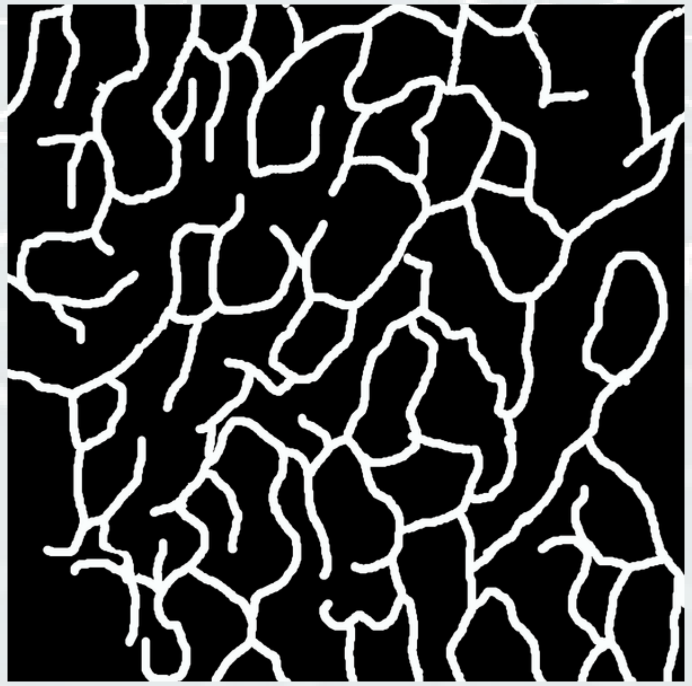
Can I classify the images starting from the predictions of the best segmentation model?

PIPELINES

Segmentation

Classification

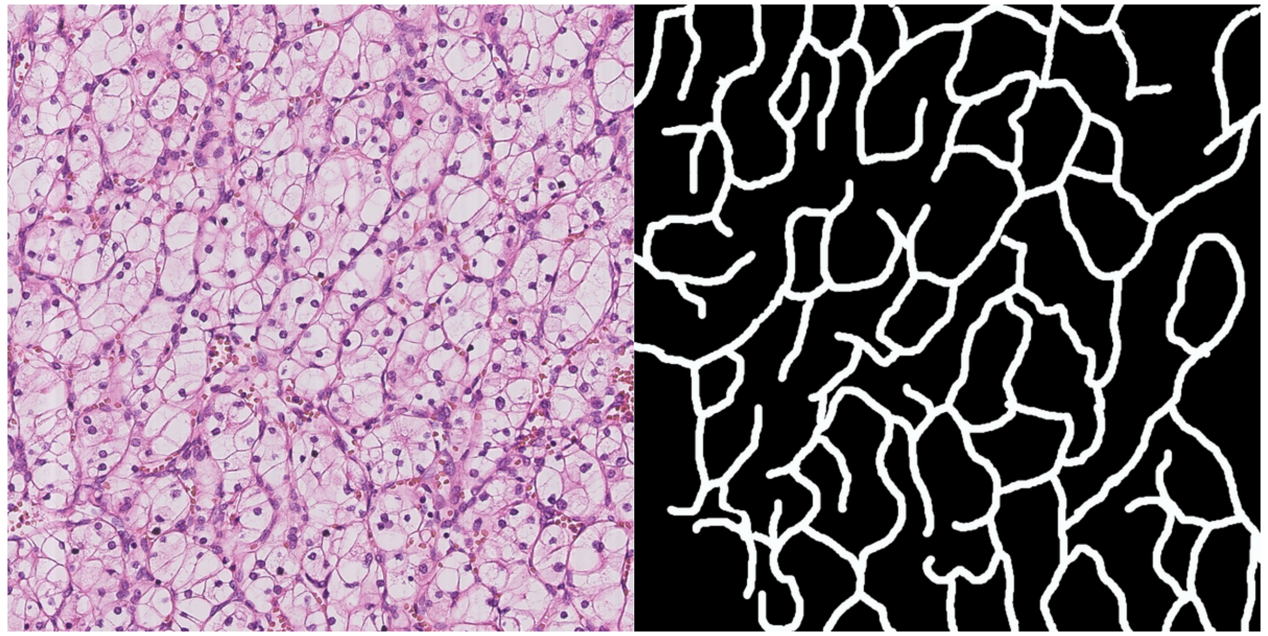




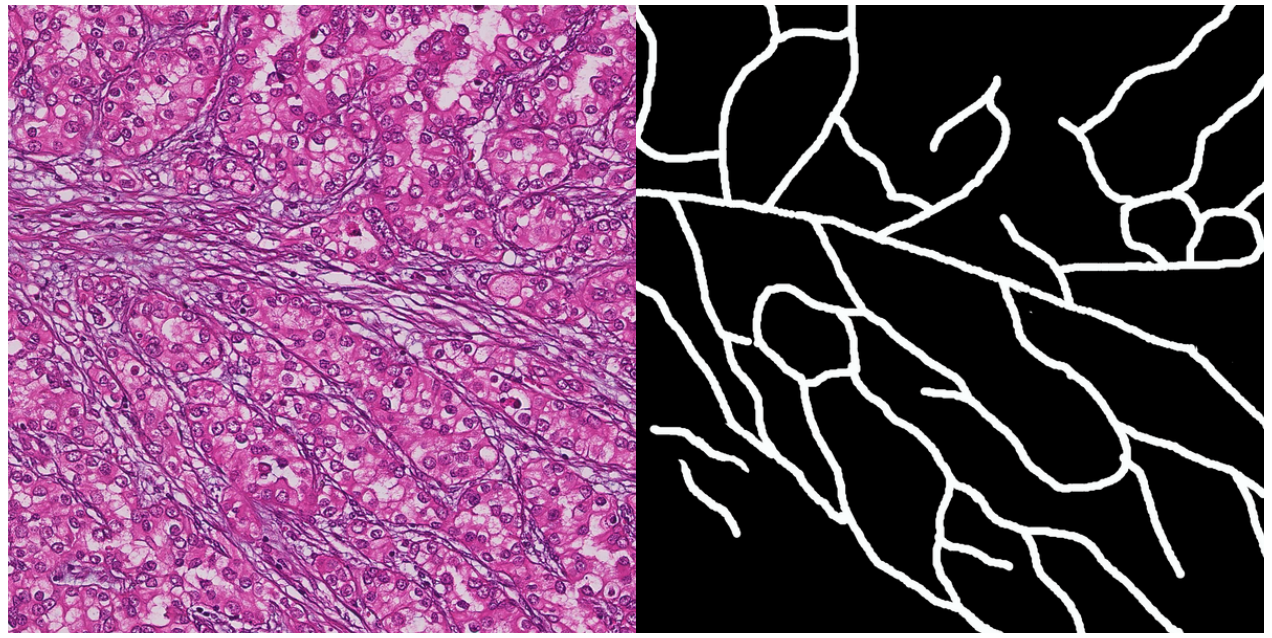
1 Clear cell renal cell carcinoma .

0 Papillary renal cell carcinoma

DATASET



Example of pRCC

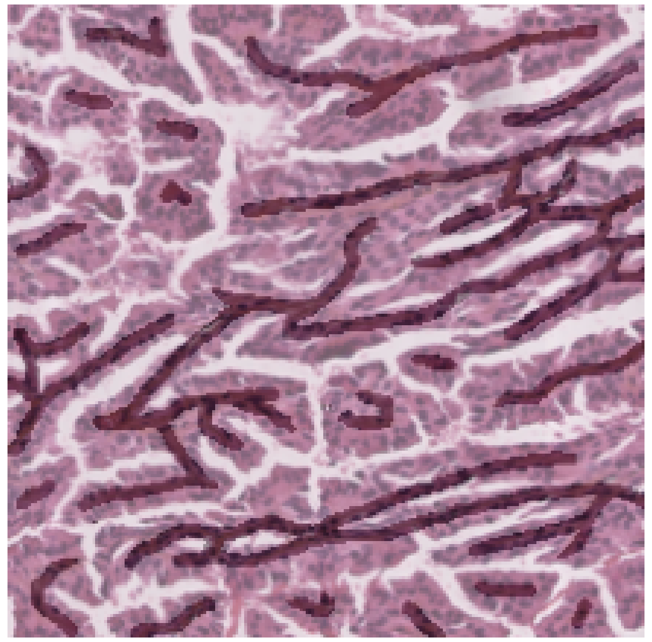


Example of ccRCC

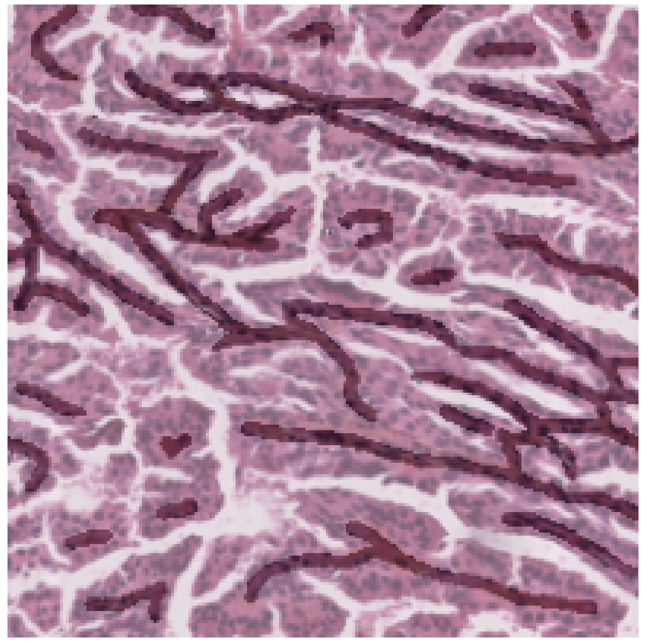
200 images with associated segmentation mask of cancerous cells depicting two types of cancer, Clear cell renal cell carcinoma and Papillary renal cell carcinoma.

Dataset is split into training set (160 images), validation set (40 images), test set (10 images).

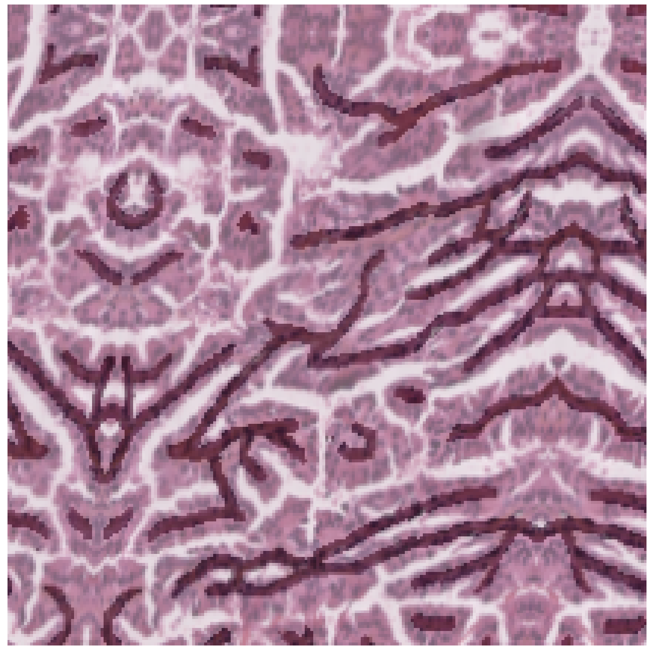
TRANSFORMATIONS



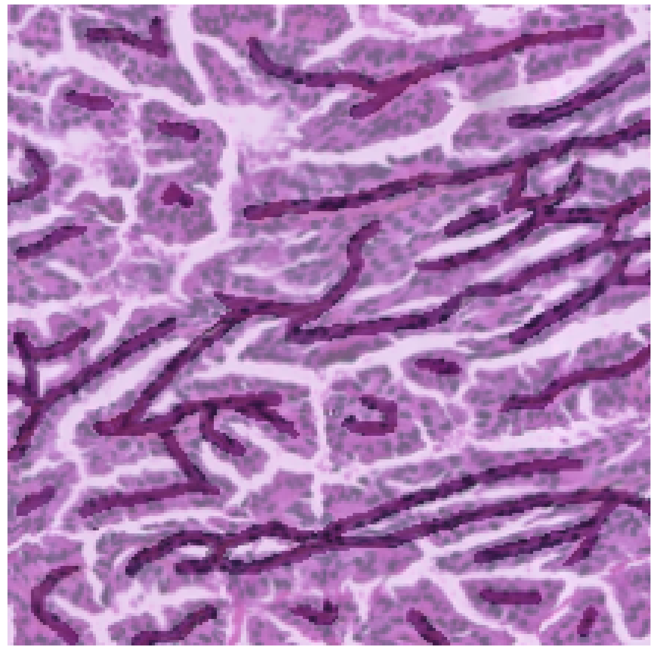
Original



Affine



Elastic



Pixel-wise

3 different types of transformations are used.

METRICS

SEGMENTATION

$$IOU = \frac{A \cap B}{A \bigcup B}$$

The dice score is more often used than the IOU, but the dice score is differentiable and can be used also as loss function

CLASSIFICATION

$$F_1 = 2 * \frac{precision * recall}{precision + recall}$$

The F1 score is more suited to class imbalance problems wrt the accuracy.

LOSSES

SEGMENTATION

Weighted CrossEntropy

Dice Loss

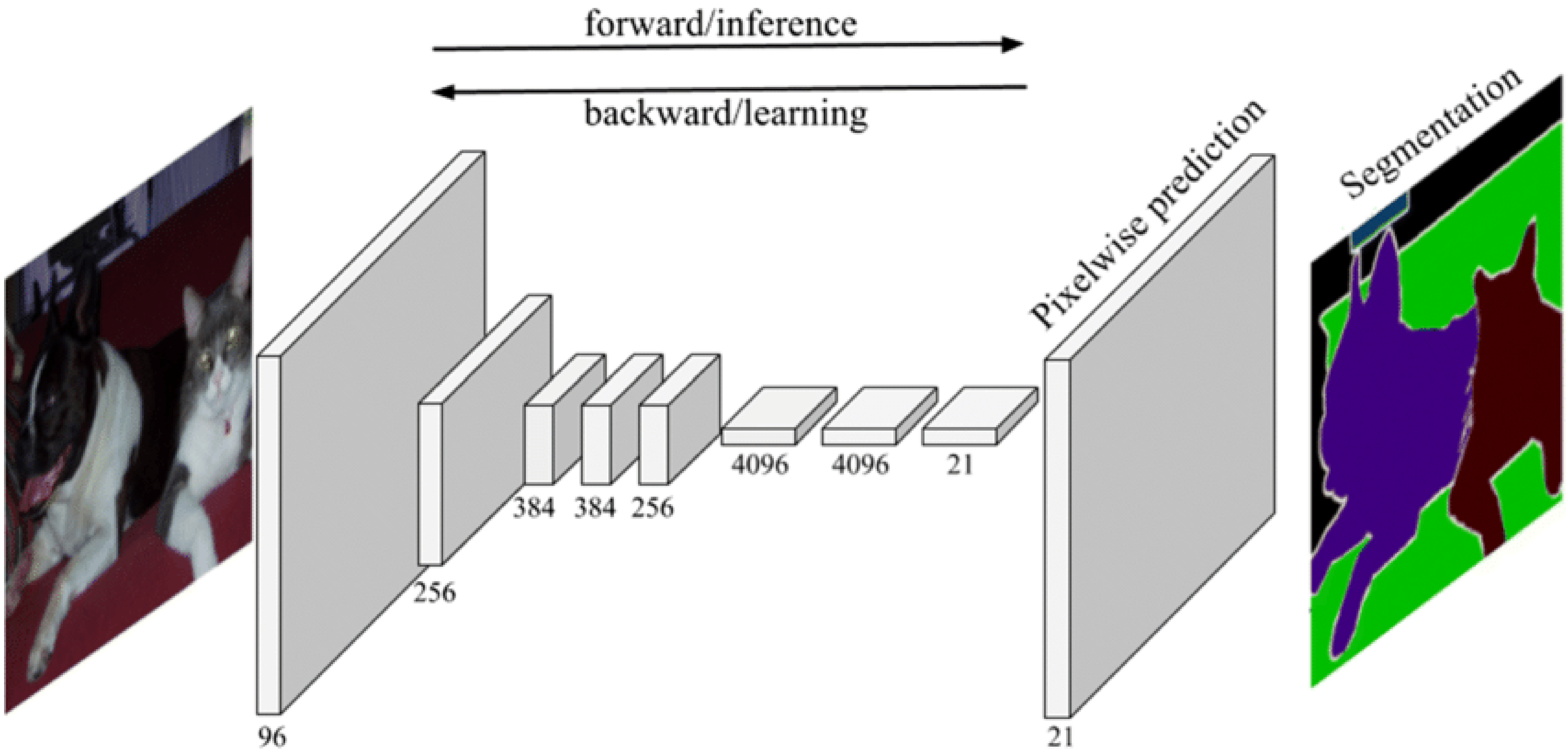
$$Dice = -\frac{2|A \cap B|}{(|A| + |B|)}$$

CLASSIFICATION

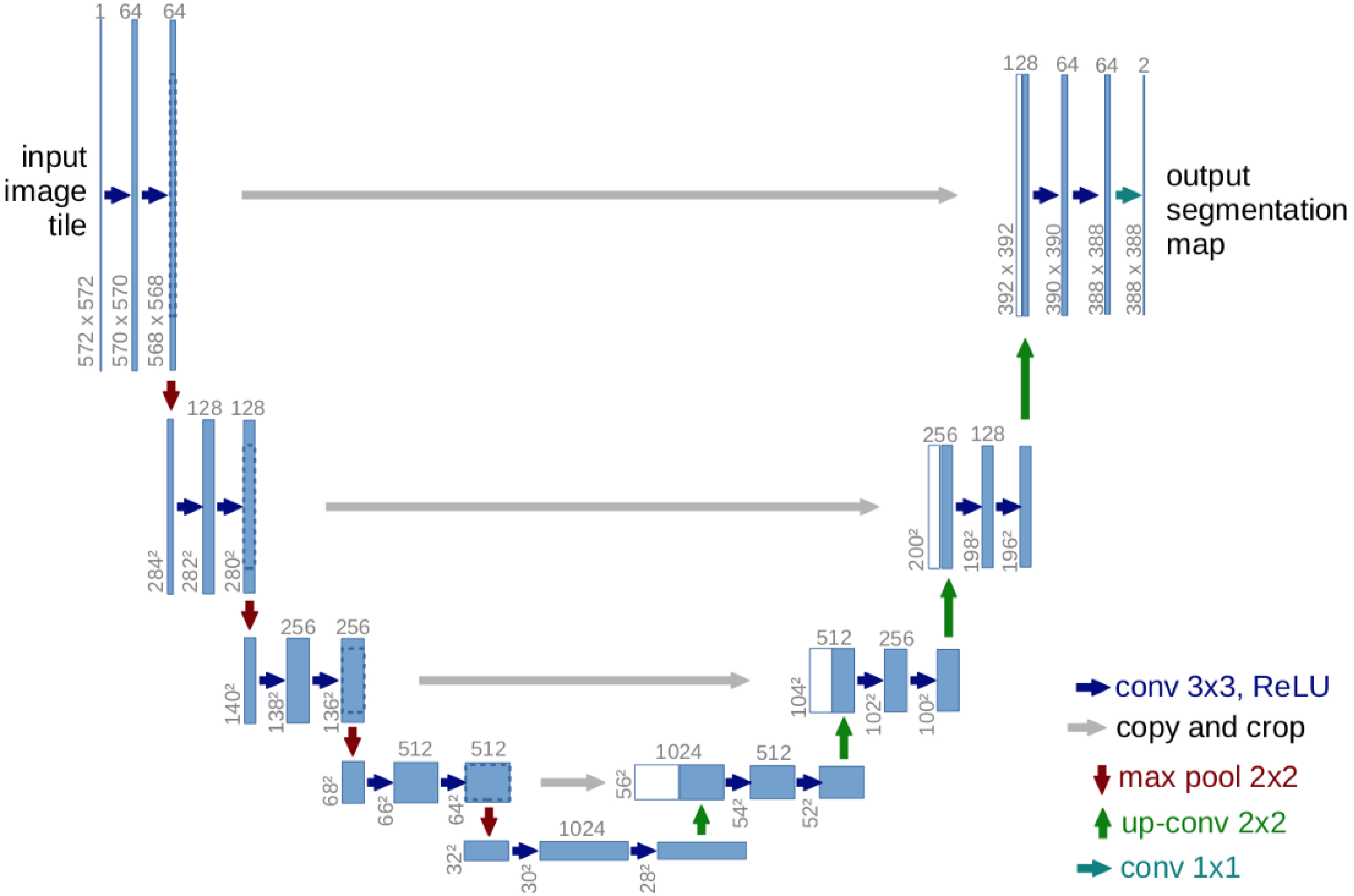
Binary CrossEntropy

$$BCE = -\frac{1}{N}\sum_{i=1}^{N}(y_i log(p(y_i)) + (1-y_i) log(1-p(y_i)))$$

FCN NETWORKS



U-NET


input
image
tile
output
segmentation
map
conv 3x3, ReLU
copy and crop
max pool 2x2
up-conv 2x2
conv 1x1

OTHER ARCHITECTURES

LINK-NET

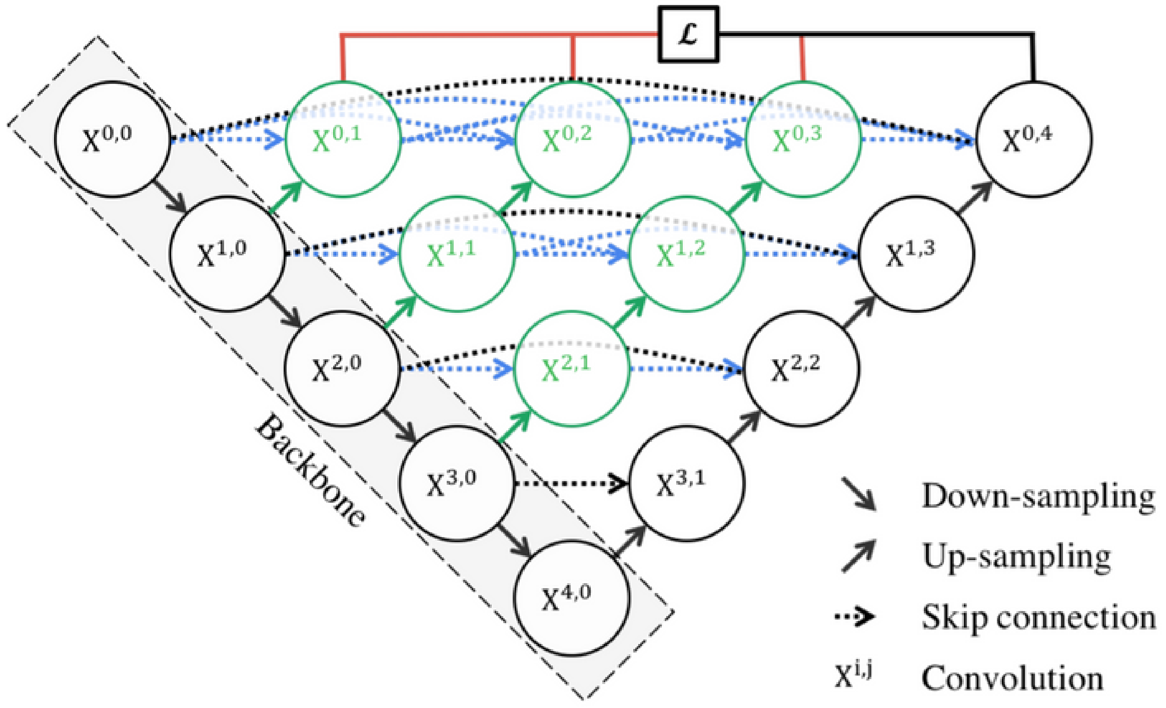
Simple addition in order to combine the contracting and up-sampling path

MA-NET

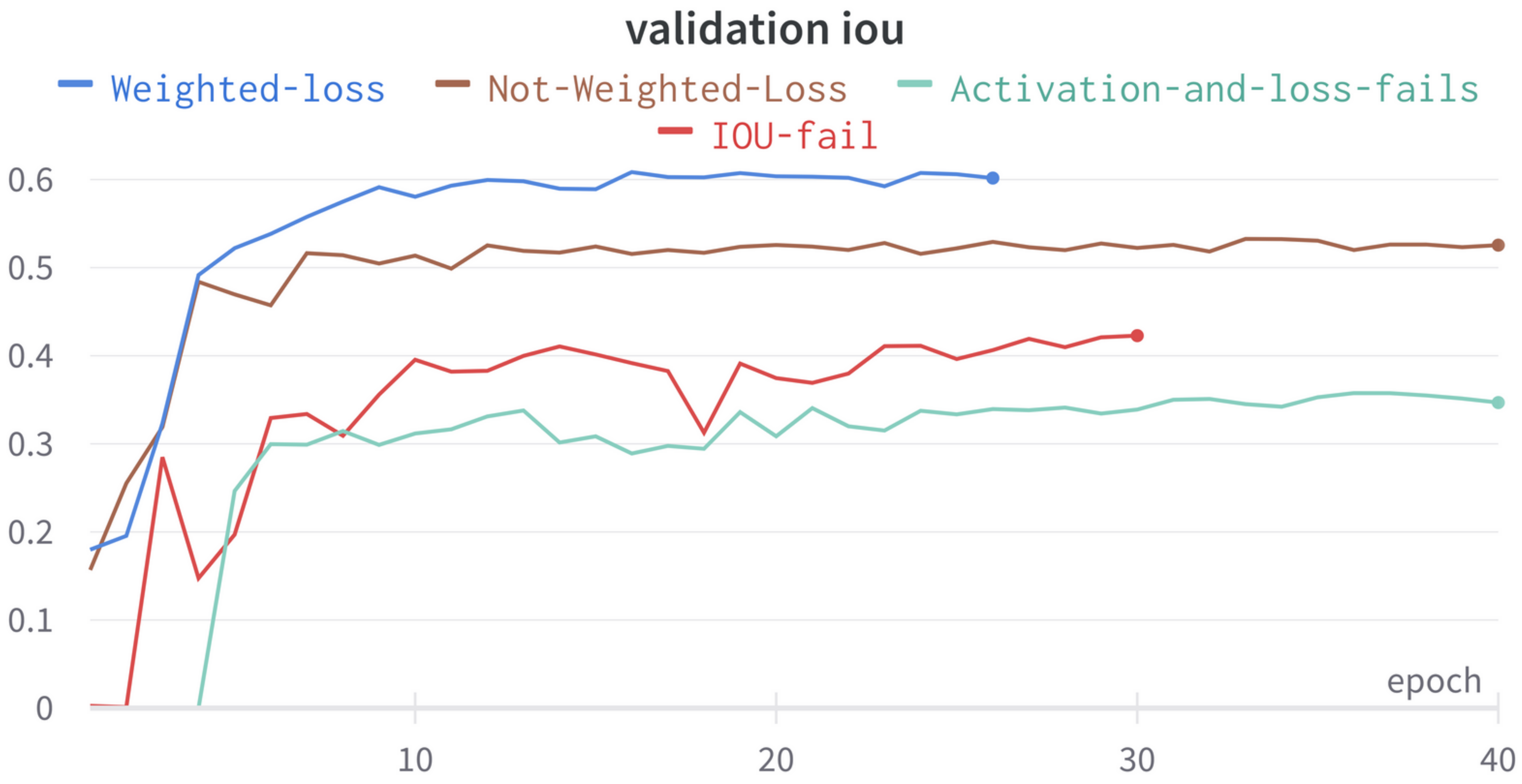
An efficient dot product attention mechanism suitable for large input images is introduced, which proves to be very effective when dealing with remote sensing tasks

U-NET++

What distinguishes U-Net++ from U-Net is the redesigned skip pathways that connect the two subnetworks, aiming at reducing the semantic gap between the feature maps of the encoder and decoder sub-networks



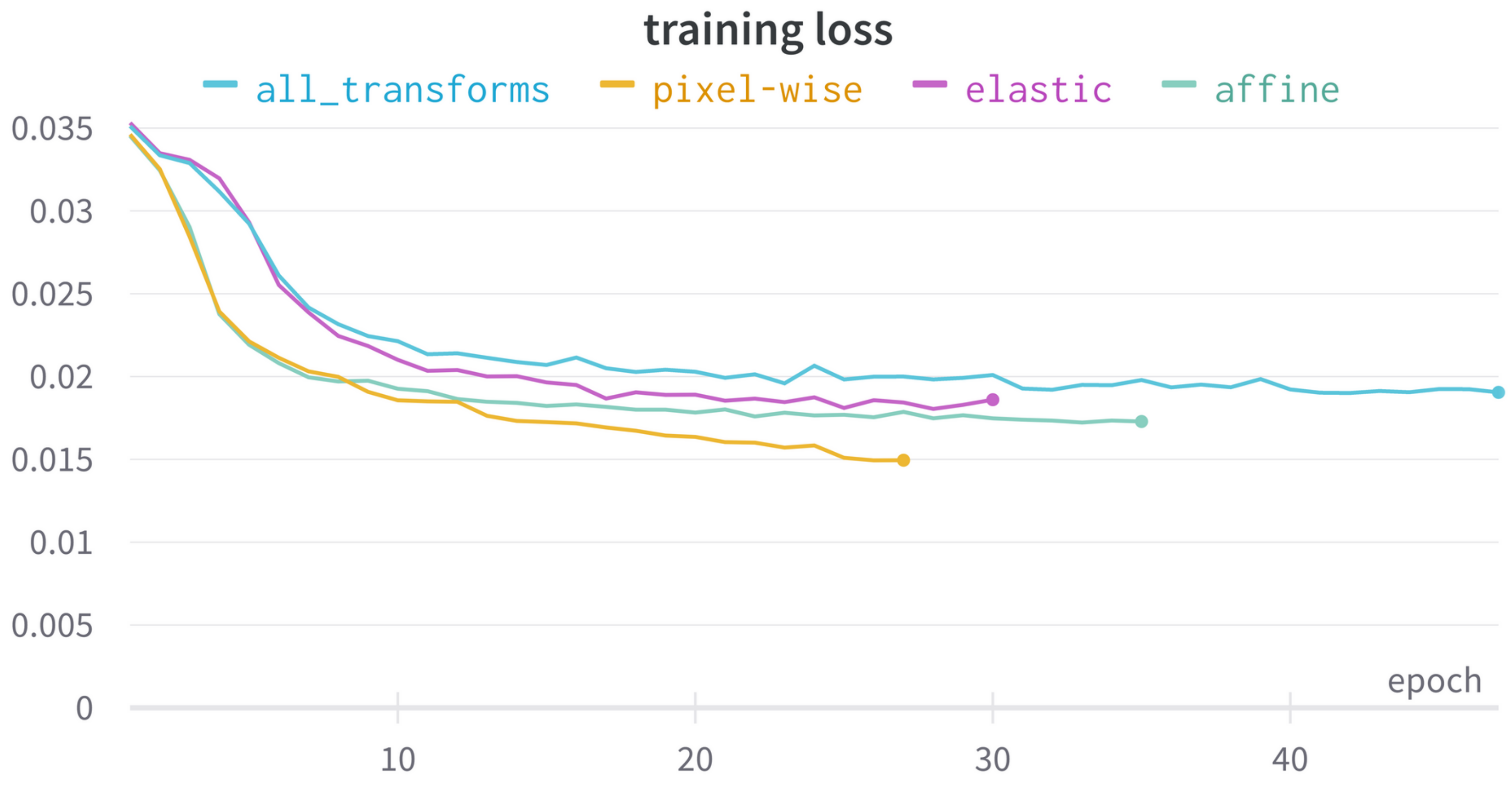
WHAT DOES NOT KILL YOU MAKES YOU STRONGER

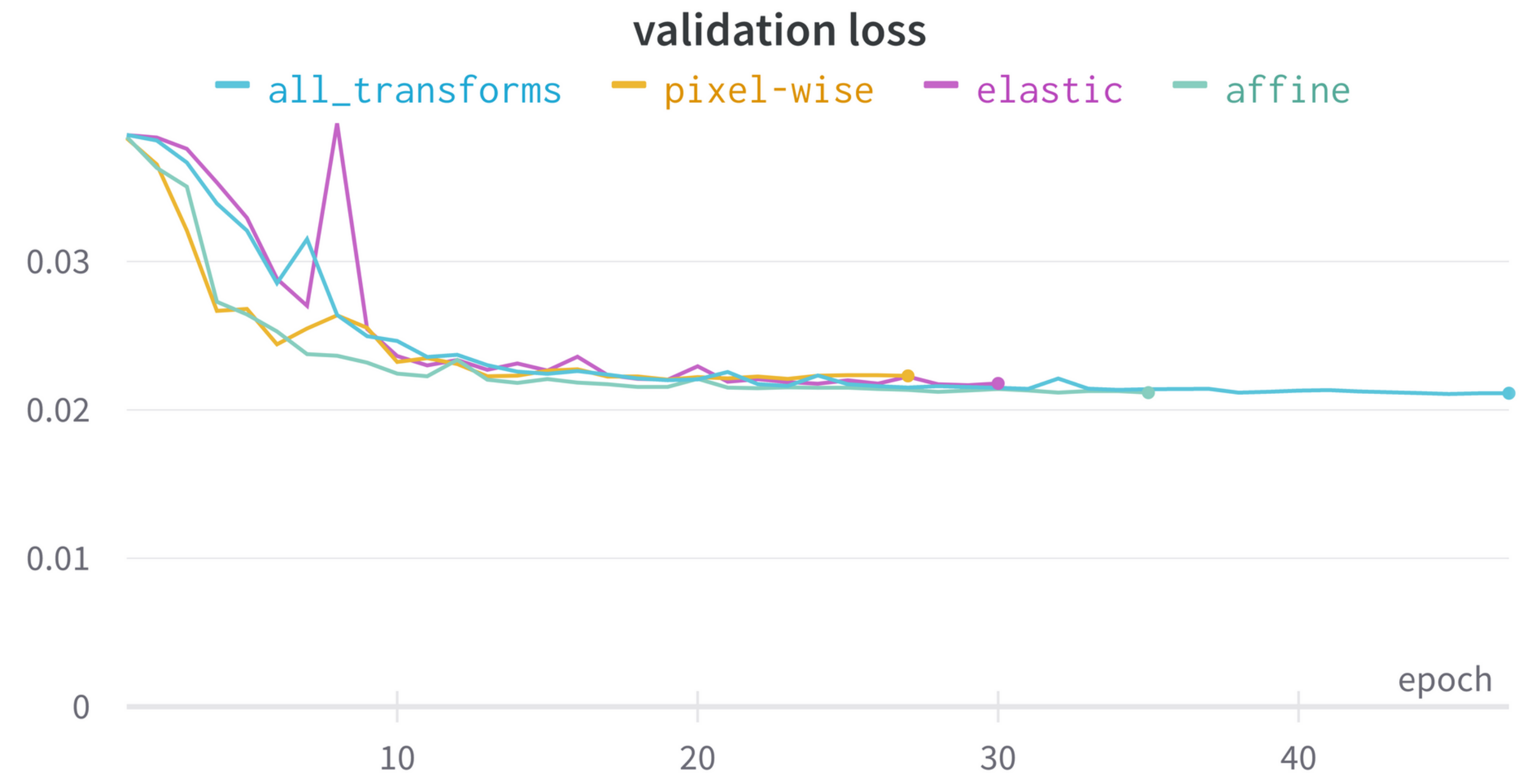


Unfortunately every mistake was repeated in multiple runs before finding it...

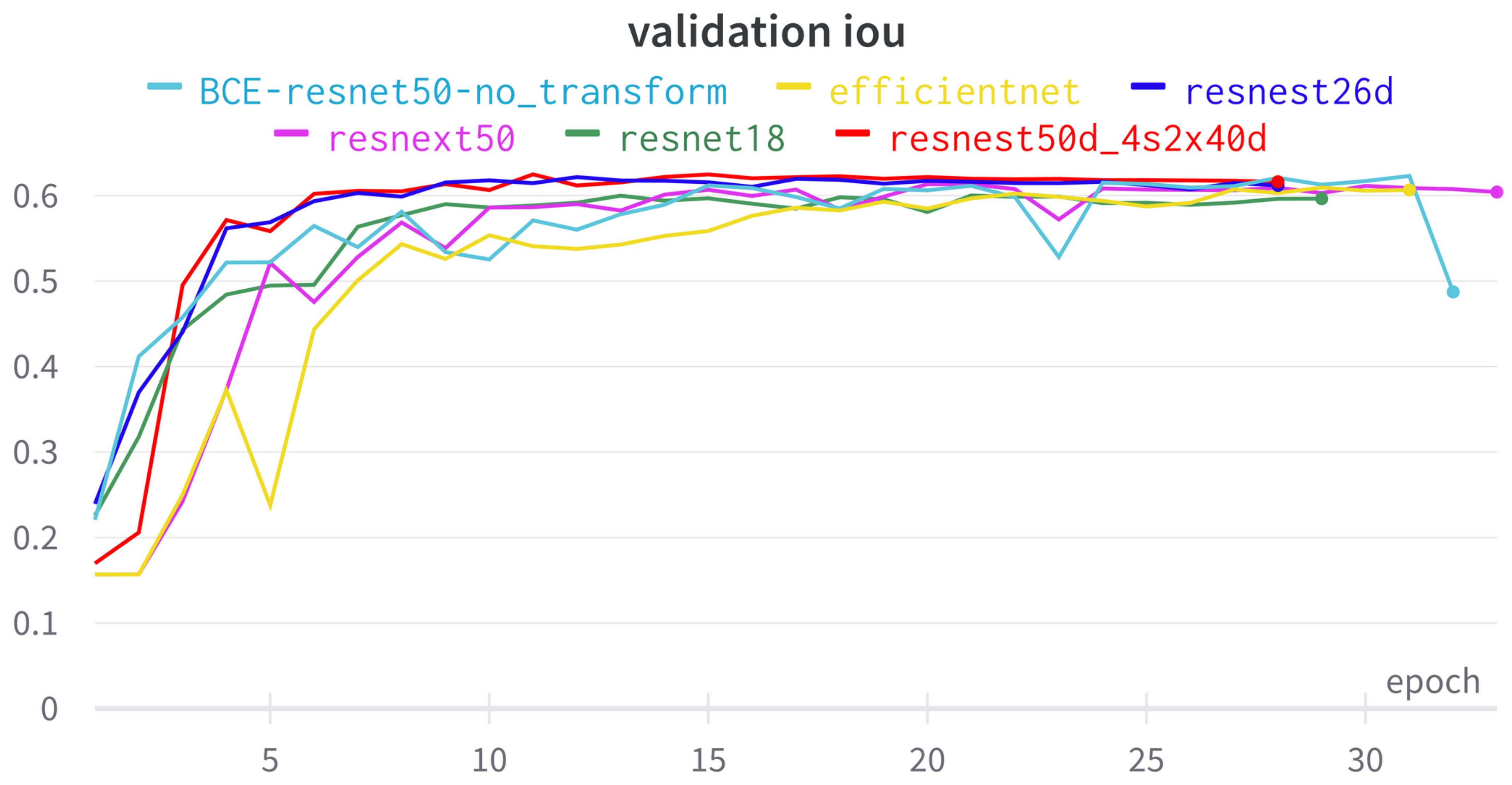
TRANSFORMATIONS EFFICACY

All there results have been obtained with U-Net and Resnet50 as backbone.





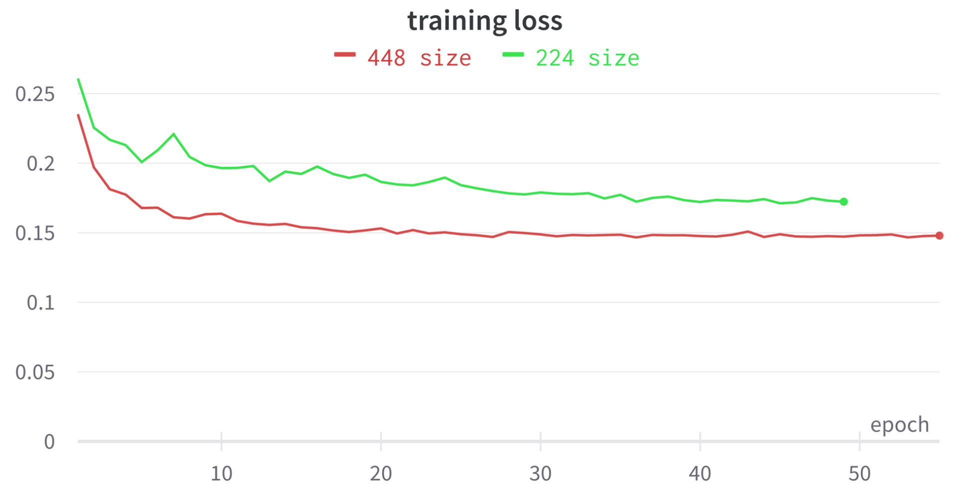
BACKBONE EFFICACY

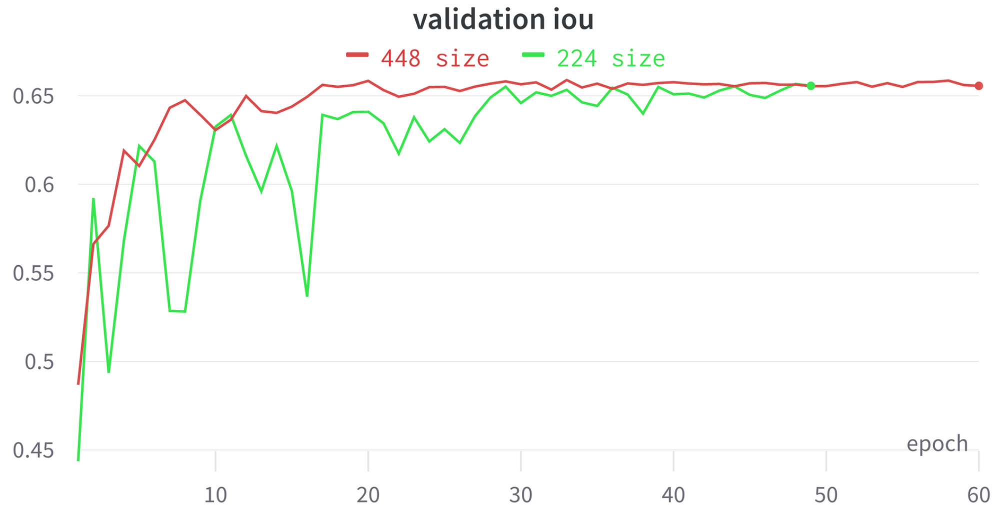


All these results have been obtained using the U-Net.

RESIZING EFFICACY

All there results have been obtained with U-Net++ and Resnest101 as backbone.





BEST MODEL?

Size	Model	Loss function	Backbone	Transformations	Training loss	Validation loss	Validation IOU
224	U-Net	Binary CE	Resnest101	Affine+Elastic	0.177	0.172	65.59
224	MA-Net	Binary CE	Resnest101	All	0.185	0.173	65.06
224	LinkNet	Binary BCE	Resnest101	Affine+Elastic	0.176	0.172	65.20
224	U-Net++	Binary BCE	Resnest101	Affine+Elastic	0.172	0.173	65.67

ALL THE SEGMENTATION EXPERIMENTS

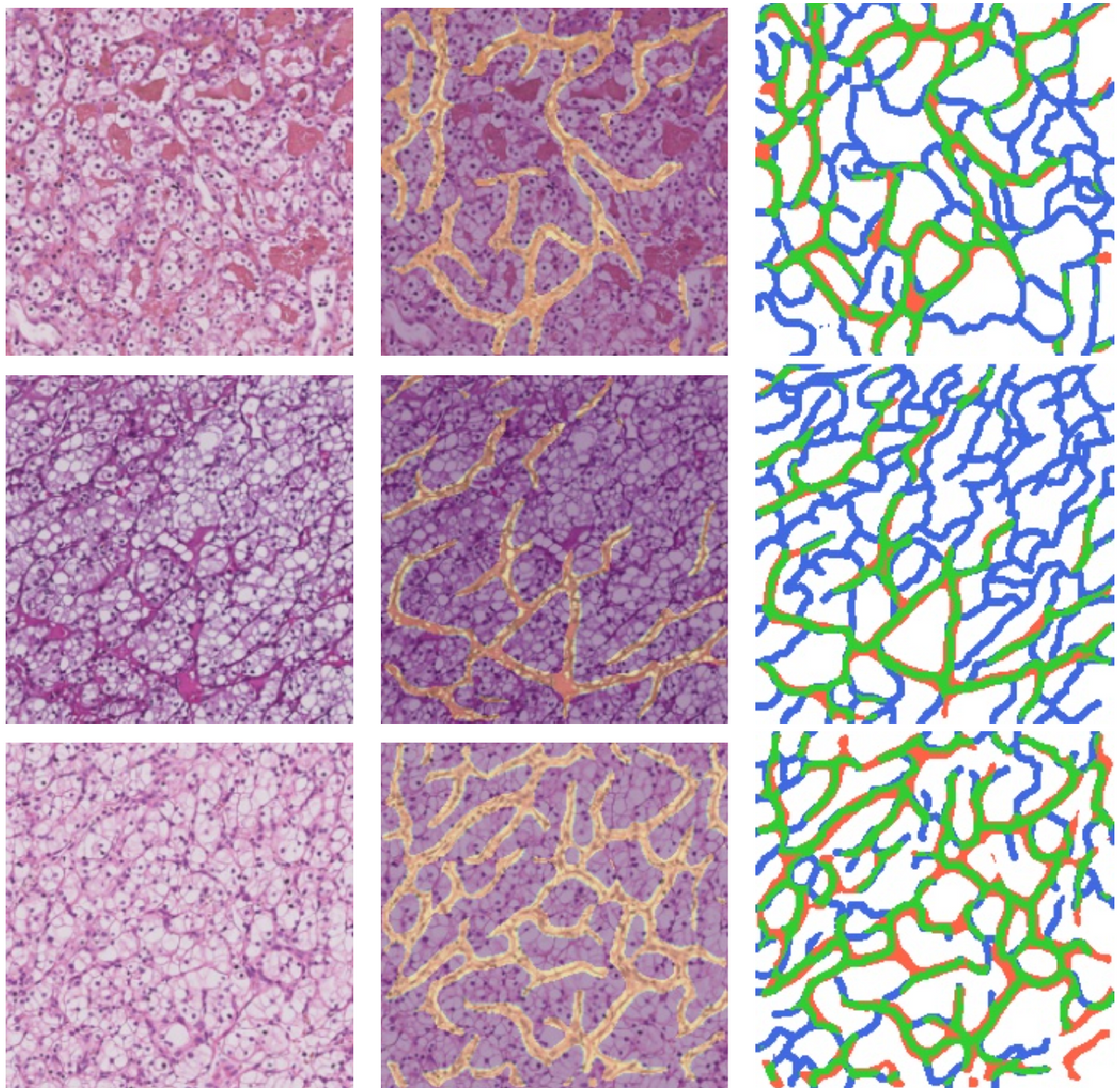
Size	Model	Loss function	Backbone	Transformations	Training loss	Validation loss	Validation IOU
224	U-Net	Dice	Resnet50	None	0.013	0.0233	60.73
224	U-Net	Dice	Resnet18	None	0.015	0.024	60.01
224	U-Net	Dice	Resnest26	None	0.012	0.023	61.61
224	U-Net	Dice	Resnest50	Affine	0.017	0.021	63.92
224	U-Net	Dice	Resnest50	Elastic	0.018	0.022	63.19
224	U-Net	Dice	Resnest50	Pixel-wise	0.015	0.022	63.01
224	U-Net	Dice	Resnest50	All	0.019	0.021	63.83
224	U-Net	Dice	Resnet101	All	0.029	0.034	62.22
224	U-Net	Dice	Resnest101	All	0.027	0.028	65.31
224	U-Net	Binary CE	Resnet50	None	0.162	0.192	62.29
224	U-Net	Binary CE	Resnet50	All	0.169	0.201	62.22
224	U-Net	Binary CE	Resnest101	All	0.154	0.191	62.67
224	U-Net	Binary CE	Resnest50	Affine+Elastic	0.180	0.173	64.62
224	U-Net	Binary CE	Resnest50	Affine+Elastic	0.180	0.173	64.62
224	U-Net	Binary CE	Resnest101	Affine+Elastic	0.177	0.172	65.59
448	U-Net	Binary CE	Resnest101	Affine+Elastic	0.147	0.151	65.86
224	MA-Net	Binary CE	Resnet50	Affine	0.166	0.200	61.33
224	MA-Net	Binary CE	Resnest50	All	0.189	0.177	64.38
224	MA-Net	Binary CE	Resnest101	All	0.185	0.173	65.06
224	MA-Net	Dice loss	Resnet18	No	0.020	0.034	60.26
224	MA-Net	Dice loss	Resnet50	No	0.026	0.031	61.98
224	MA-Net	Dice loss	Resnest50	No	0.026	0.031	62.39
224	MA-Net	Dice loss	Resnest50	All	0.027	0.031	61.88
224	MA-Net	Dice loss	Efficient-net	All	0.034	0.030	60.94
224	LinkNet	Dice loss	Resnet50	All	0.029	0.030	61.93
224	LinkNet	Dice loss	Resnet101	All	0.032	0.035	58.60
224	LinkNet	Dice loss	Resnest50	All	0.027	0.029	64.56
224	LinkNet	Binary BCE	Resnest50	All	0.028	0.030	64.02
224	LinkNet	Binary BCE	Resnest101	Affine+Elastic	0.176	0.172	65.20
448	Linknet	Binary BCE	Resnest101	Affine+Elastic	0.374	0.411	61.92
224	U-Net++	Dice loss	Resnet50	All	0.033	0.030	61.51
224	U-Net++	Dice loss	Resnest101	All	0.028	0.027	65.38
224	U-Net++	Binary BCE	Resnest101	Affine+Elastic	0.172	0.173	65.67

Table 1. Segmentation experiments

WINNER WITH BIGGER SIZE

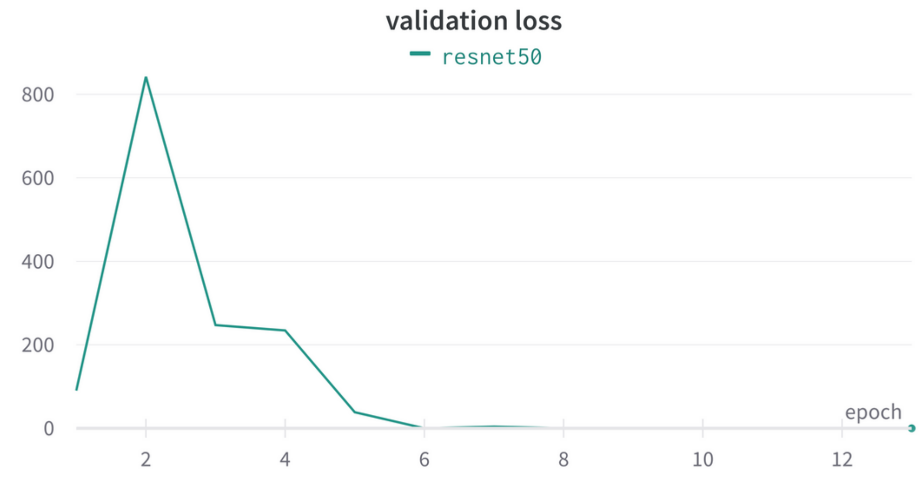
WINNER WITH STANDARD SIZE

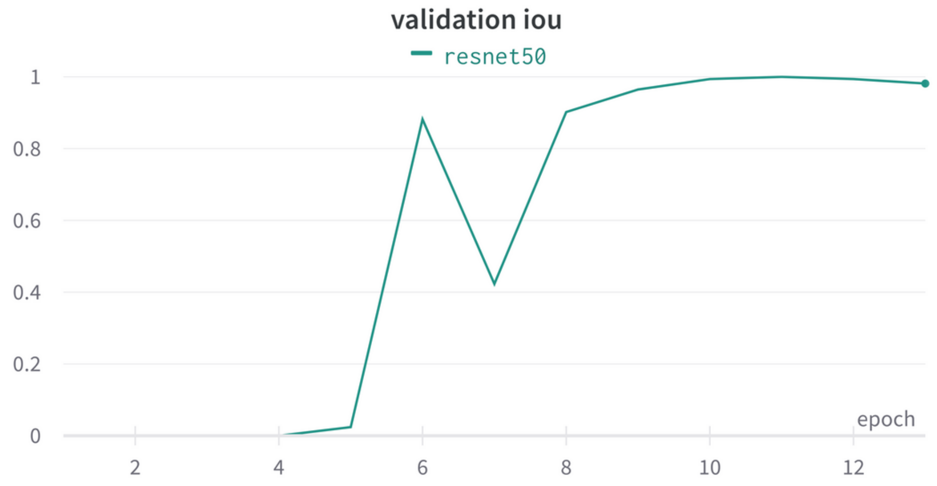
SOME SEGMENTATION PREDICTIONS



CLASSIFICATION RESULTS

100% F1-score on the test set obtained with the Resnet50 after a training with only 10 epocs.





CONCLUSIONS

All the U-Net like models performed well, probably also due to their similarities, and it is proved to be possible to classify the cancer type from the segmentation predictions.

Some segmentation experiments were performed also with the FPN (Feature Pyramid Network), but satisfying results could not be obtained.