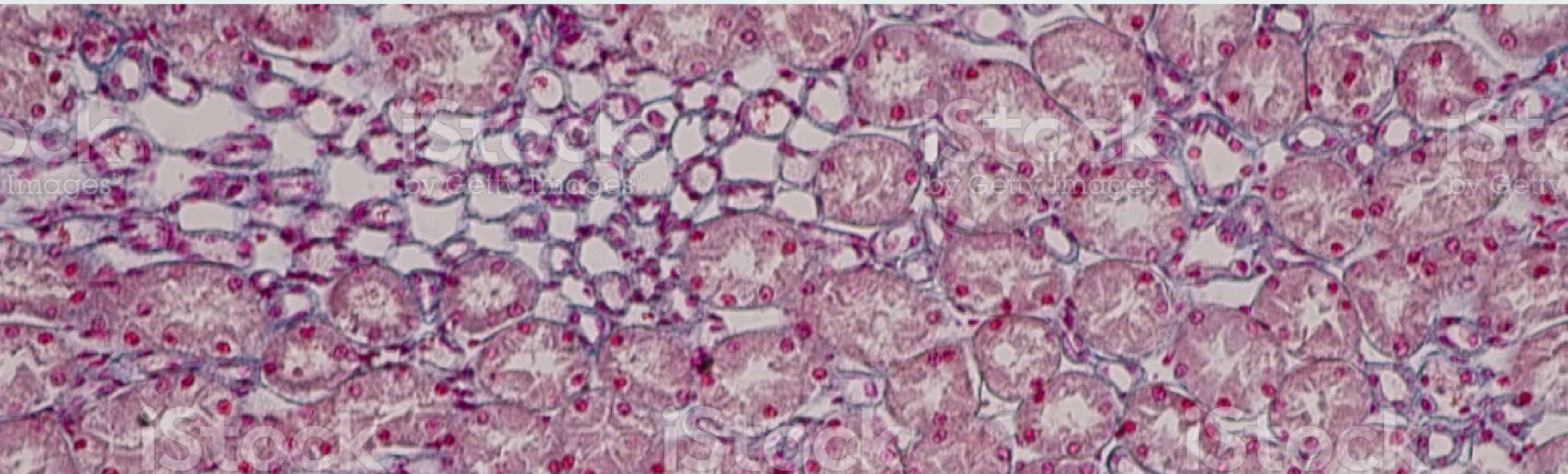


SEGMENTATION AND CLASSIFICATION ON HUMAN RENAL TISSUE



Bioinformatics
Emanuele Fasce
S277983

QUESTIONS

What transformations are the most useful?

What backbone is the most useful?

Does resizing images helps?

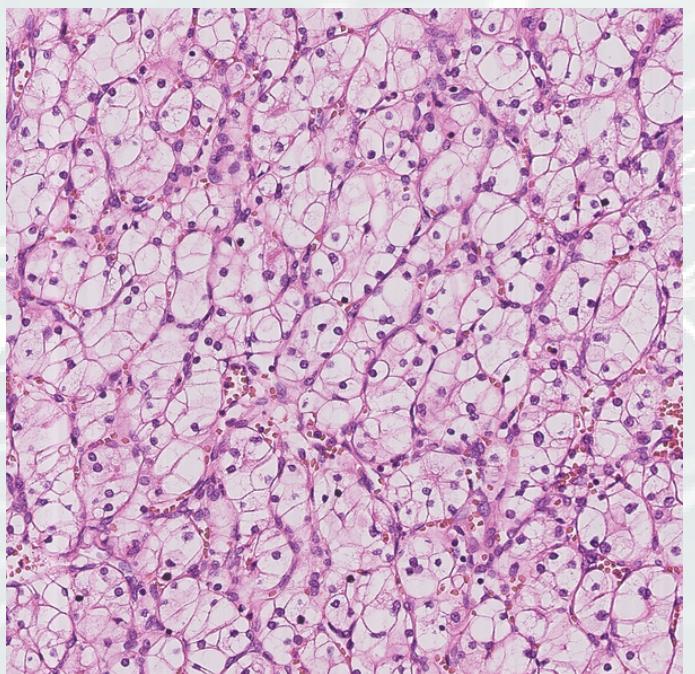
What segmentation model performs best?

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

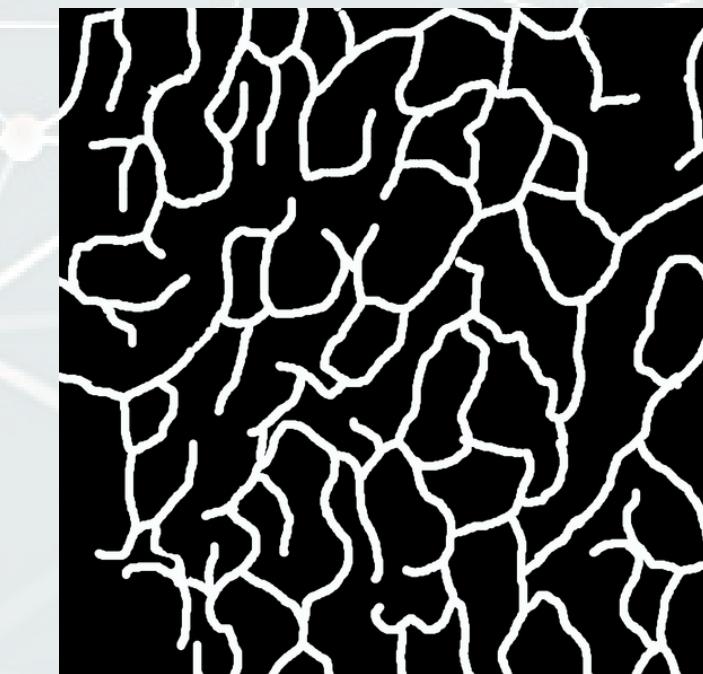
PIPELINES



Segmentation



Classification



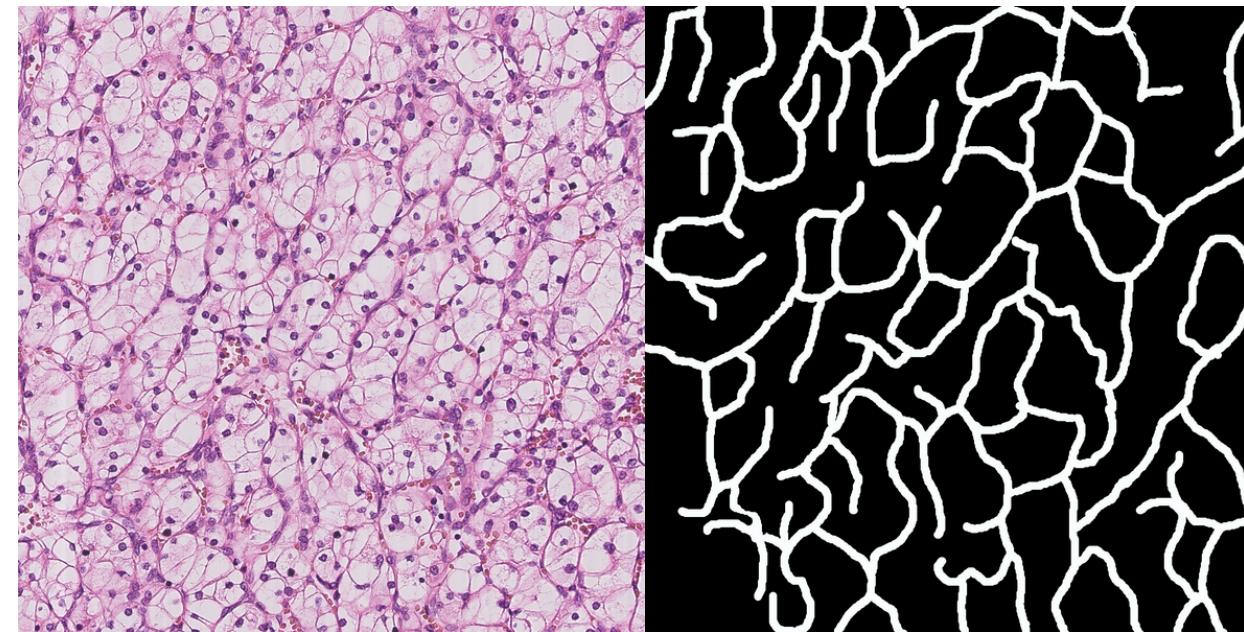
1

Clear cell renal
cell carcinoma .

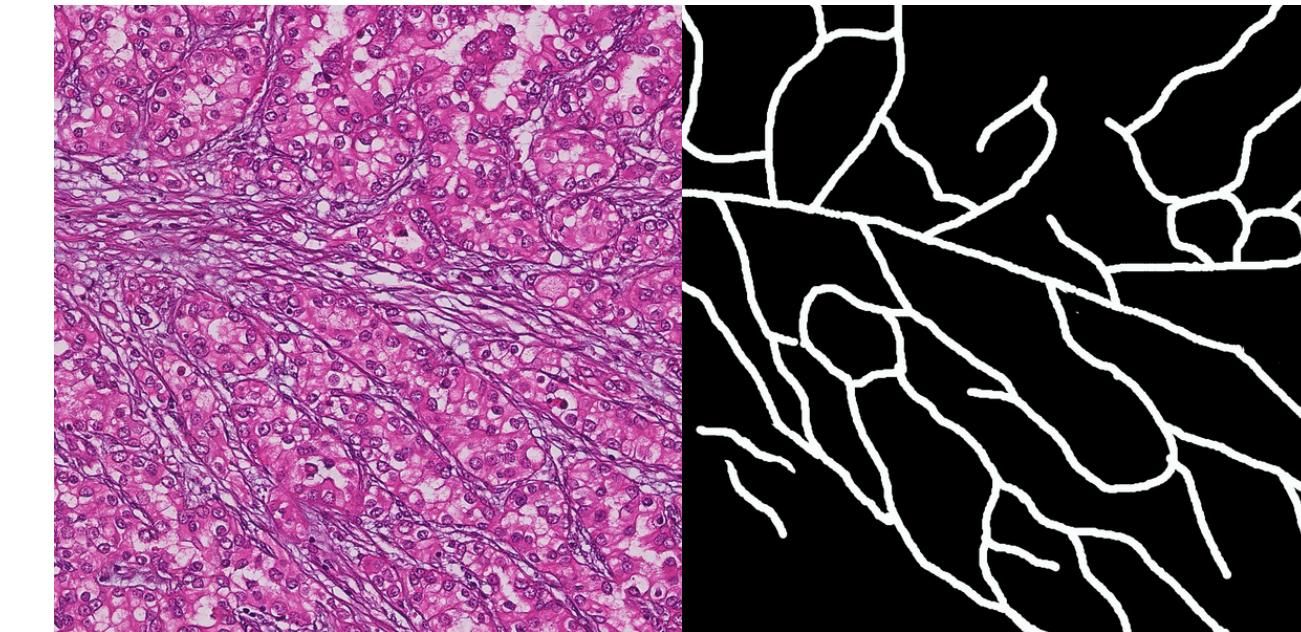
0

Papillary renal
cell carcinoma

DATASET



Example of pRCC

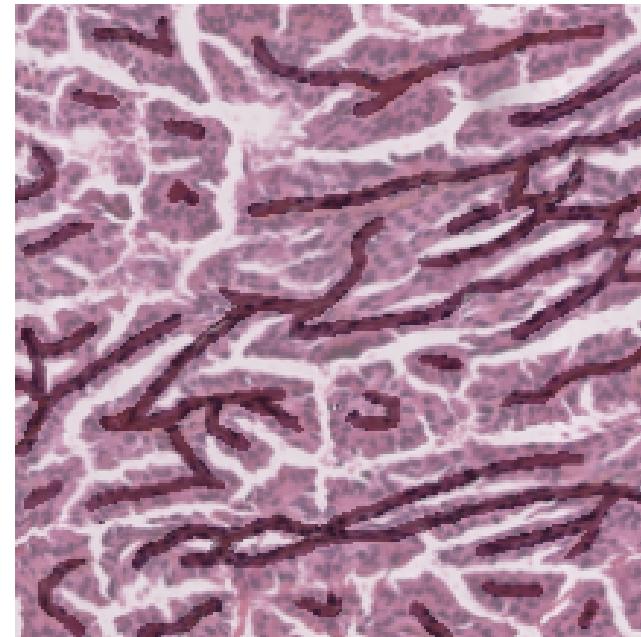


Example of ccRCC

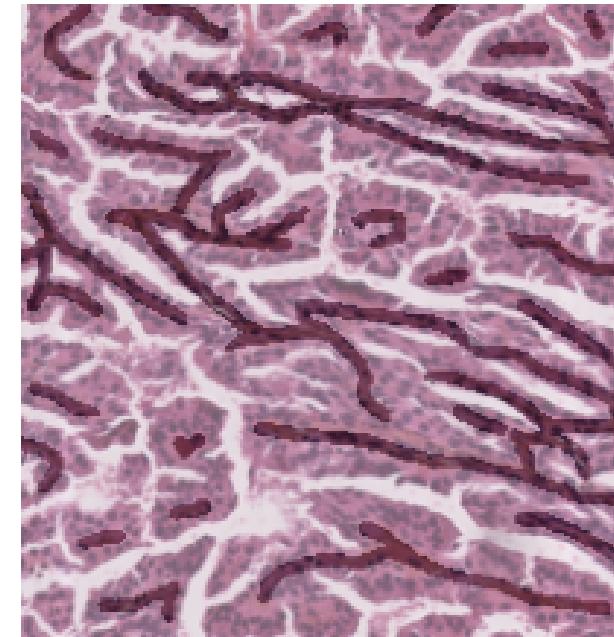
200 images with associated segmentation mask of cancerous cells depicting two types of cancer,
Clear cell renal cell carcinoma and Papillary renal cell carcinoma.

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

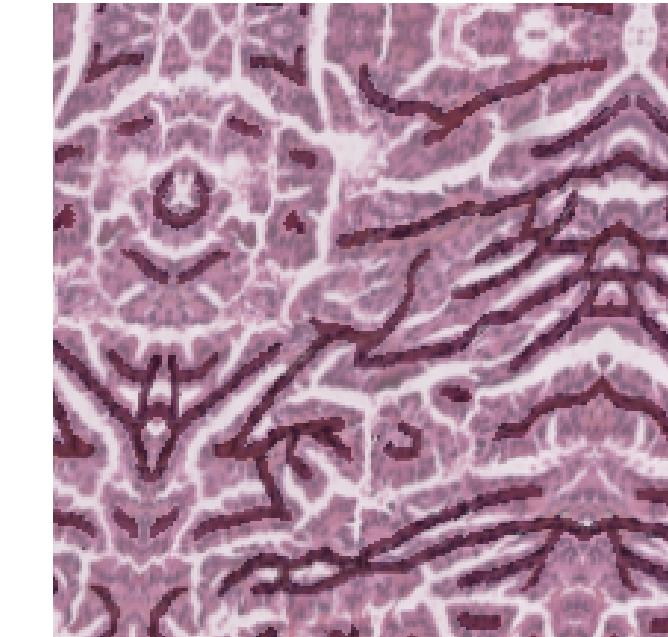
TRANSFORMATIONS



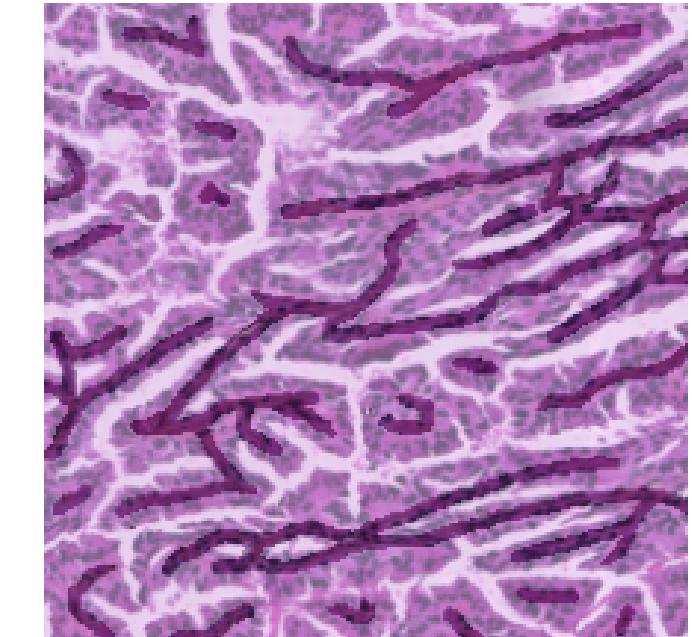
Original



Affine



Elastic



Pixel-wise

3 different types of transformations are used.

METRICS

SEGMENTATION

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

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

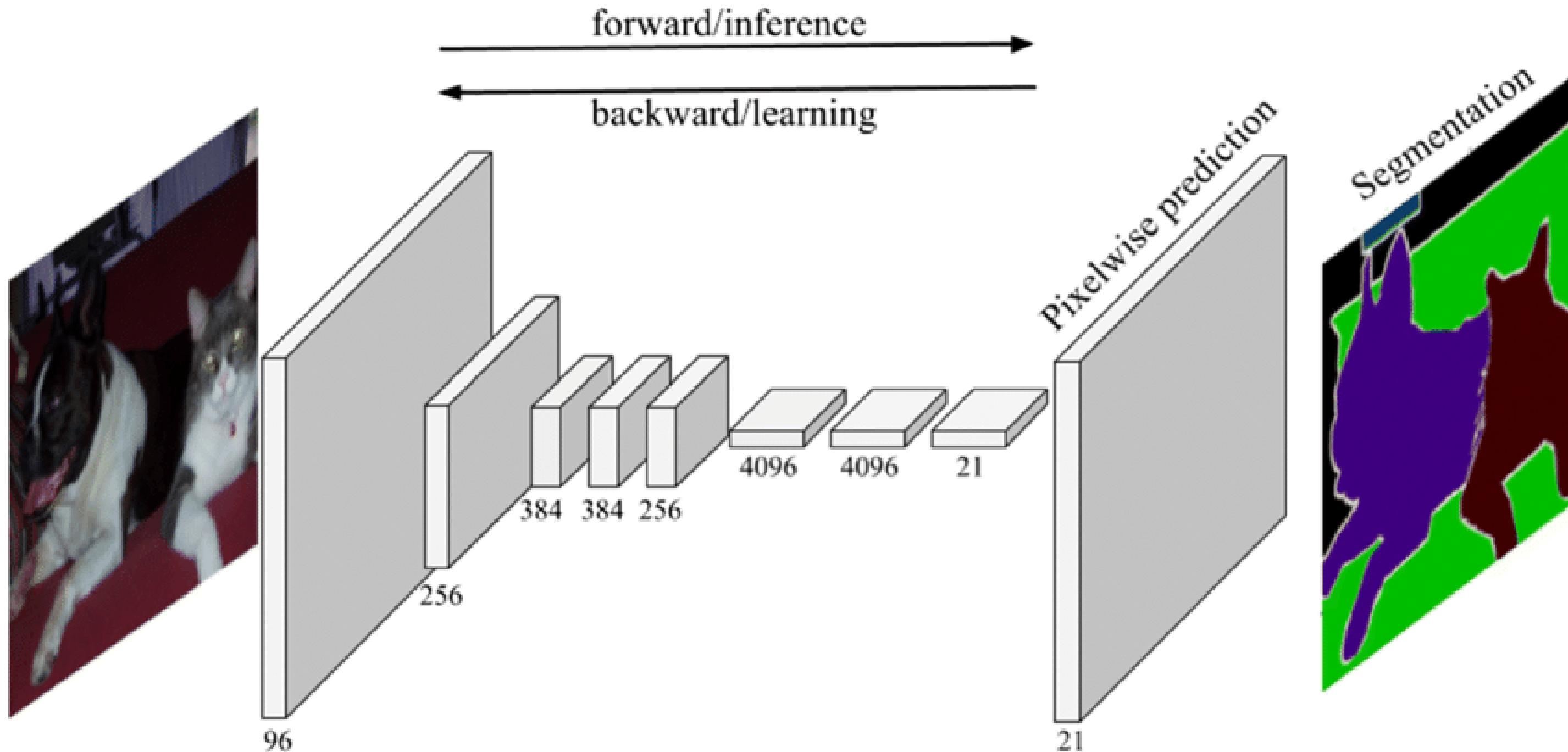
$$Dice = -\frac{2|A \cap B|}{(|A| + |B|)}$$

CLASSIFICATION

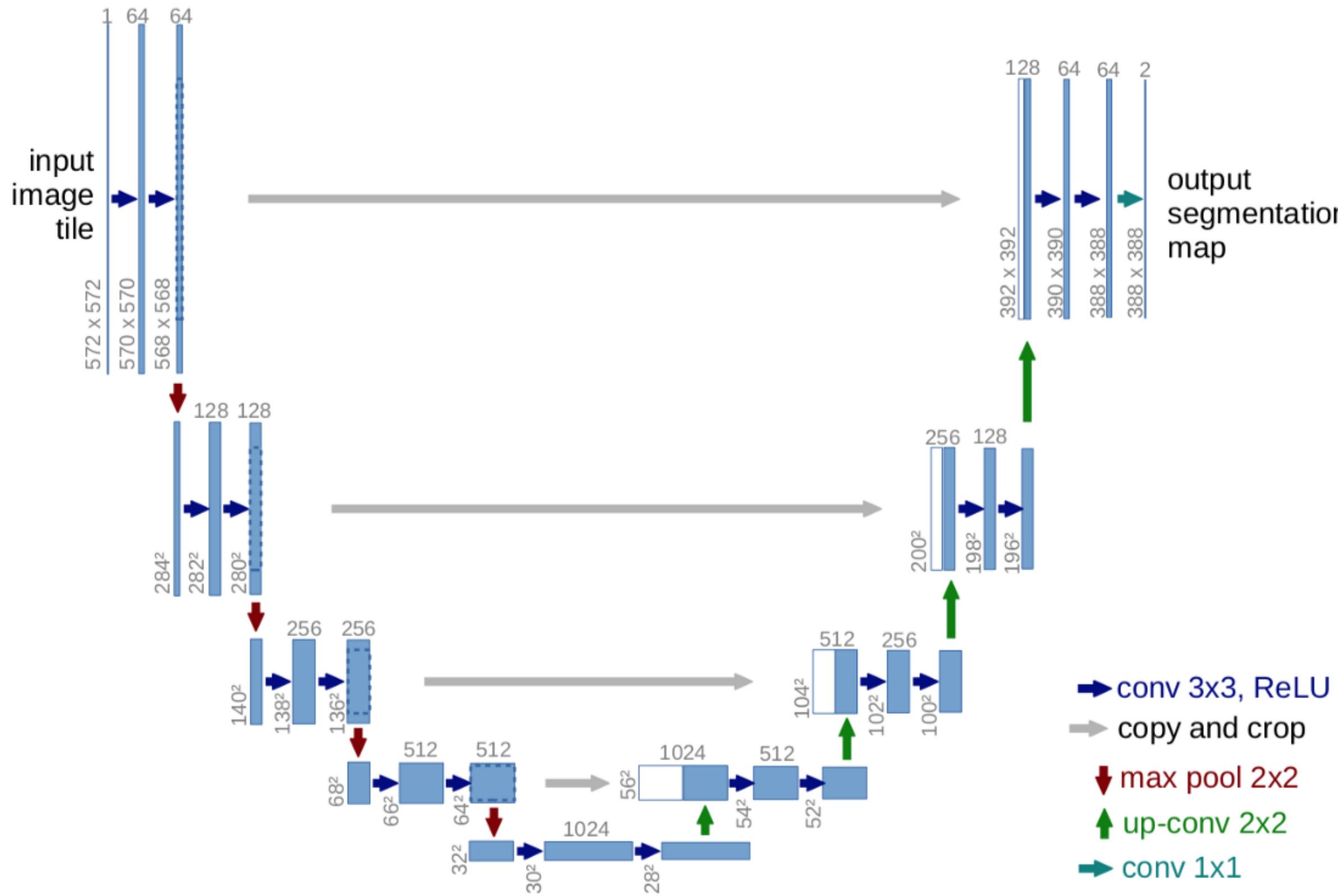
Binary CrossEntropy

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

FCN NETWORKS



U-NET



OTHER ARCHITECTURES

LINK-NET

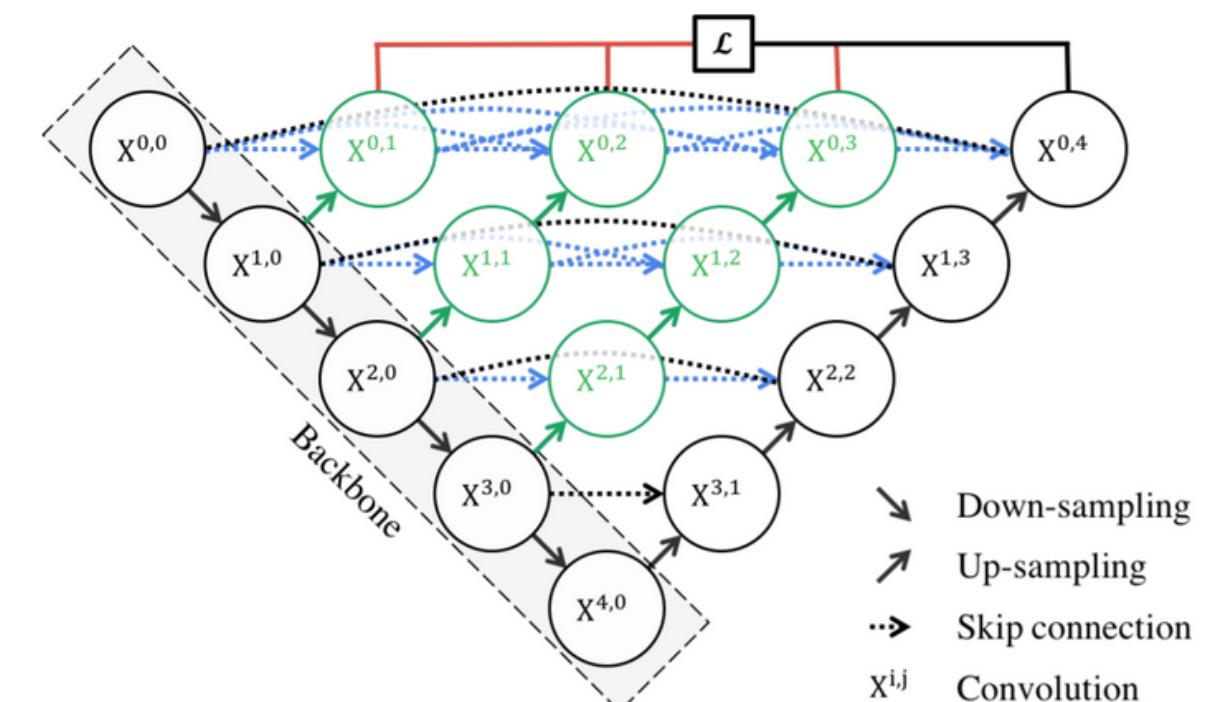
Simple addition in order to combine the contracting and up-sampling path

MA-NET

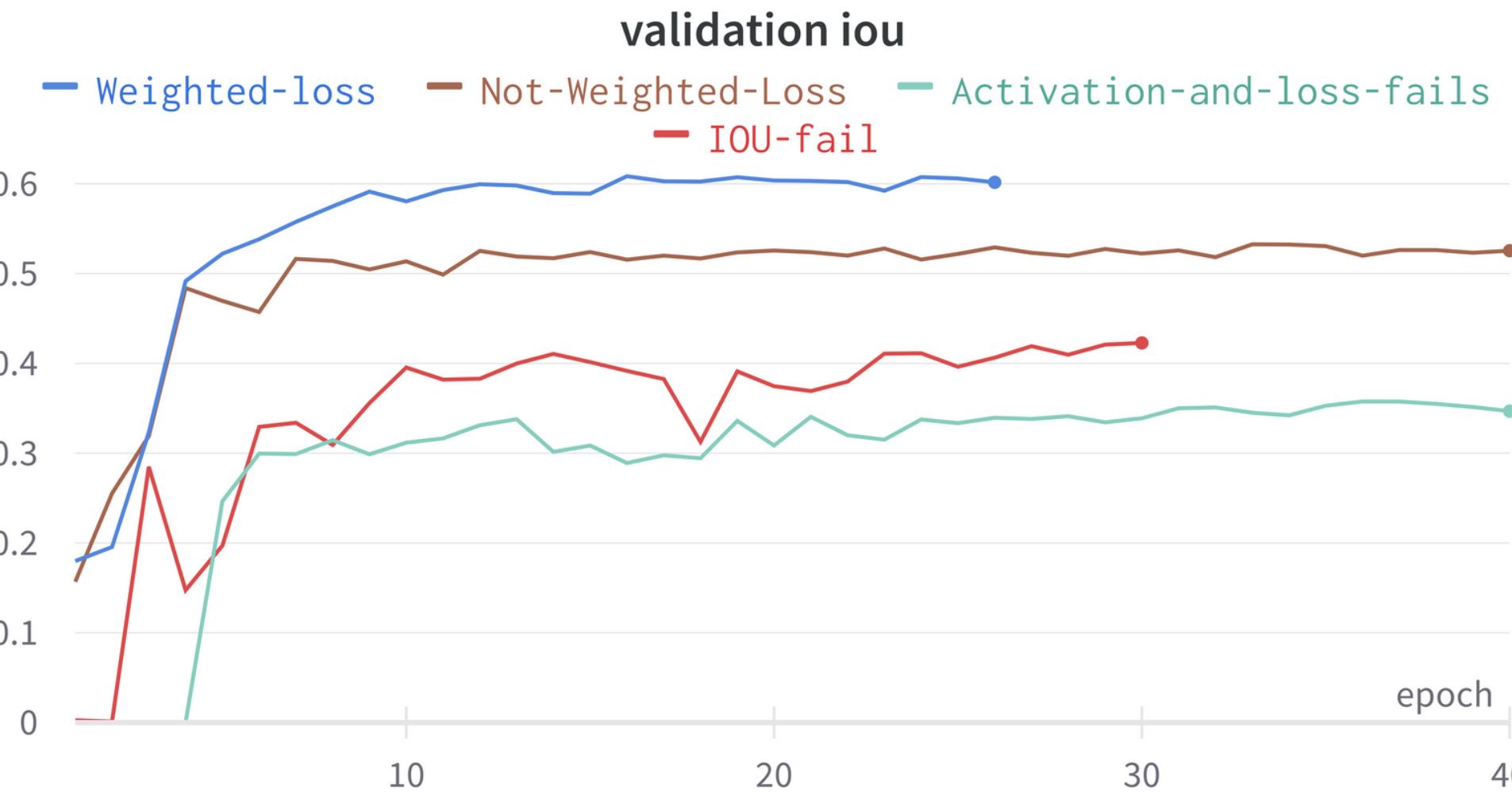
An efficient dot product attention mechanism suitable for large input images is introduced, which proves to be very effective when dealing with remote sensing tasks

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



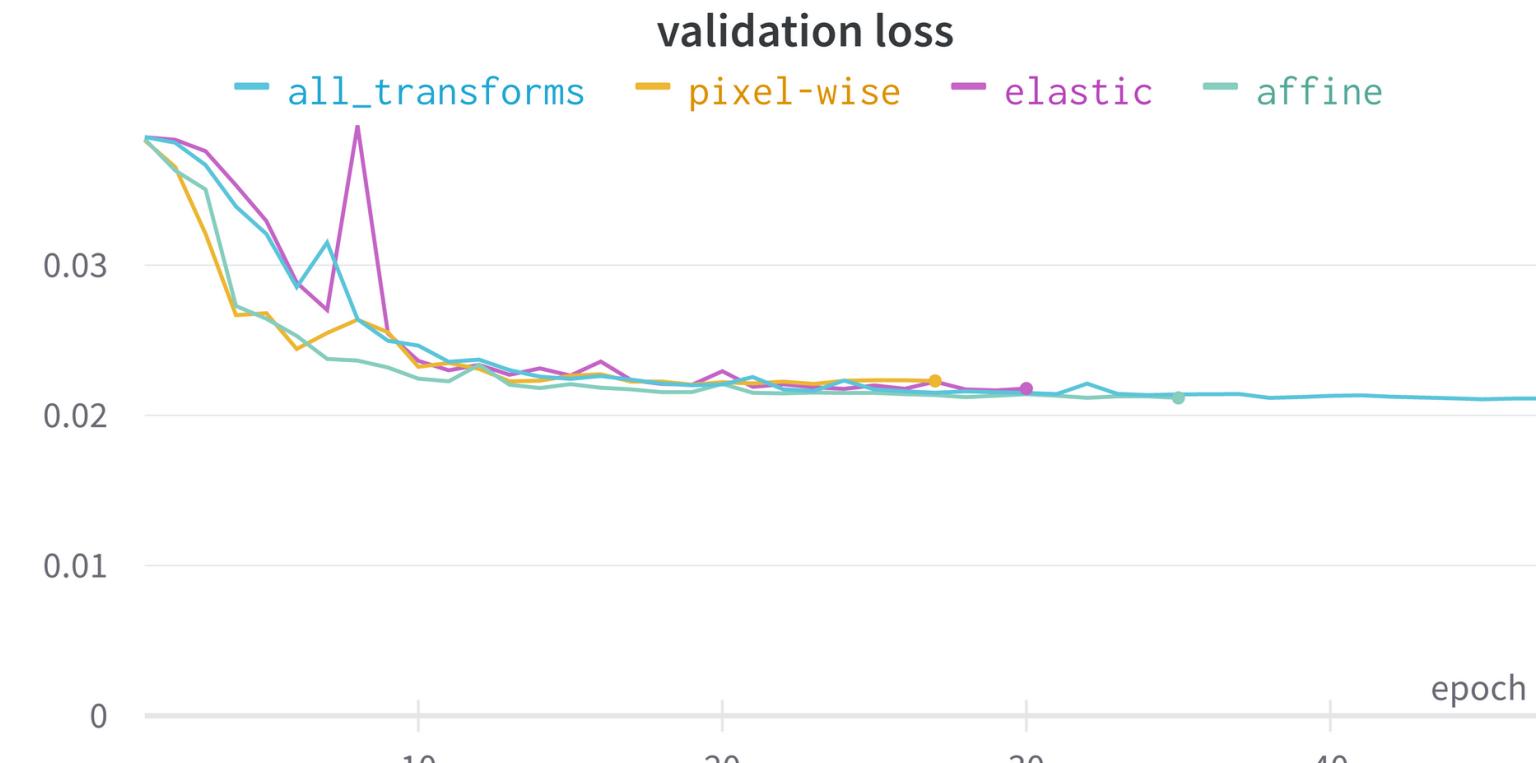
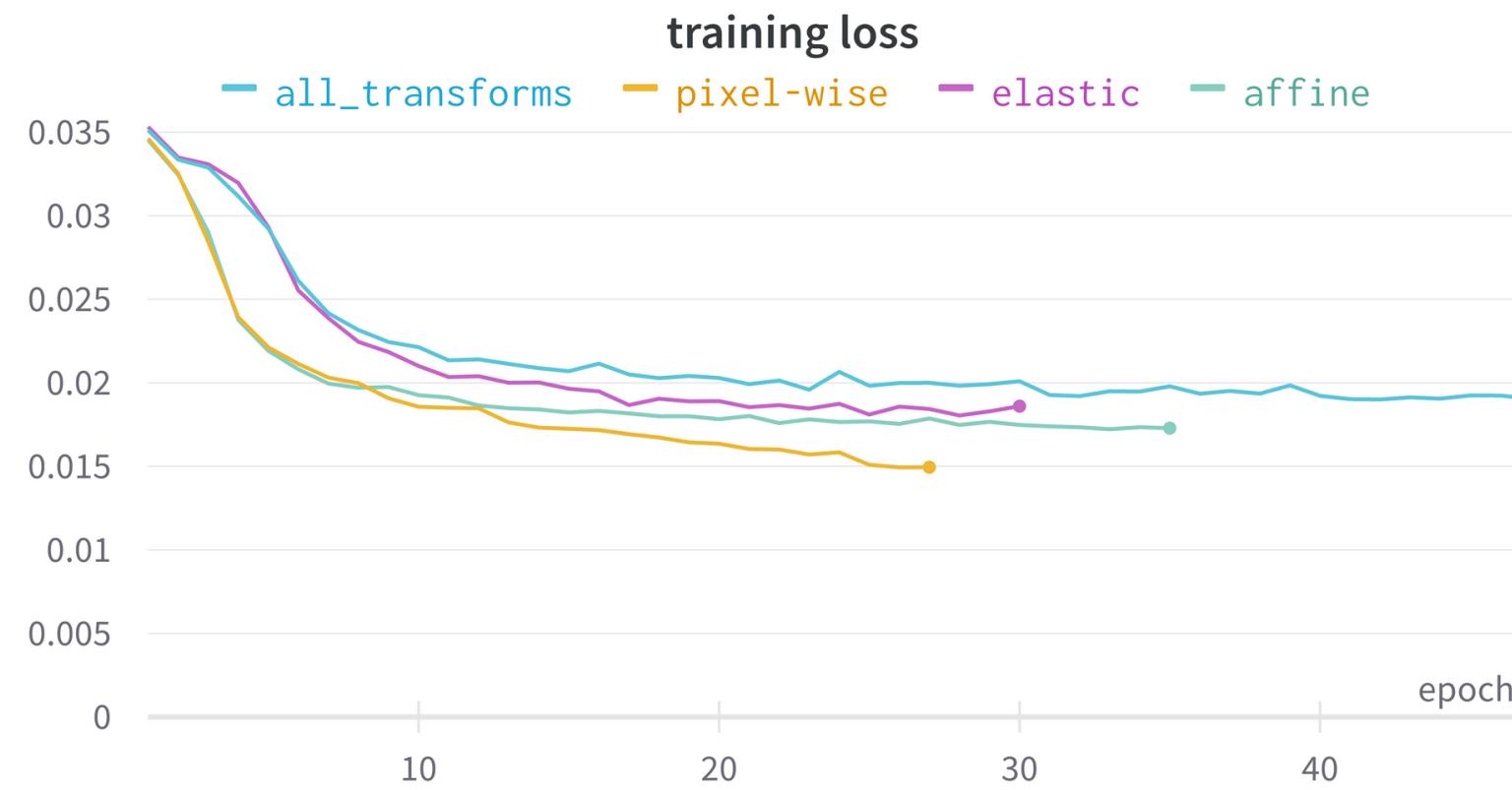
WHAT DOES NOT KILL YOU MAKES YOU STRONGER



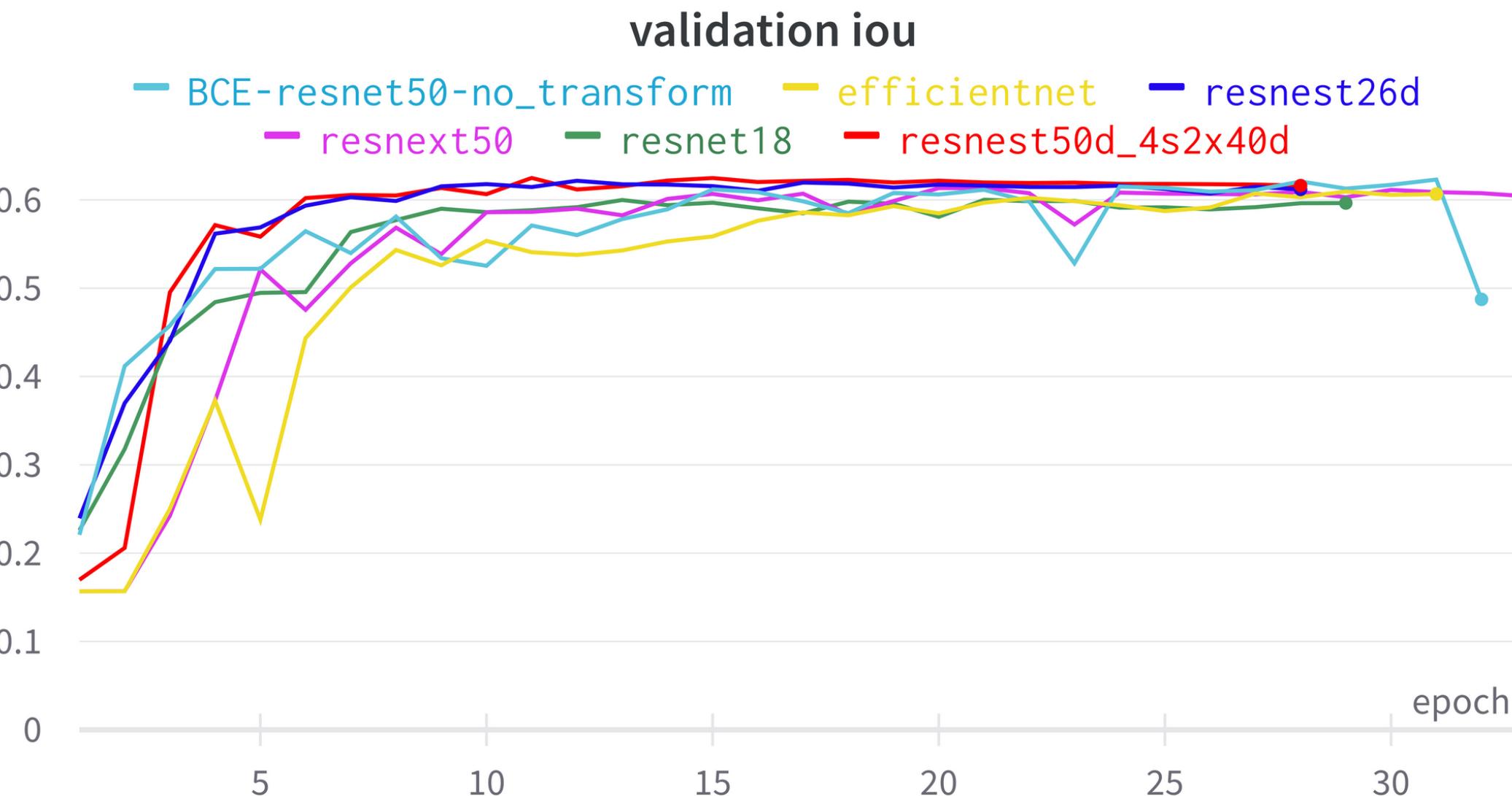
Unfortunately every mistake was repeated in multiple runs before finding it...

TRANSFORMATIONS EFFICACY

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



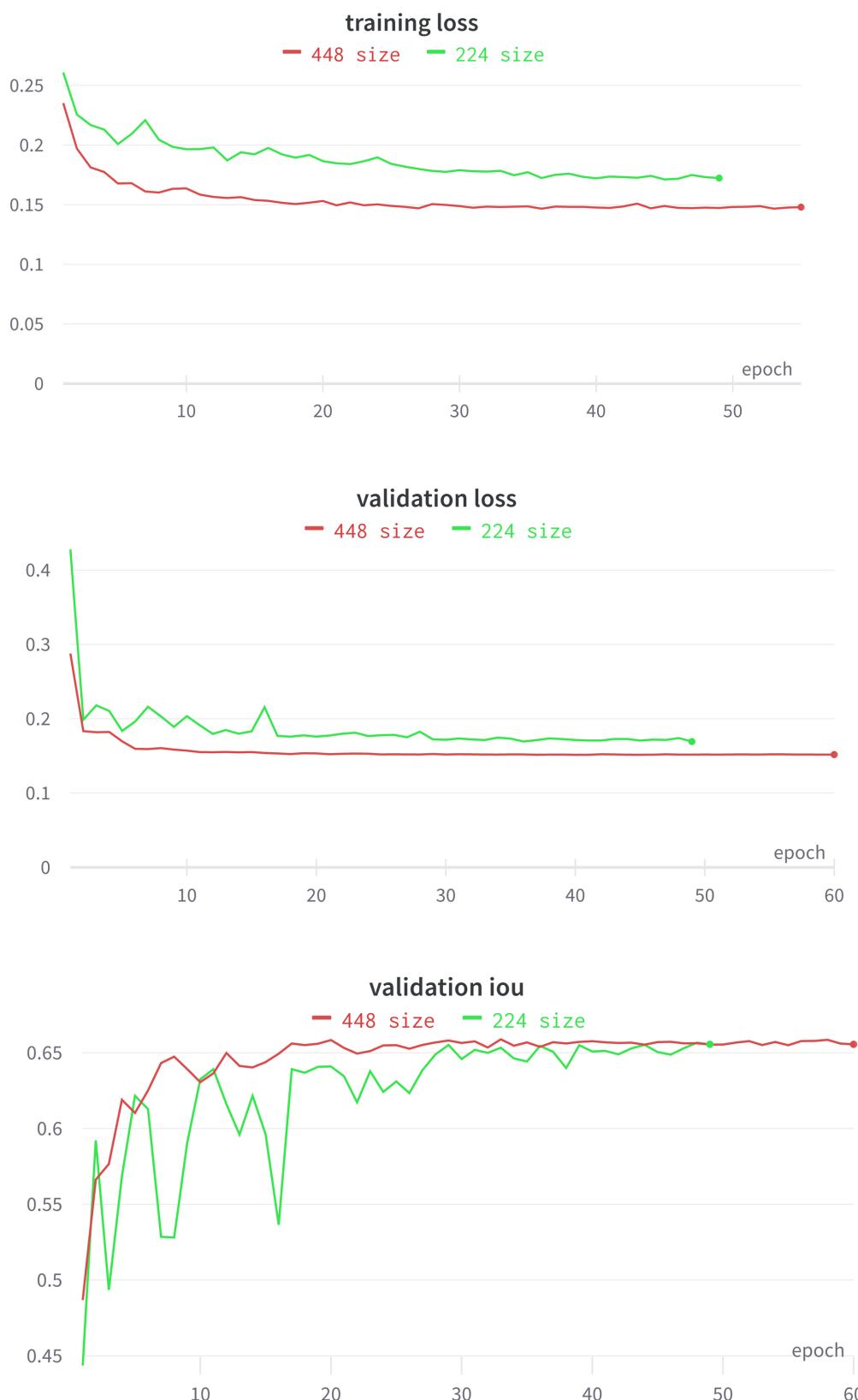
BACKBONE EFFICACY



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?

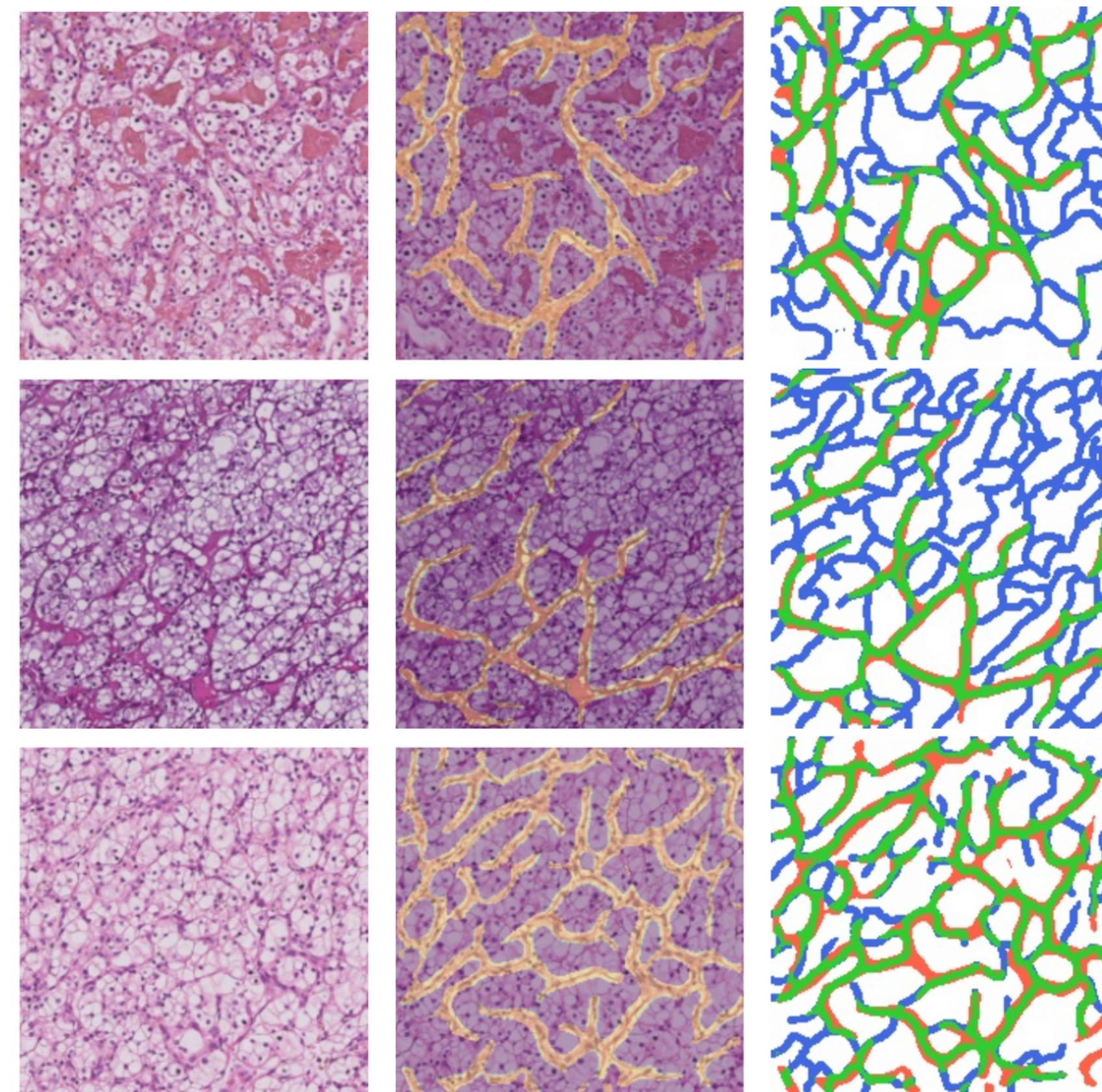
Size	Model	Loss function	Backbone	Transformations	Training loss	Validation loss	Validation IOU
224	U-Net	Binary CE	Resnest101	Affine+Elastic	0.177	0.172	65.59
224	MA-Net	Binary CE	Resnest101	All	0.185	0.173	65.06
224	LinkNet	Binary BCE	Resnest101	Affine+Elastic	0.176	0.172	65.20
224	U-Net++	Binary BCE	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
WINNER WITH BIGGER SIZE	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		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	0.182	0.175	64.42
	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
WINNER WITH STANDARD SIZE	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	Resnet18	No	0.020	0.034	60.26
	224	MA-Net	Dice	Resnet50	No	0.026	0.031	61.98
	224	MA-Net	Dice	Resnest50	No	0.026	0.031	62.39
	224	MA-Net	Dice	Resnest50	All	0.027	0.031	61.88
	224	MA-Net	Dice	Efficient-net	All	0.034	0.030	60.94
	224	LinkNet	Dice	Resnet50	All	0.029	0.030	61.93
	224	LinkNet	Dice	Resnet101	All	0.032	0.035	58.60
	224	LinkNet	Dice	Resnest50	All	0.027	0.029	64.56
	224	LinkNet	Binary CE	Resnest50	All	0.028	0.030	64.02
	224	LinkNet	Binary CE	Resnest101	Affine+Elastic	0.176	0.172	65.20
	448	LinkNet	Binary CE	Resnest101	Affine+Elastic	0.374	0.411	61.92
WINNER WITH STANDARD SIZE	224	U-Net++	Dice	Resnet50	All	0.033	0.030	61.51
	224	U-Net++	Dice	Resnest101	All	0.028	0.027	65.38
WINNER WITH STANDARD SIZE	224	U-Net++	Binary CE	Resnest101	Affine+Elastic	0.172	0.173	65.67

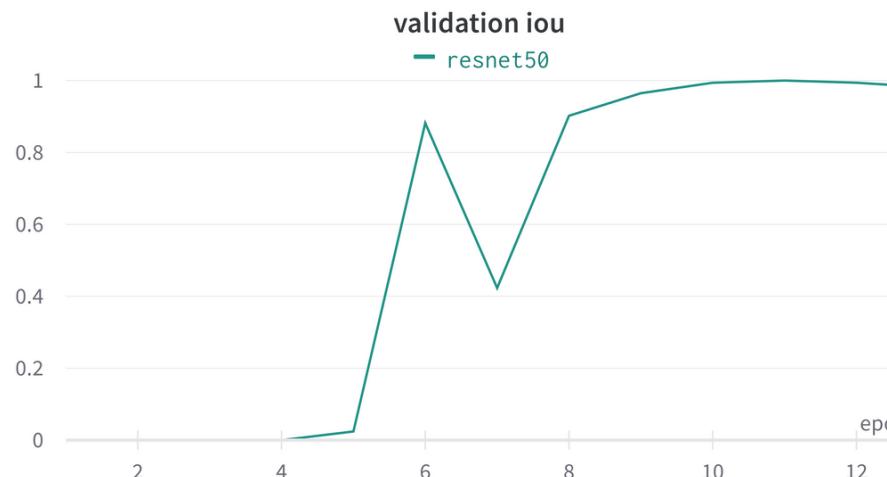
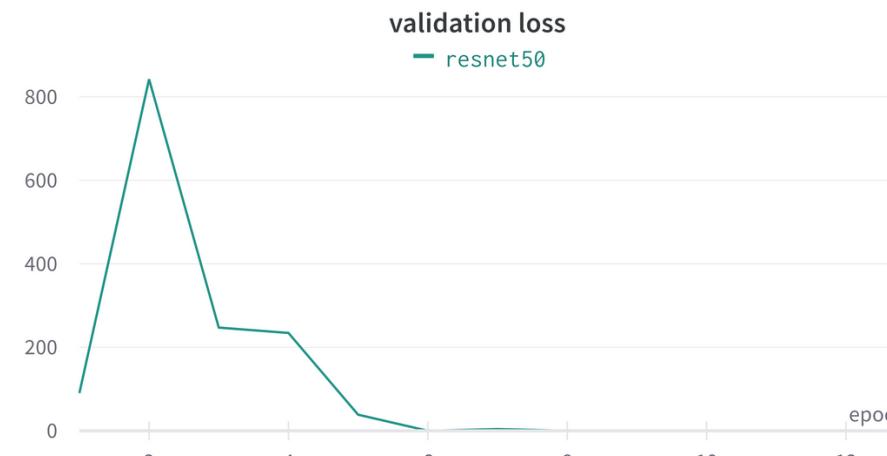
Table 1. Segmentation experiments

SOME SEGMENTATION PREDICTIONS



CLASSIFICATION RESULTS

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



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.