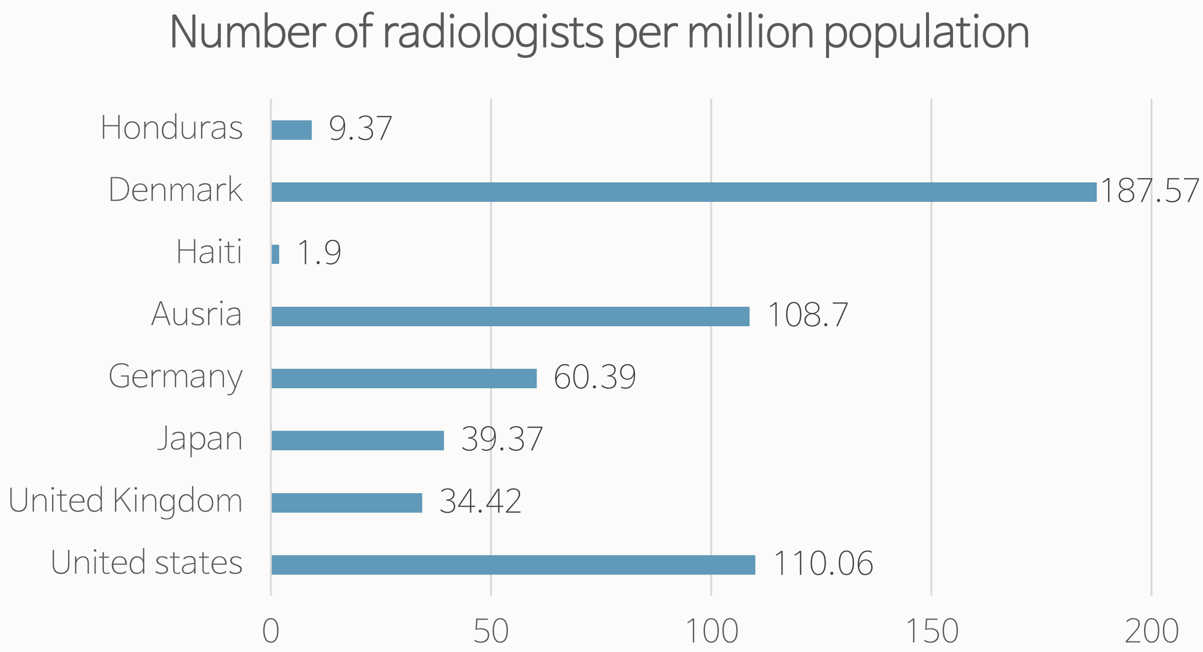
Medical Image Segmentation with U-Net

2019.07.11 장성은

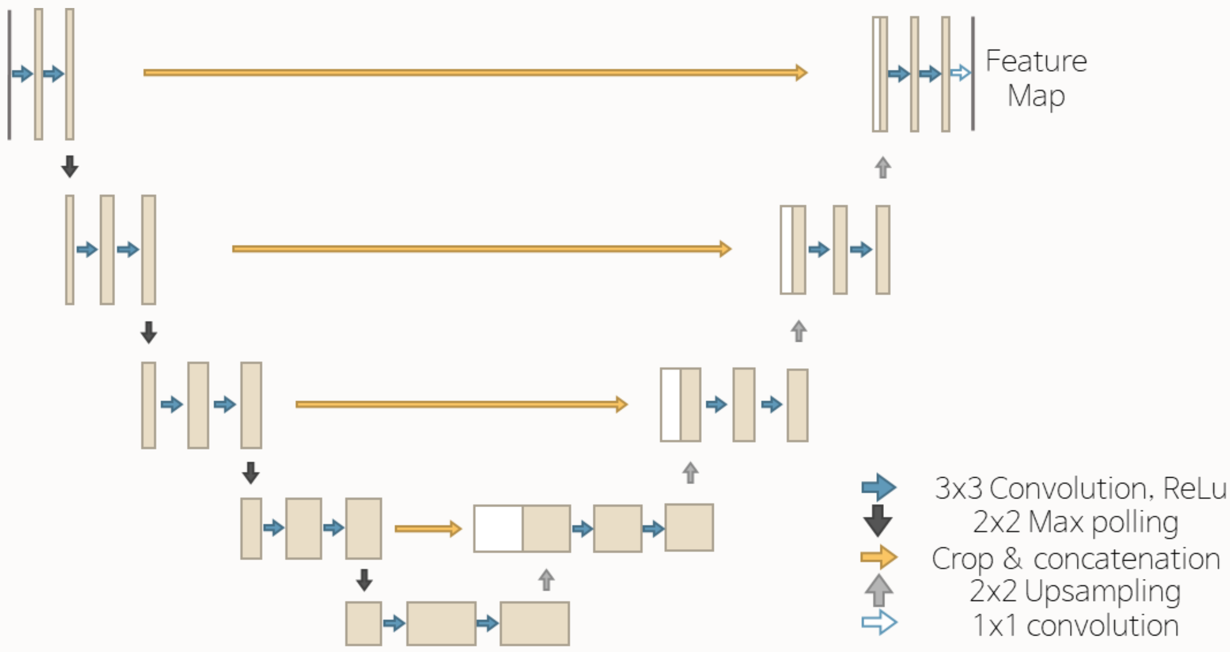
Medical Image Analysis

- Lack of Radiologists



U-Net

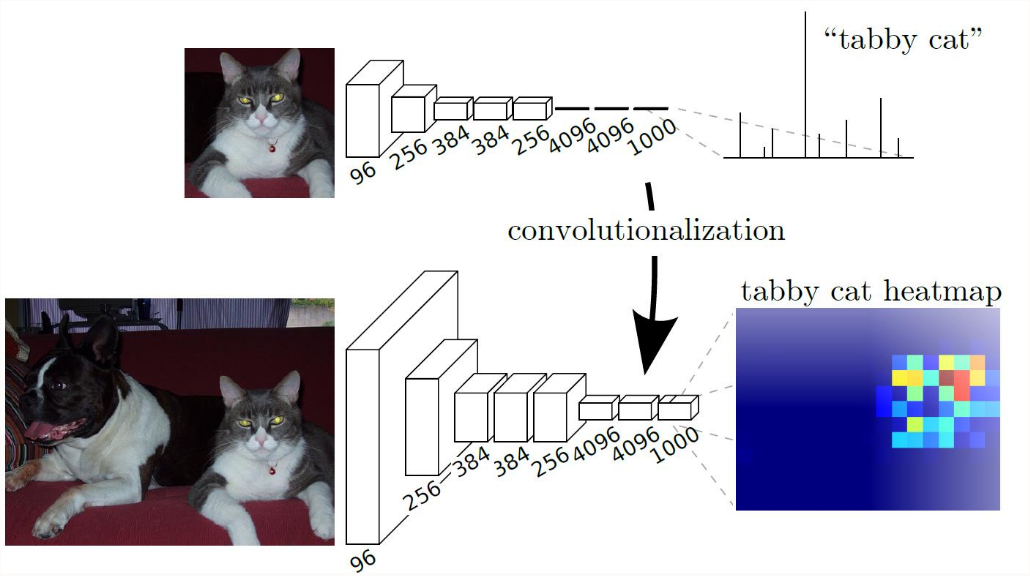
- U-Net



- Modify and extend fully convolutional network (FCN) such that it works with very few training images and yields more precise segmentations
- Has been published in 2015 MICCAI with more than 3000 citations

U-Net

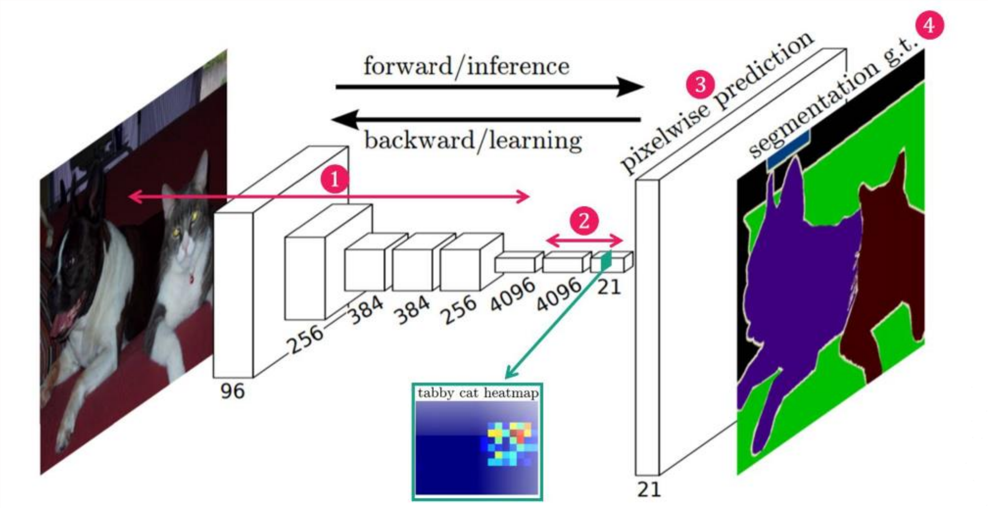
- Fully Convolutional Networks (FCN)

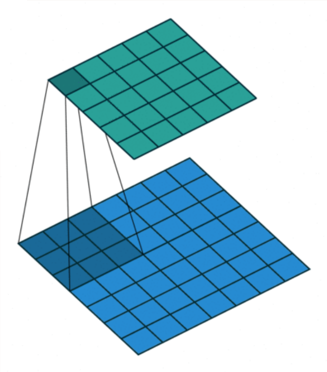


  - Obtaine a coarse segmentation heatmap using convolution 1x1 layer instead of fully connected layer in CNN

U-Net

- Fully Convolutional Networks (FCN)



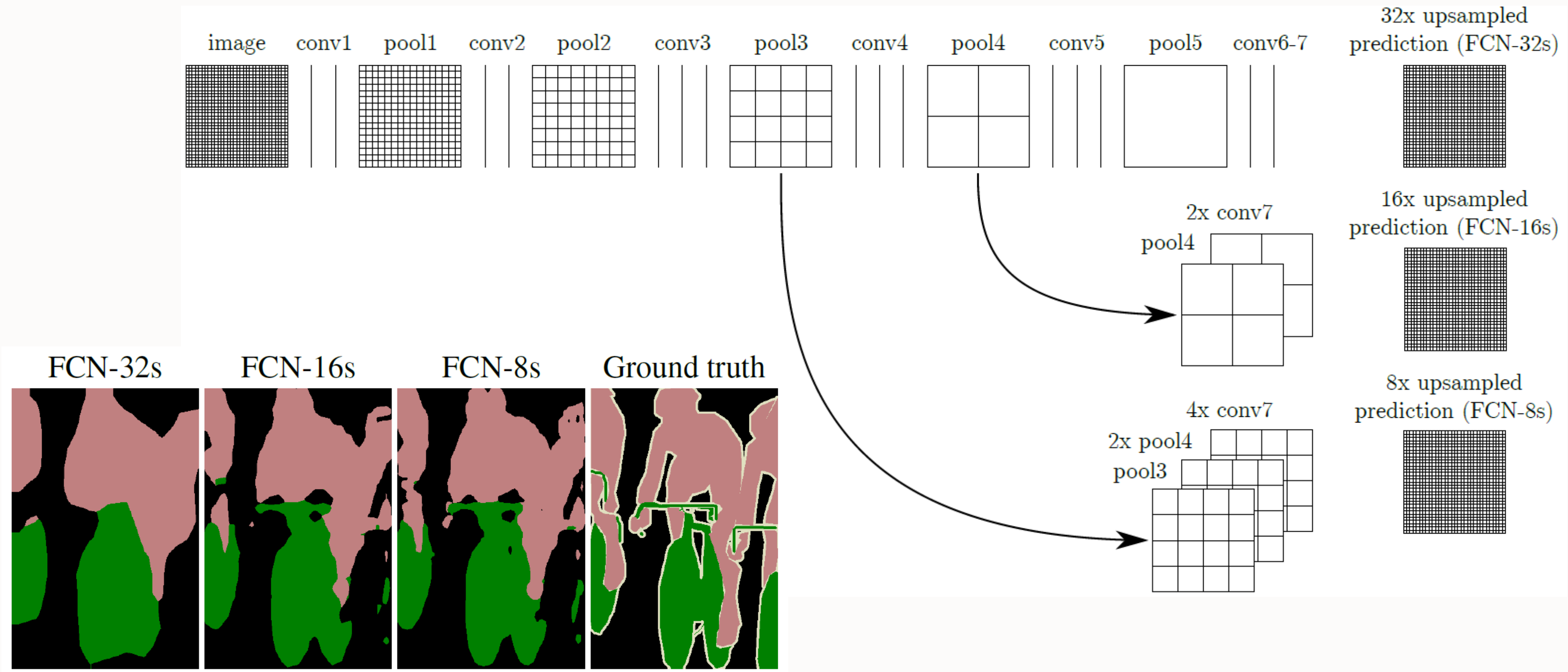


upsampling

1) Feature Extraction
2) Feature-level Classification
3) Upsampling
4) Segmentation

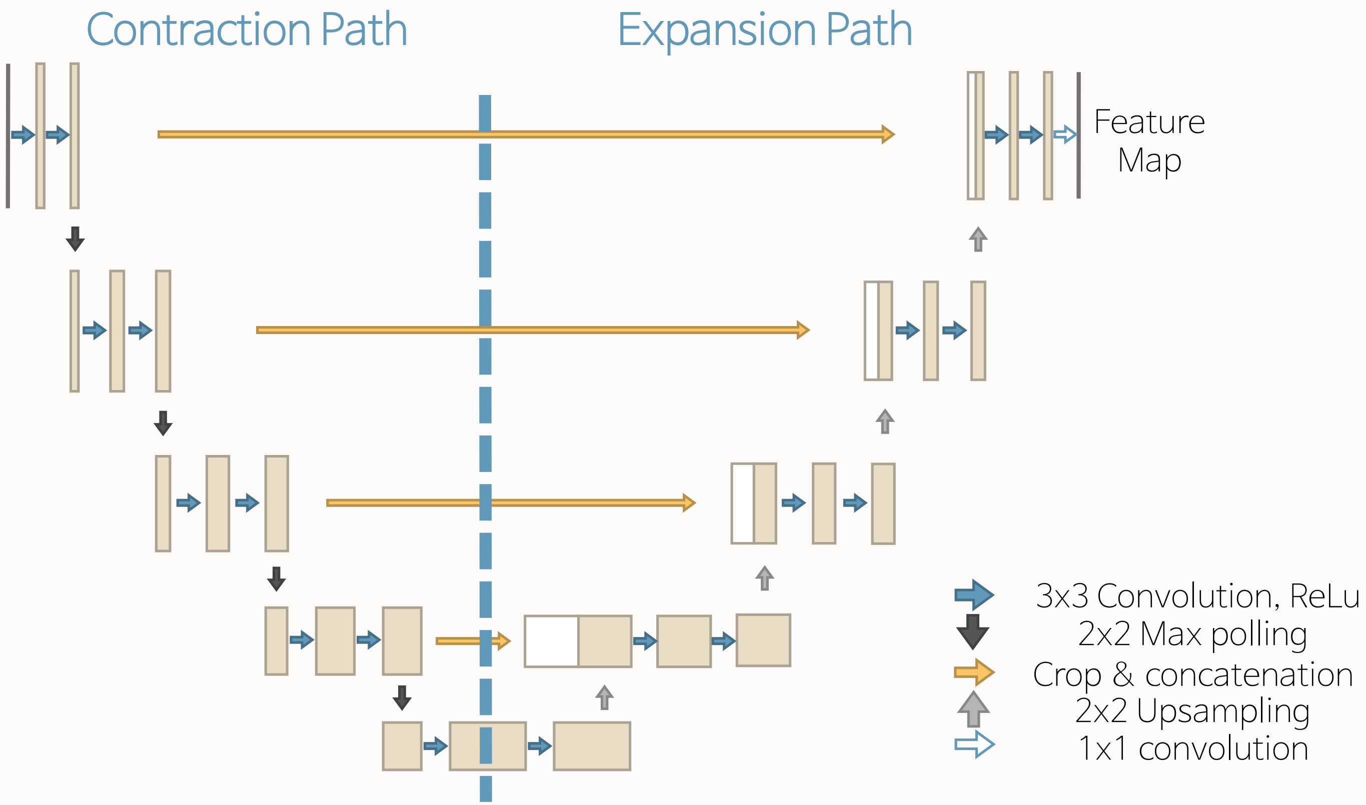
U-Net

- Fully Convolutional Networks (FCN)



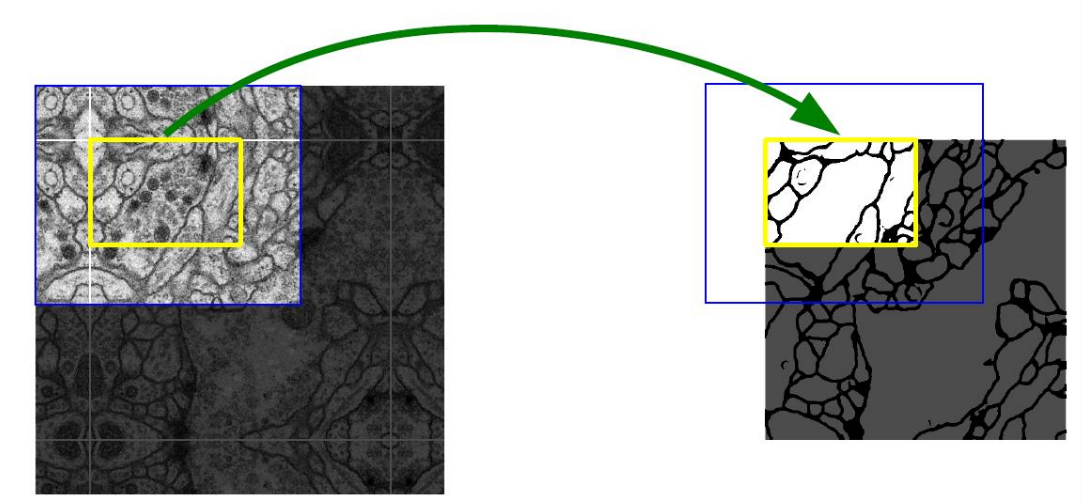
U-Net

- Architecture



U-Net

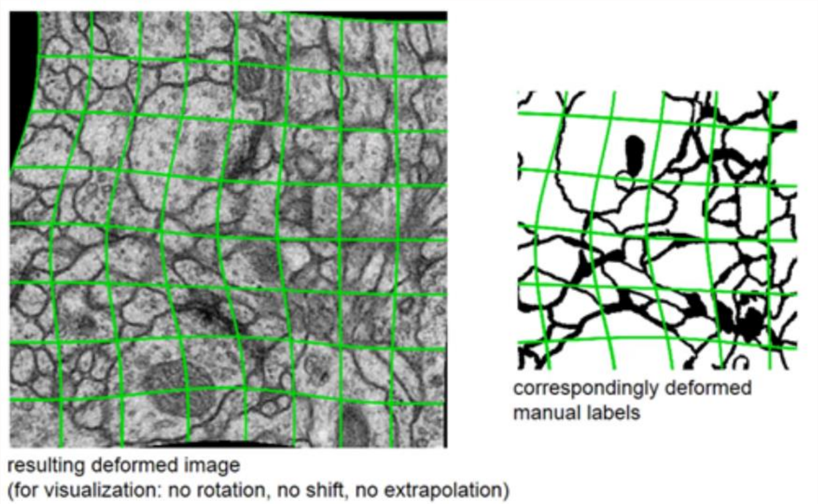
- Overlap Tile Strategy



- Instead of downsizing before network and upsampling after network, overlap tile strategy is used.
- The whole image is predicted part by part

U-Net

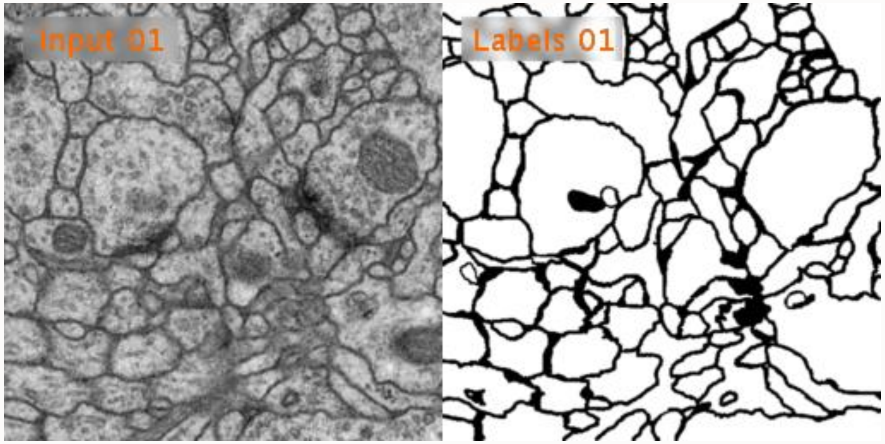
- Data Augmentation



- There is very little training data available
- Use data augmentation by applying elastic deformations to the available training images

U-Net

- Dataset – ISBI 2012 Dataset (EM segmentation challenge)

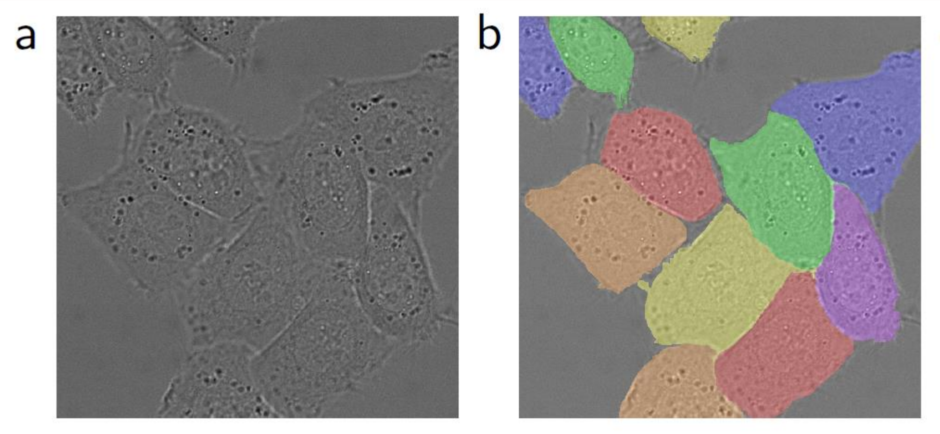


  - Set of images (512x512 pixels) from serial section transmission electron microscopy

  - Train 30 images, test 30 images

U-Net

- Dataset – ISBI 2014 & 2015 Dataset (cell tracking challenge)



  - PhC-U373 and DIC-HeLa Datasets
  - contains 35 partially annotated training images

U-Net

- Train

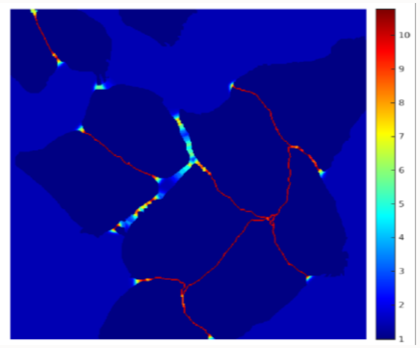
  - Large input tiles over a large batch size & small batch to a single image
  - Use a high momentum (0.99)
  - Stochastic gradient descent (Caffe)

U-Net

- Train
  - Cross Entropy Loss with w(x)
    - To separate the touching objects, a pre-computed pixel-wise loss weight map is applied to the output of network

$$w(\mathbf{x}) = w_c(\mathbf{x}) + w_0 \cdot \exp\left(-\frac{(d_1(\mathbf{x}) + d_2(\mathbf{x}))^2}{2\sigma^2}\right)$$

Segmentation mask



Weight map

U-Net

- Train
  - Cross Entropy Loss with w(x)

$$p_k(\mathbf{x}) = \exp(a_k(\mathbf{x}))/\left(\sum_{k'=1}^{K}\exp(a_{k'}(\mathbf{x}))\right)$$

$$E = \sum_{\mathbf{x}\in\Omega} w(\mathbf{x})\log(p_k(\mathbf{x}))$$

Melanoma Segmentation with U-Net

- Evaluation

  - Pixel Error
    A standard pixel-wise error

  - Intersection over Union (IOU)
    An accuracy of an object detector

  - Warping Error
    A segmentation metric that penalizes topological disagreements.

  - Rand Error
    A measure of similarity between two clusters or segmentations.

U-Net

- Result (ISBI 2012 Dataset)

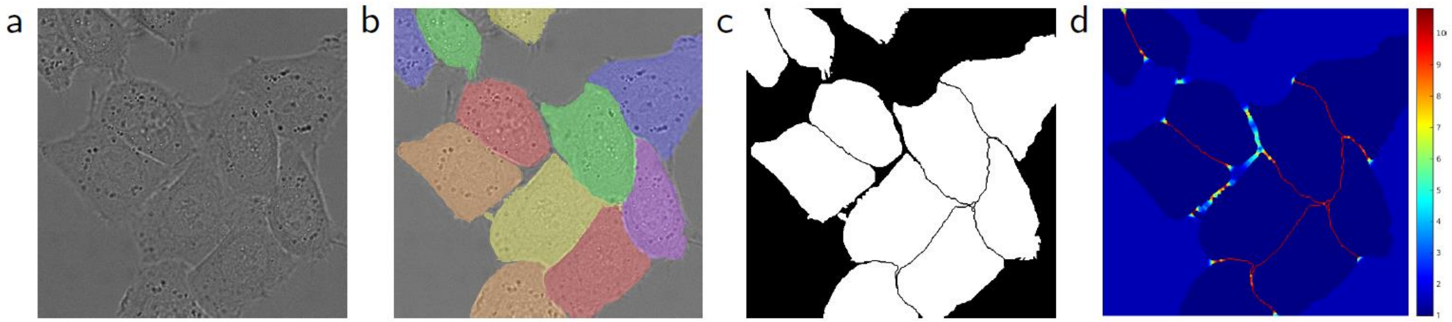


Table 1. Ranking on the EM segmentation challenge [14] (march 6th, 2015), sorted by warping error.

Rank	Group name	Warping Error	Rand Error	Pixel Error
	** human values **	0.000005	0.0021	0.0010
1.	u-net	**0.000353**	0.0382	0.0611
2.	DIVE-SCI	0.000355	0.0305	0.0584
3.	IDSIA [1]	0.000420	0.0504	0.0613
4.	DIVE	0.000430	0.0545	**0.0582**
⋮				
10.	IDSIA-SCI	0.000653	**0.0189**	0.1027

U-Net

- Result (ISBI 2014 & 2015 Dataset)

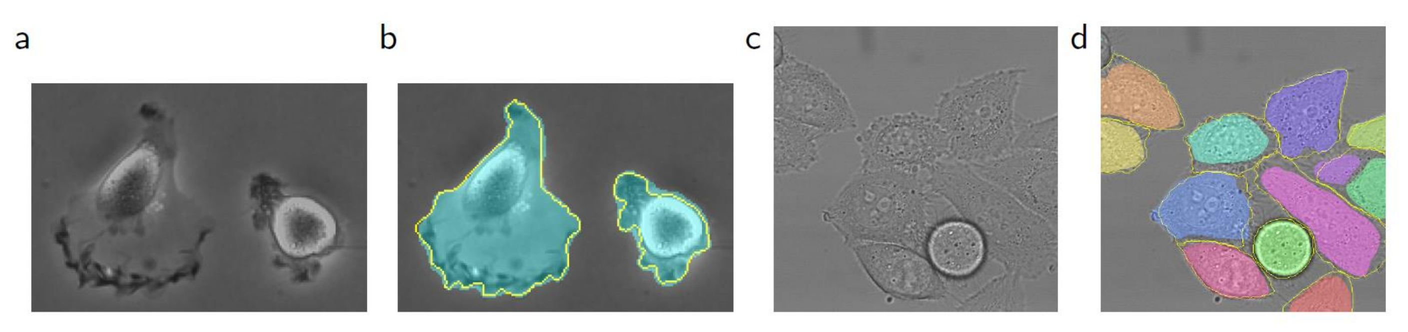
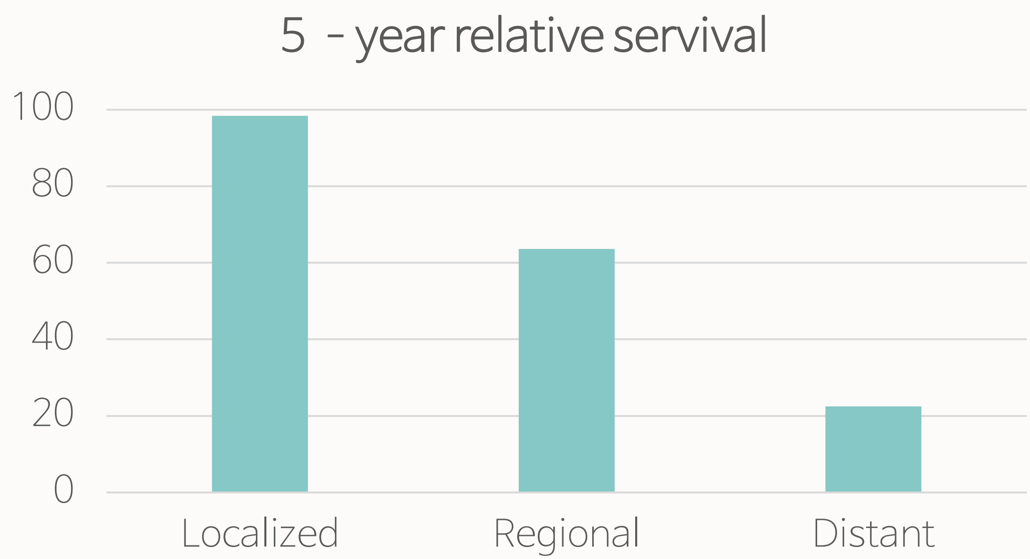


Table 2. Segmentation results (IOU) on the ISBI cell tracking challenge 2015.

Name	PhC-U373	DIC-HeLa
IMCB-SG (2014)	0.2669	0.2935
KTH-SE (2014)	0.7953	0.4607
HOUS-US (2014)	0.5323	-
second-best 2015	0.83	0.46
u-net (2015)	**0.9203**	**0.7756**

Melanoma Segmentation with U-Net

- Melanoma (악성흑색종)
  - Most dangerous type of skin cancer that develops from the melanocytes
  - Typically occur in the skin, but may rarely occur in the mouth or eye



Melanoma Segmentation with U-Net

- Melanoma Segmentation

Naked eye examination

Dermoscopy

- The ABCDE rule was used to score the morphological characteristics and use it for diagnosis

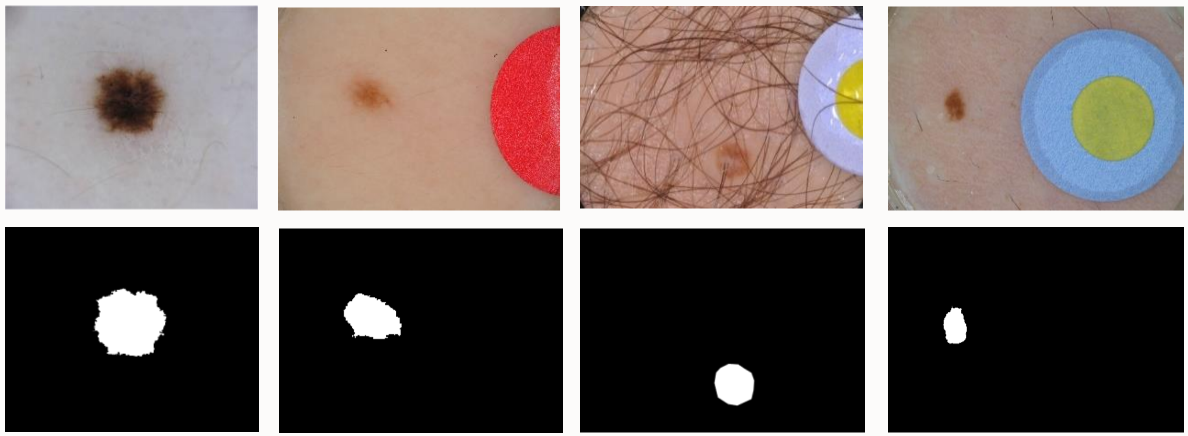
- There is a limit to the diagnosis by the subjective judgment of the doctors

Melanoma Segmentation with U-Net

- Dataset

Dermoscopy

Segmentation mask



		Train (7000)	Validation (150)	Test(3000)
Height(pixels)	Min	300	1024	1024
	Max	492	6688	4288
Weight(pixels)	Min	300	768	768
	Max	400	4459	2848

Melanoma Segmentation with U-Net

- Train
  - Modify the u-net code implemented in PyTorch from GitHub
  - Epoch 100, Batch size 10
  - Binary cross entropy loss
  - Stochastic Gradient Descent
  - Thresholding with Gaussian filter and Otsu

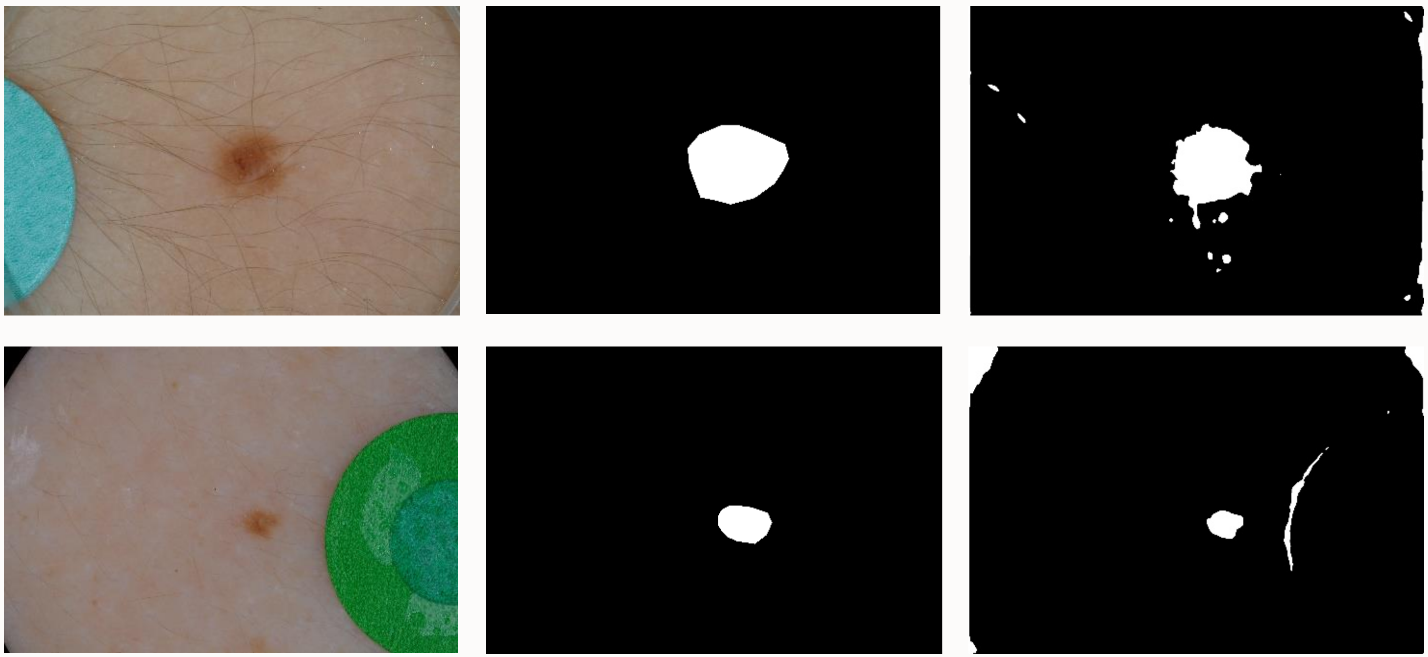
Melanoma Segmentation with U-Net

- Evaluation
  - Accuracy $\frac{TP+TN}{TP+FP+TN+FN}$
  - Sensitivity $\frac{TP}{TP+FN}$
  - Specificity $\frac{TN}{FP+TN}$
  - Positive predictive value $\frac{TP}{TP+FP}$
  - Negative predictive value $\frac{TN}{TN+FN}$
  - Jaccard distance $1 - \frac{|A \cap B|}{|A \cup B|}$

Melanoma Segmentation with U-Net

- Result

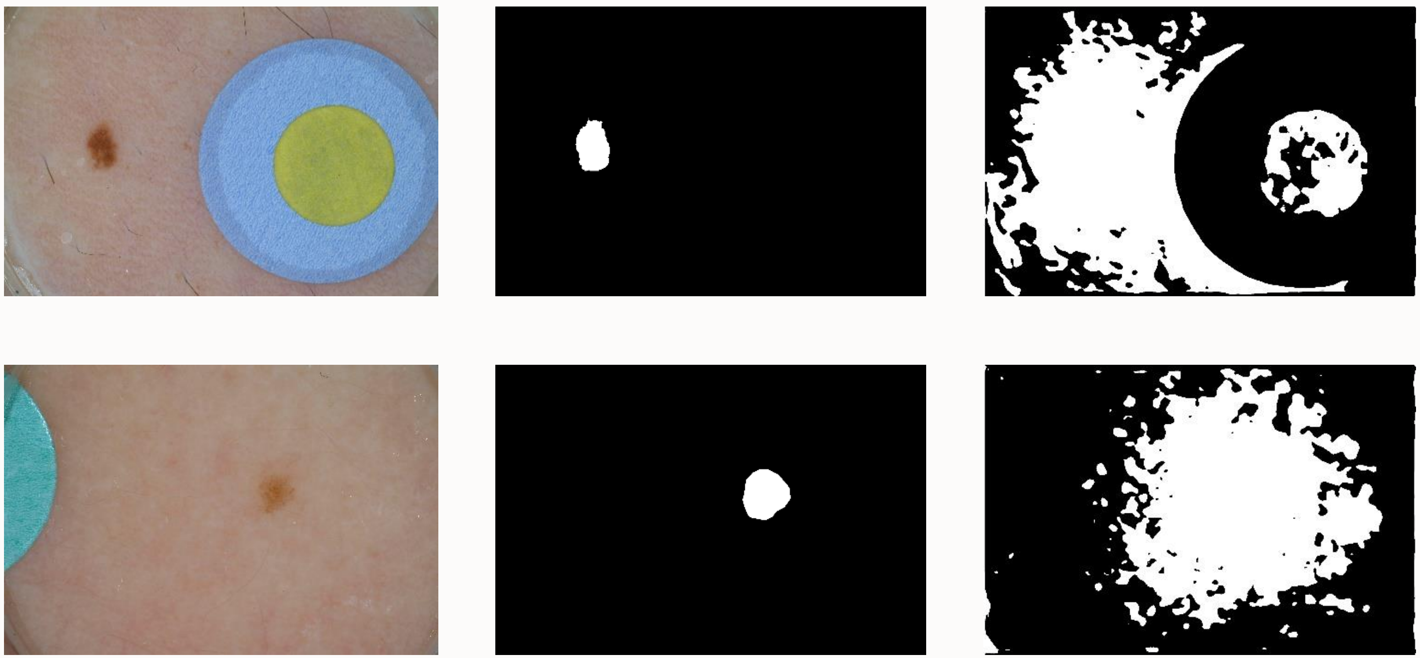
Dermoscopy | Ground truth | Segmentation result



Melanoma Segmentation with U-Net

- Result

Dermoscopy | Ground truth | Segmentation result



Melanoma Segmentation with U-Net

- Result

		accuracy	sensitivity	specificity	positive predictive value	negative predictive value	Jaccard distance
Train	average	0.35	0.97	0.34	0.04	0.99	0.04
	standard deviation	0.20	0.13	0.20	0.04	0.02	0.04
Valid	average	0.38	0.95	0.26	0.22	0.91	0.21
	standard deviation	0.25	0.11	0.26	0.24	0.21	0.21
Test	average	0.44	0.87	0.27	0.32	0.80	0.29
	standard deviation	0.21	0.18	0.21	0.26	0.27	0.23

Reference

- Litjens, Geert, et al. "A survey on deep learning in medical image analysis." Medical image analysis 42 (2017): 60-88.
- Shen, Dinggang, Guorong Wu, and Heung-Il Suk. "Deep learning in medical image analysis." *Annual review of biomedical engineering* 19 (2017): 221-248.
- Long, Jonathan, Evan Shelhamer, and Trevor Darrell. "Fully convolutional networks for semantic segmentation." Proceedings of the IEEE conference on computer vision and pattern recognition. 2015.
- https://modulabs-biomedical.github.io/FCN
- https://m.blog.naver.com/PostView.nhn?blogId=laonple&logNo=220958109081&proxyReferer=https%3A%2F%2Fwww.google.com%2F
- Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." International Conference on Medical image computing and computer-assisted intervention. Springer, Cham, 2015.
- https://towardsdatascience.com/review-u-net-biomedical-image-segmentation-d02bf06ca760
- https://github.com/milesial/Pytorch UNet

Thank you!