U-Net: Convolutional Networks for Biomedical Image Segmentation

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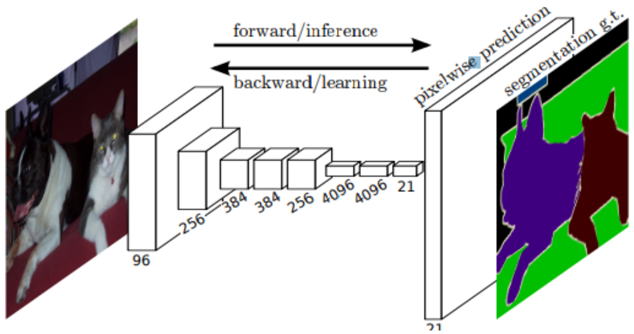
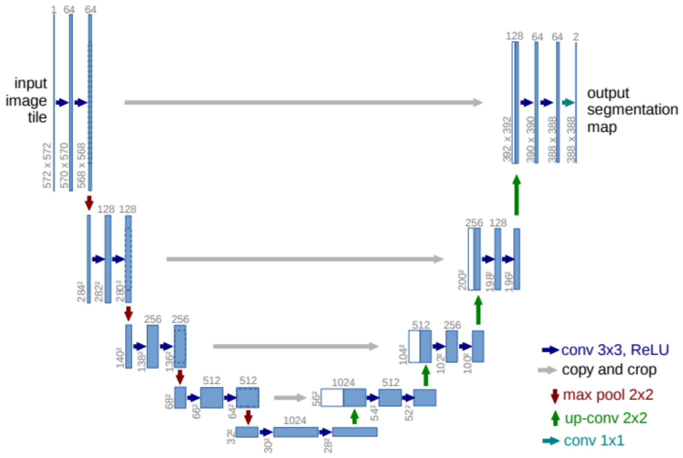
Content

Introduction to U-Net

- Biomedical Image Segmentation을 위한 네트워크
- U-Net은 FCN을 기반으로 한 네트워크
- 더 적은 데이터를 가지고 더욱 정확한 Segmentation을 수행





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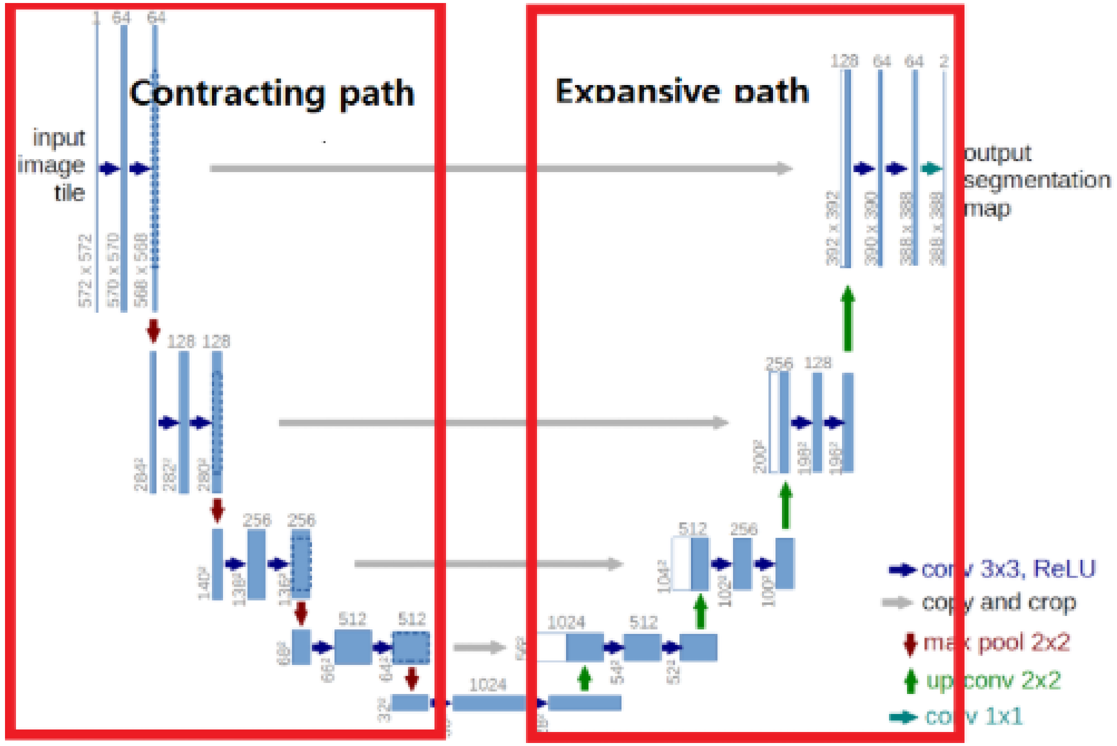
Introduction to U-Net



- Contracting Path : capture image's context
- Expanding Path : upsampling the feature map
- Concatenation : provides local information to the global information while upsampling

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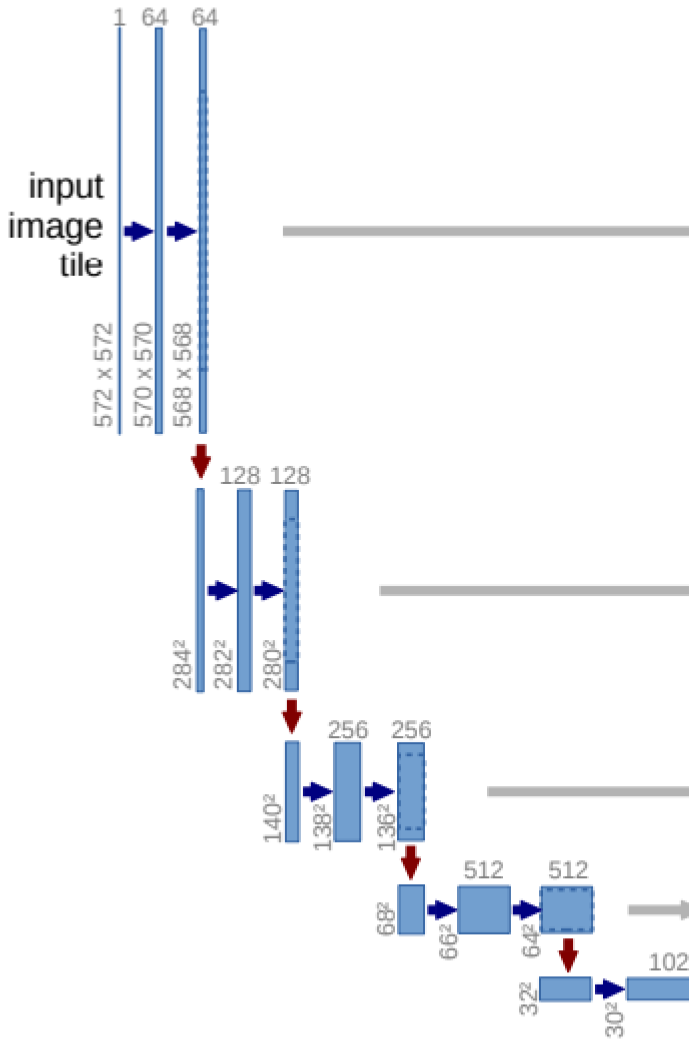
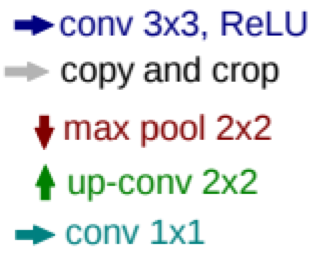
Architecture – Contracting Path





- Repeat 3x3 Convolution twice (feature map's size decrease since there's no padding)

- Activation Function -> ReLU

- 2x2 Maxpooling with stride2

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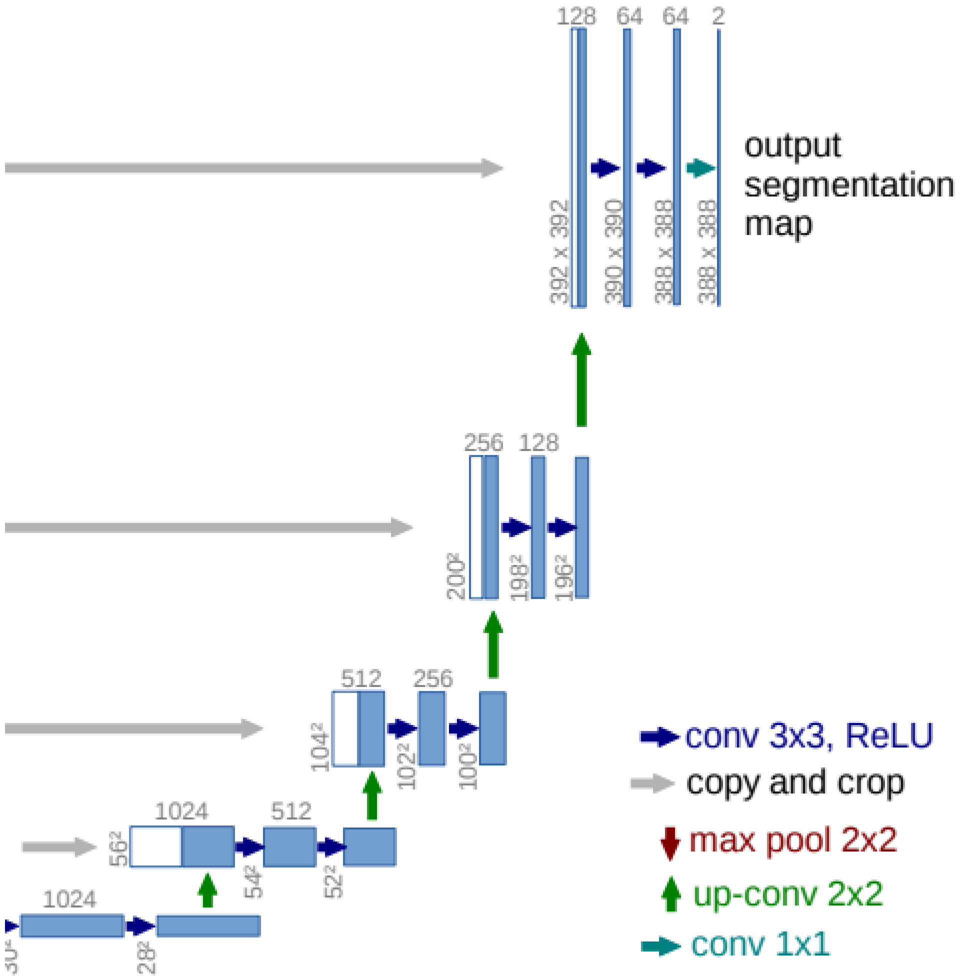
Architecture – Contracting Path

- 2x2 Up-Convolution
- Activation Function -> ReLU
- Repeat 3x3 Convolution twice (no padding)
- Concatenate upsampled feature map with cropped contracting path's feature map
- 1x1 Convolution at the end



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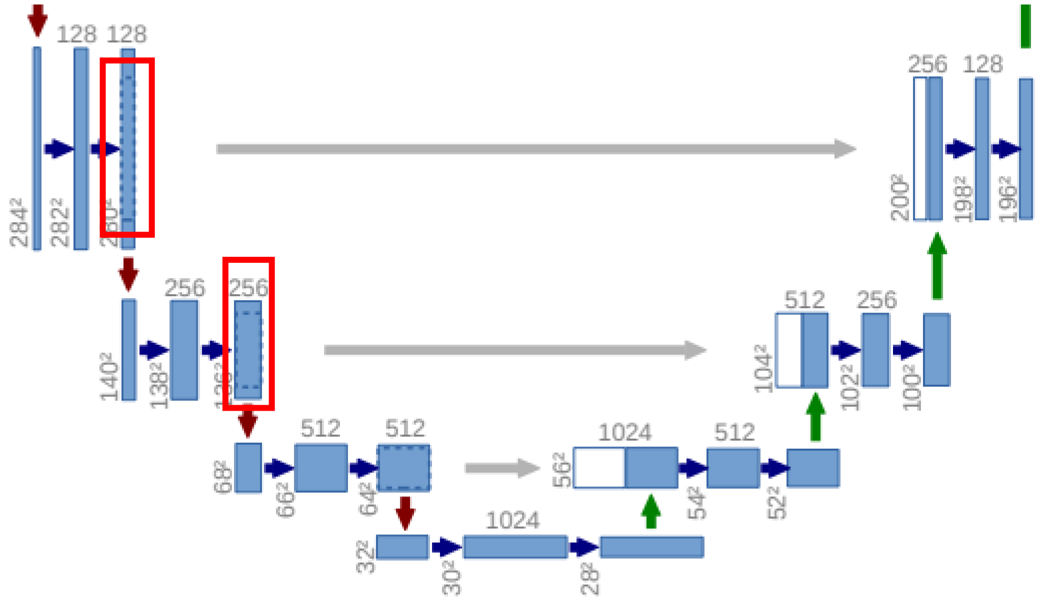
Architecture – Concatenation



- Similar to Skip Architecture from FCN

- Concatenation with the correspondingly cropped feature map from the contracting path

- Makes output image more clear

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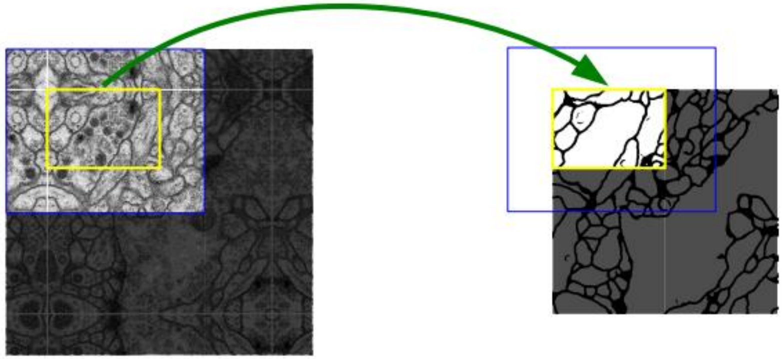
Training

- Overlap-Tile Strategy
- Mirroring Extrapolate
- Weight Loss



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

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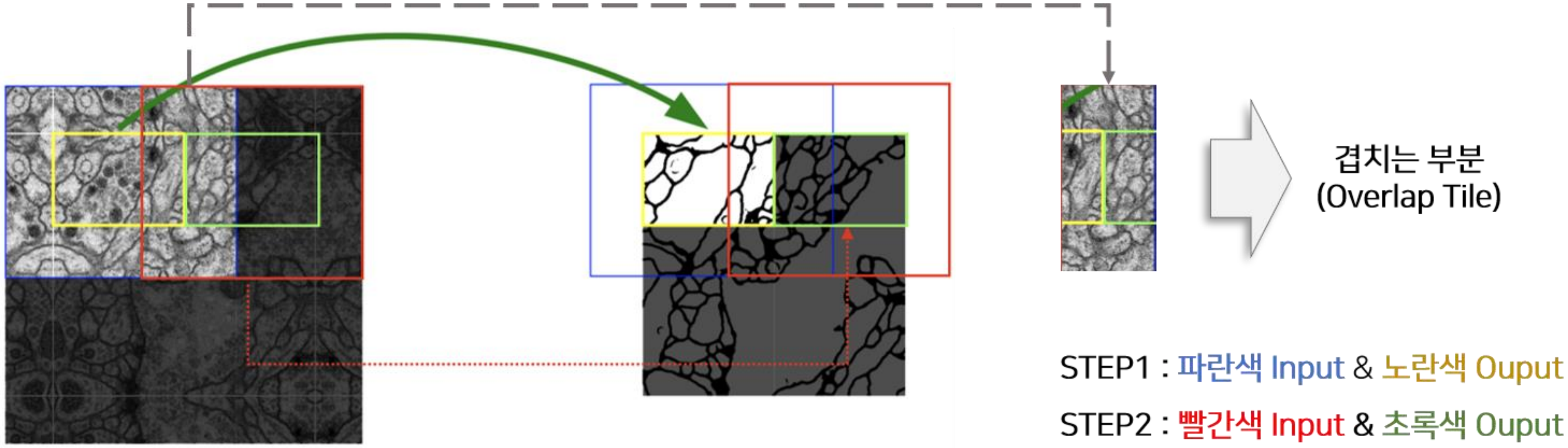
Training – Overlap Tile Strategy

- Image inputs into Tile-Patch style rather than whole image
- Called Overlap Time Strategy due to overlapped part of input patch
- Improves training speed



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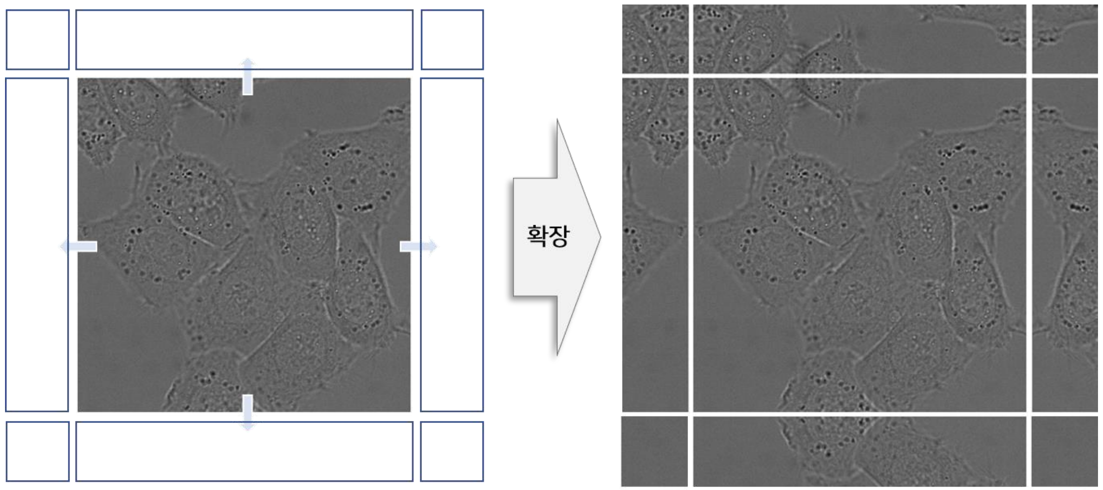
Training – Mirroring Extrapolate

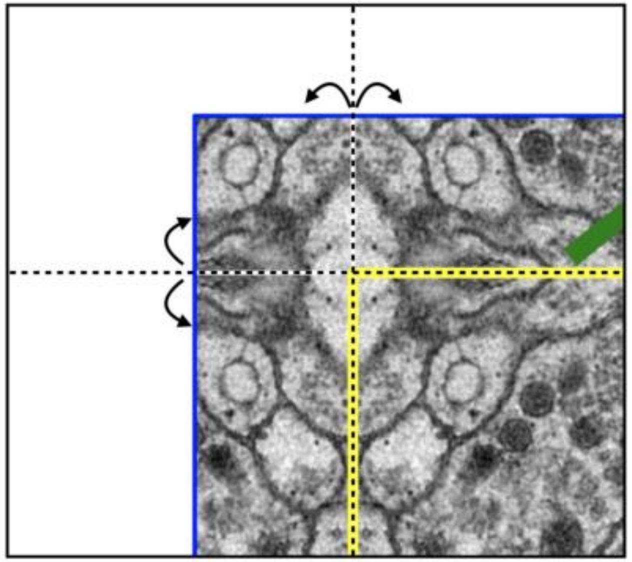
- Missing context is extrapolated by mirroring the input image rather using zero padding
- Important to apply the network to maintain images



원본 이미지

Mirroring 후 이미지

Mirroring extrapolatation



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Training – Weight Loss

• The model must be trained to seperate small boundaries as shown in the figure below

• Designed a weight-map according to how close each pixel is to the boundary and designed to learn the boundary well by increasing the loss of the pixel close to the boundary in proportion to the weight-map during training

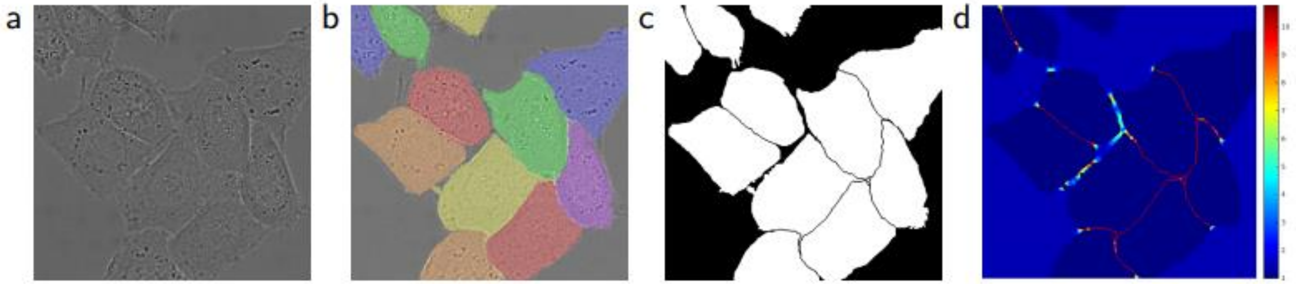

Fig. 3. HeLa cells on glass recorded with DIC (differential interference contrast) microscopy. (**a**) raw image. (**b**) overlay with ground truth segmentation. Different colors indicate different instances of the HeLa cells. (**c**) generated segmentation mask (white: foreground, black: background). (**d**) map with a pixel-wise loss weight to force the network to learn the border pixels.

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Training – Weight Loss

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

$$\mathrm{w}(\mathrm{x}) = w_c(x) + w_0 \cdot e^{-\frac{(d_1(x)+d_2(x))^2}{2\sigma^2}}$$

where $w_c: \Omega \rightarrow \mathbb{R}$ is the weight map to balance the class frequencies

$d_1: \Omega \rightarrow \mathbb{R}$ denotes the distance to the border of the nearest cell

$d_2: \Omega \rightarrow \mathbb{R}$ denotes the distance to the border of the second nearest cell

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

- The output value of the network is predicted as a softmax in pixels
- w(x) has a large value when the distance between the pixel x and the boundary is close, so the loss ratio of the pixel increases. That is, when training, it learns the pixels corresponding to the boundary well
- Cross-entropy function is used for the loss function. However, the weight map loss is included to consider the separation of the touching cells.

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Training – Additional

- In order to maximize the use of GPU memory, large input tiles are preferred rather than large batch sizes
- Used high momentum (0.99) to make the training sample conducted in the past more involved in the current update
- Initialize and train the model parameters using Gaussian Distribution

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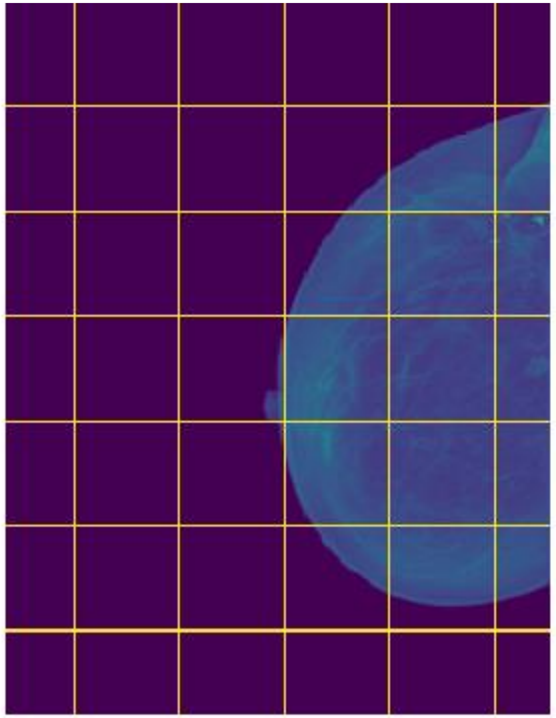
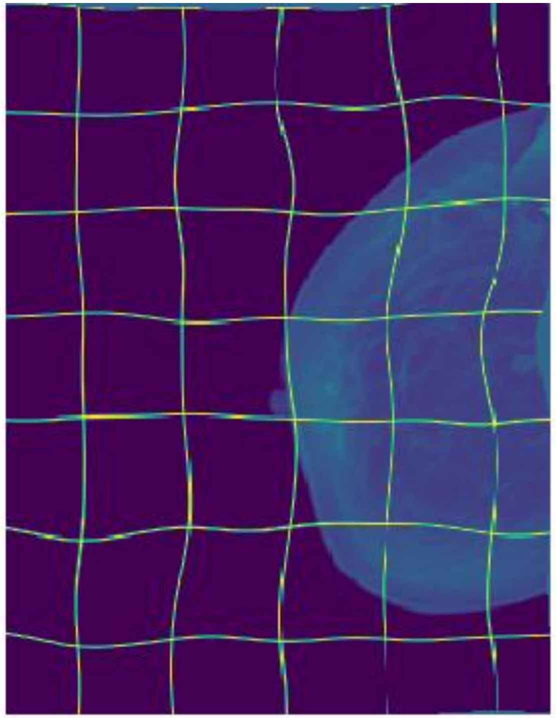
Data Augmentation



(a) Original



(b) Deformed

- Elastic Deformation
- Added noise to each pixel to make more natural distortion
- More suitable for medical data

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Results

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

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Results

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**

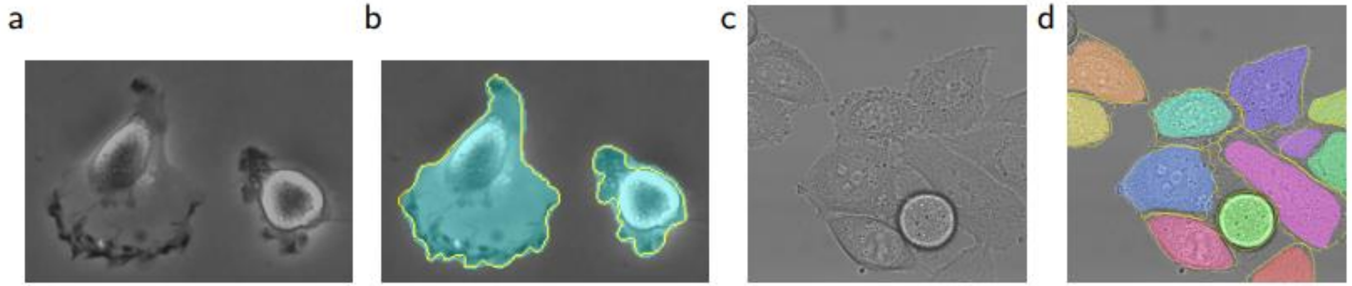

Fig. 4. Result on the ISBI cell tracking challenge. (**a**) part of an input image of the "PhC-U373" data set. (**b**) Segmentation result (cyan mask) with manual ground truth (yellow border) (**c**) input image of the "DIC-HeLa" data set. (**d**) Segmentation result (random colored masks) with manual ground truth (yellow border).

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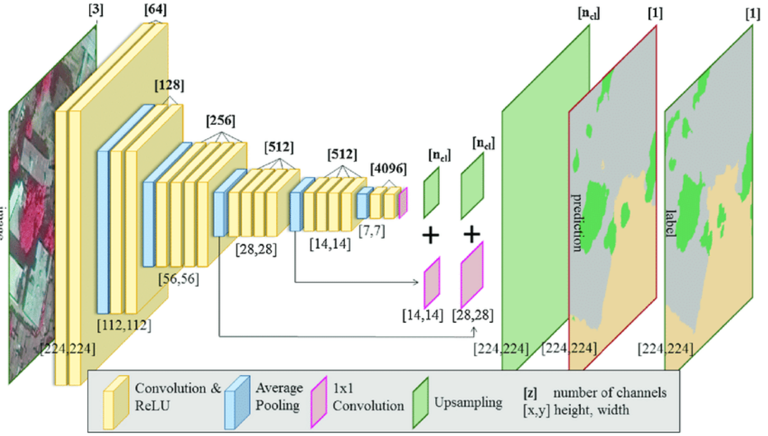
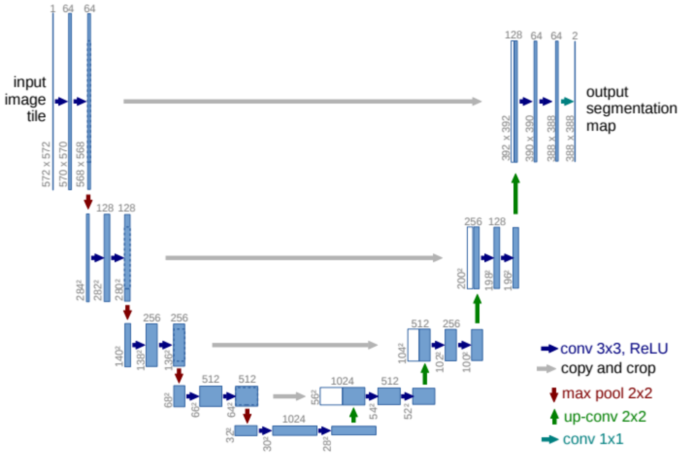
Conclusion

- U-Net proposed a model that applied Up-sampling and Skip Architecture of an expanded concept than FCNs

- The structure of U-Net showed excellent performance in various biomedical image segmentation problems by utilizing Data Augmentation with only a very small amount of training data





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