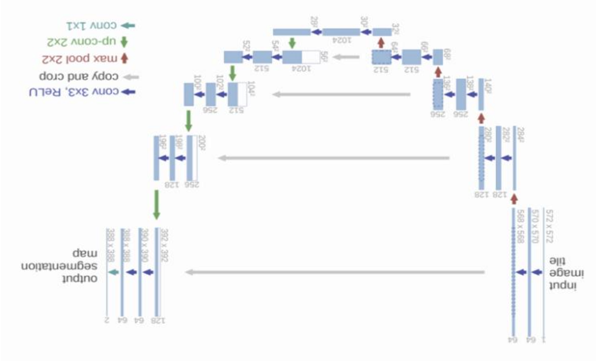
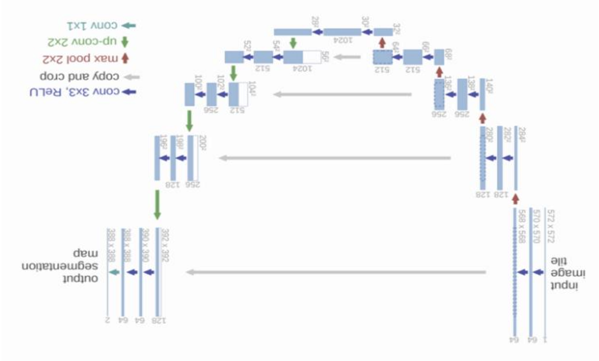
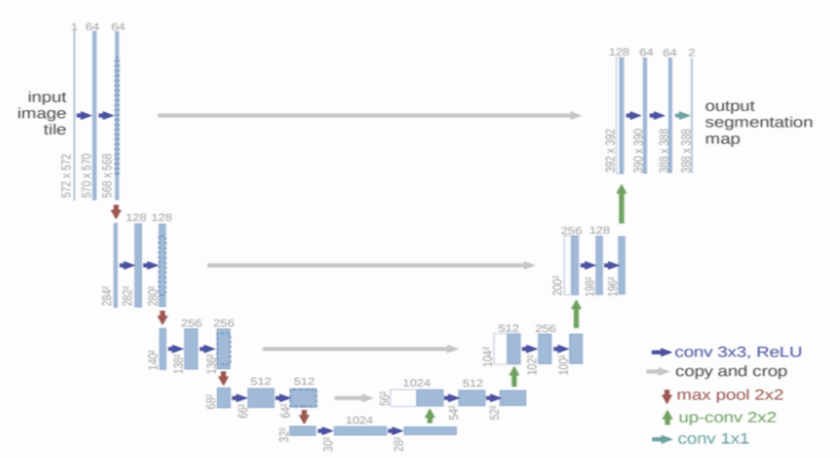




U-Net: Convolutional Networks for Biomedical Image Segmentation



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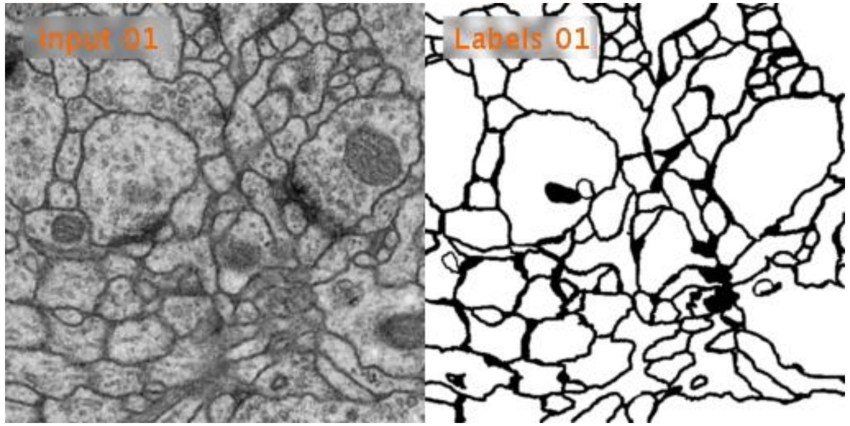
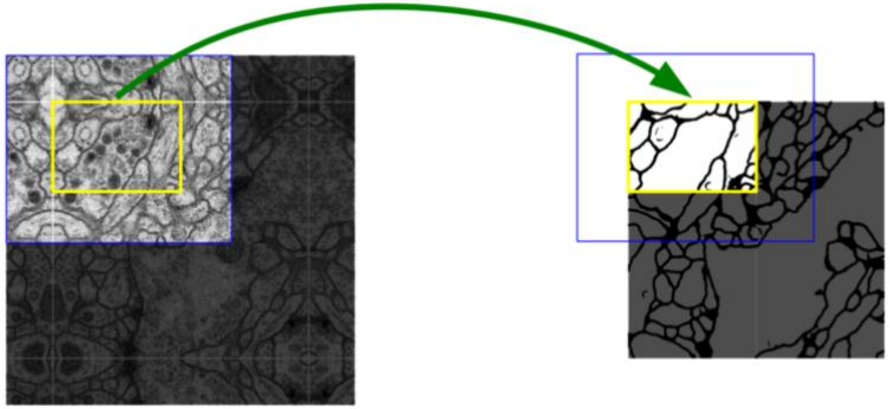
Introduction

U-Net: Convolutional Networks for Biomedical Image Segmentation



Biomedical task

- Output이 classification뿐만 아닌 **위치 정보**를 포함해야함
- 대부분의 상황에서 training image의 수가 적음
- 같은 class 객체들이 접촉하여 있는 경우가 많음



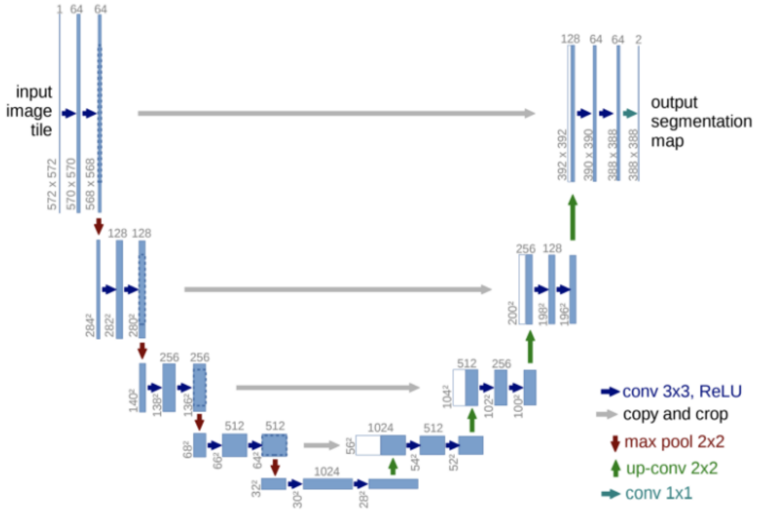
Patch : 이미지 인식 단위

이 논문에선 sliding window처럼 이미지를 잘라 인식하는 단위를 만들었는데, 이것이 Patch입니다. 파란색, 노란색 박스 부분입니다.

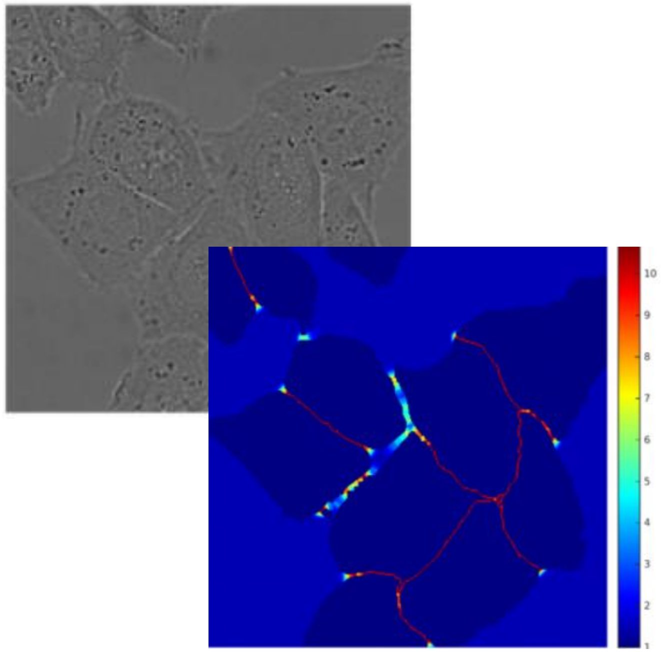
Context: 이웃한 픽셀들 간의 관계. 글을 읽고 문맥을 파악하듯 이미지 일부를 보고 이미지의 문맥을 파악하는 것

https://medium.com/@codecompose/u-net-174d1bc7627c

Short Summary



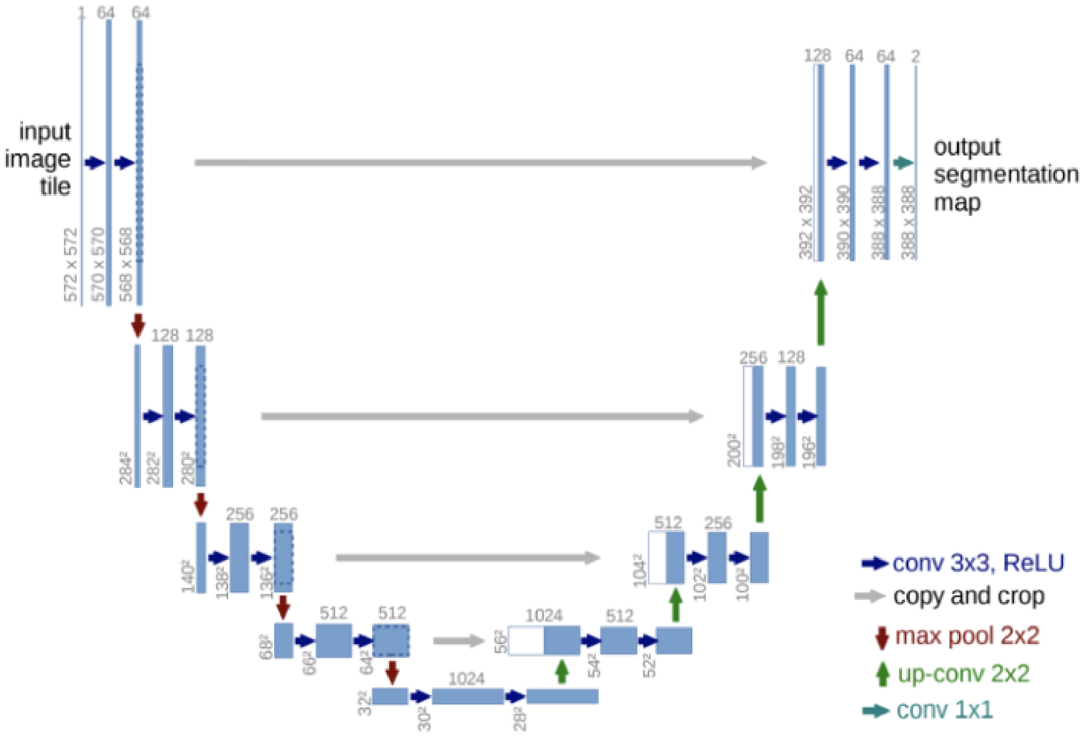
U-Net Architecture



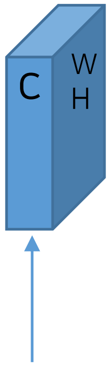
U-Net의 특징

1. ‘U’모양의 End-To-End 구조
2. 넓은 범위의 이미지 픽셀로부터 의미정보(Context Information)를 추출하고
   의미정보를 기반으로 각 픽셀마다 객체를 분류
3. 서로 근접한 객체 경계를 잘 구분하도록 학습하기 위하여 Weighted Loss를 제시

U-net Architecture

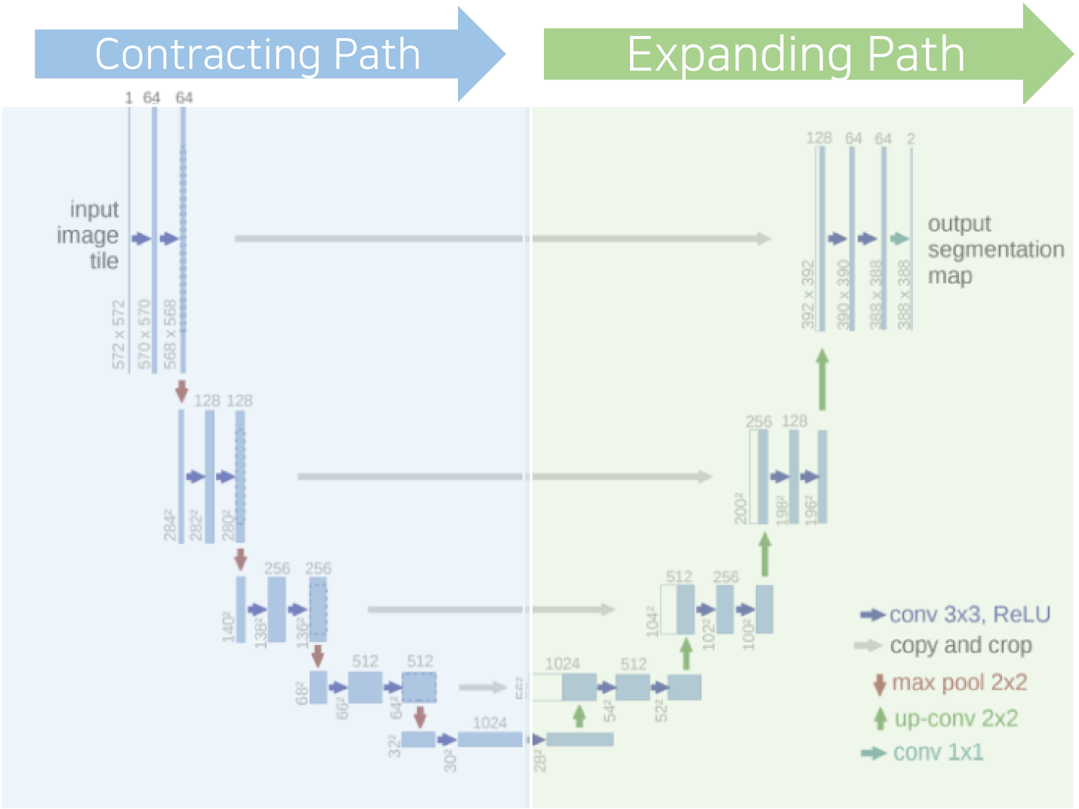


U-Net Architecture



채널 방향에서 바라봄

U-net Architecture



U-Net Architecture

$$Input(Width \times Height \times RGB) -> Model -> Output(Width \times Height \times Class)$$

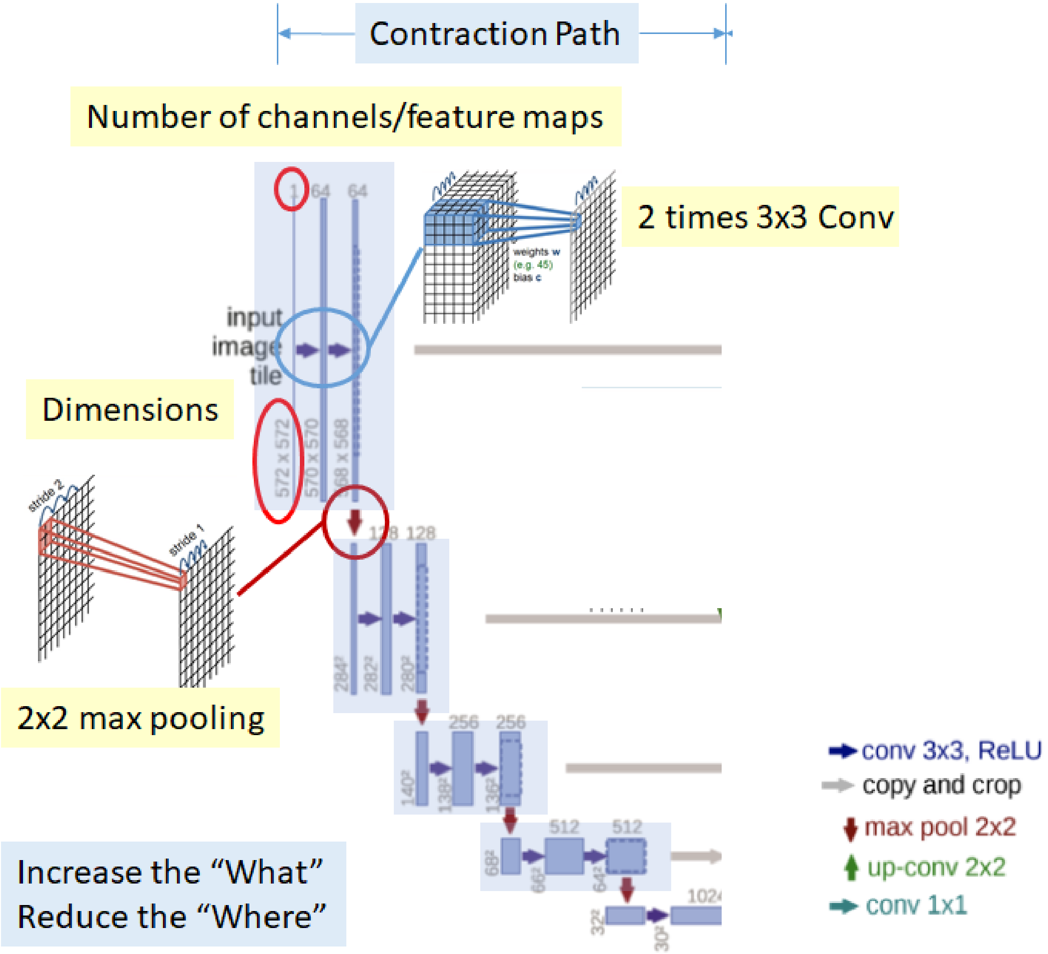
Contracting Path(수축경로)

- 이미지 feature map에서 context를 추출

Expanding Path(확장경로)

- Upsampling을 통해 정확한 localization

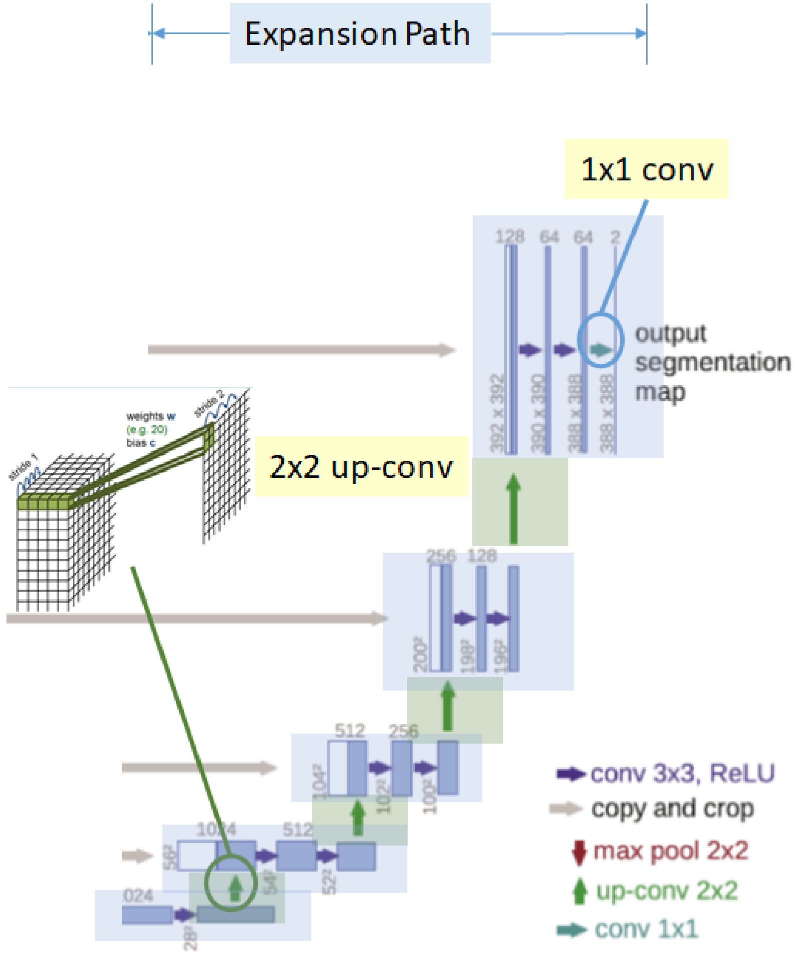
Contracting Path



Contracting Path(수축경로)
- 이미지 feature map에서 context를 추출

Down sampling 과정을 반복하면서 feature map을 생성

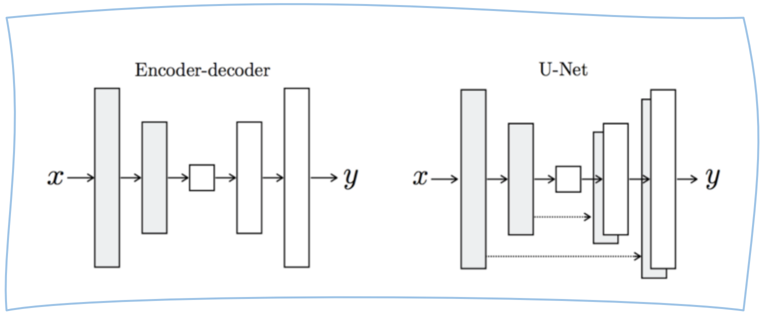
Expading Path



Expanding Path(확장경로)
: 정확한 localization을 위한 단계

Up-sampling의 최대 단점 : feature map 정보 소실

해결 : 이전 layer의 정보를 concatenate



Training - Overlap tile strategy

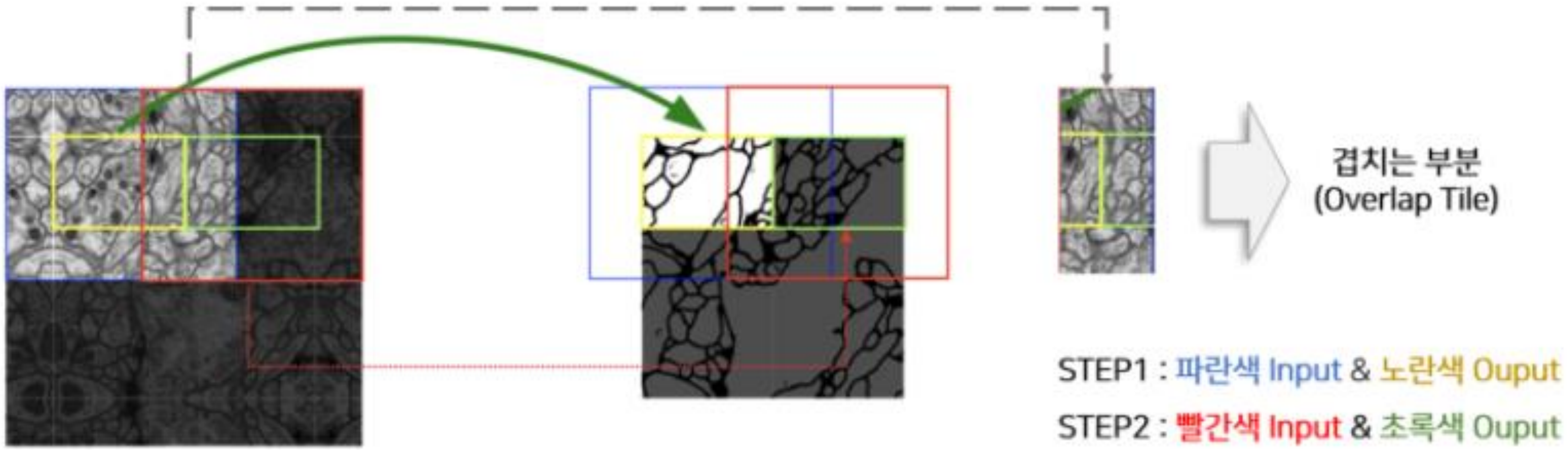
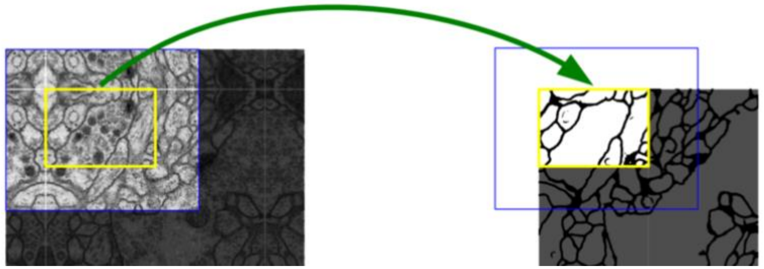


image : https://joungheekim.github.io/2020/09/28/paper-review/

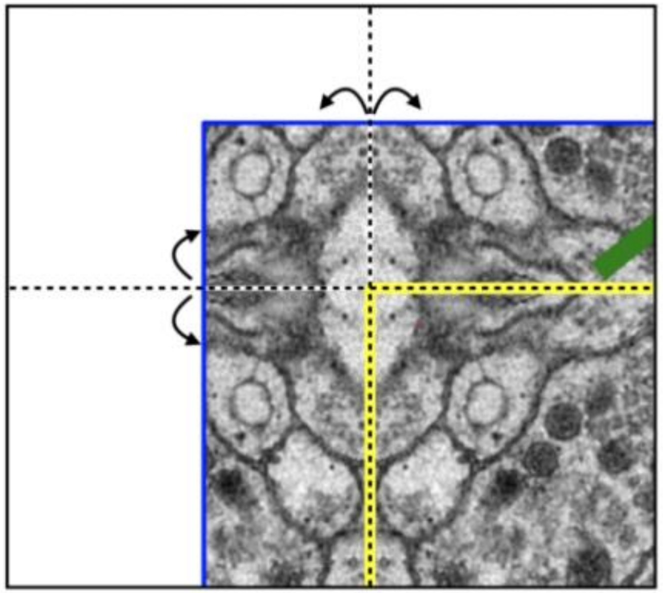
Training - Mirroring Extrapolatation

572 x 572

392 x 392

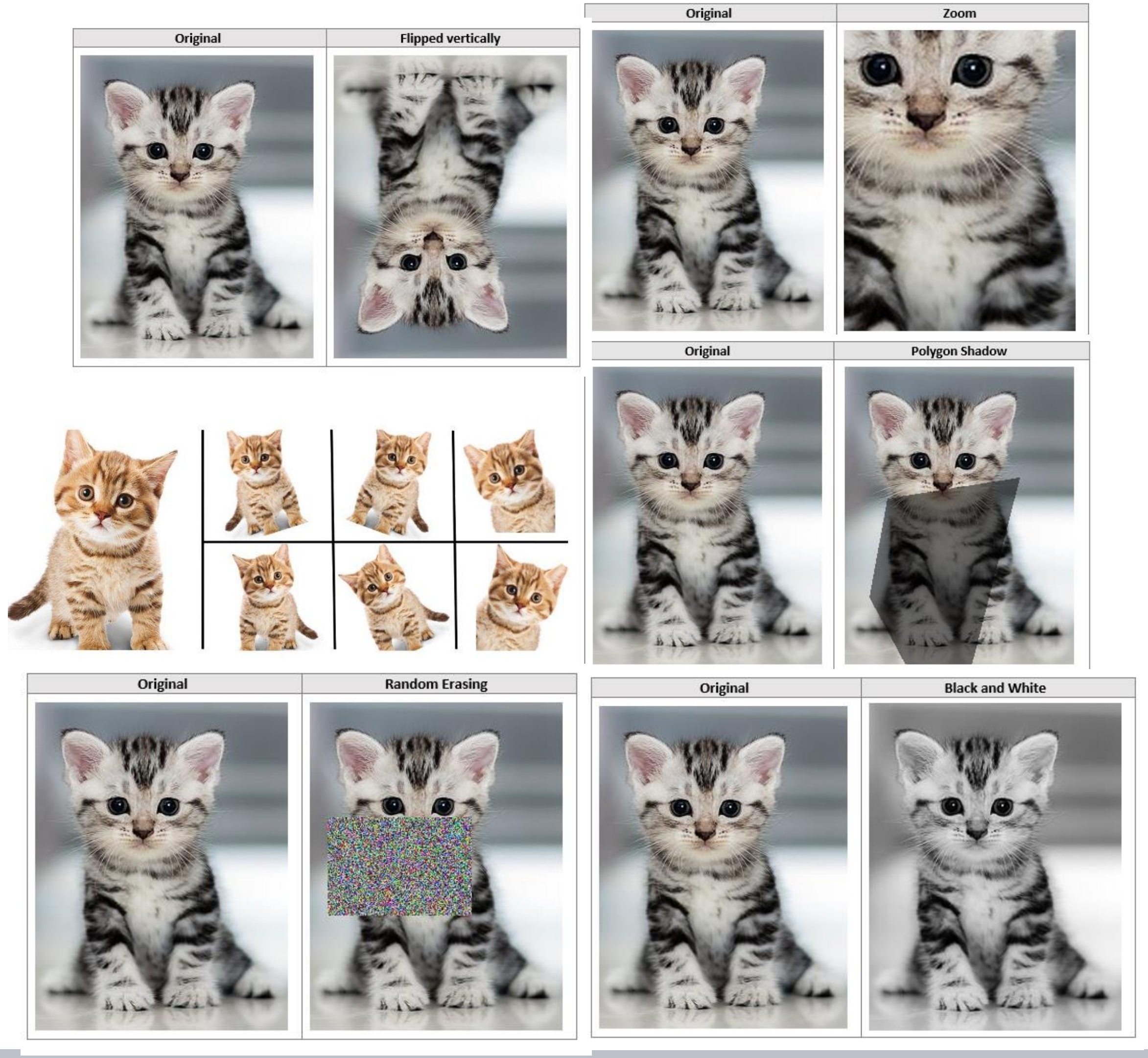


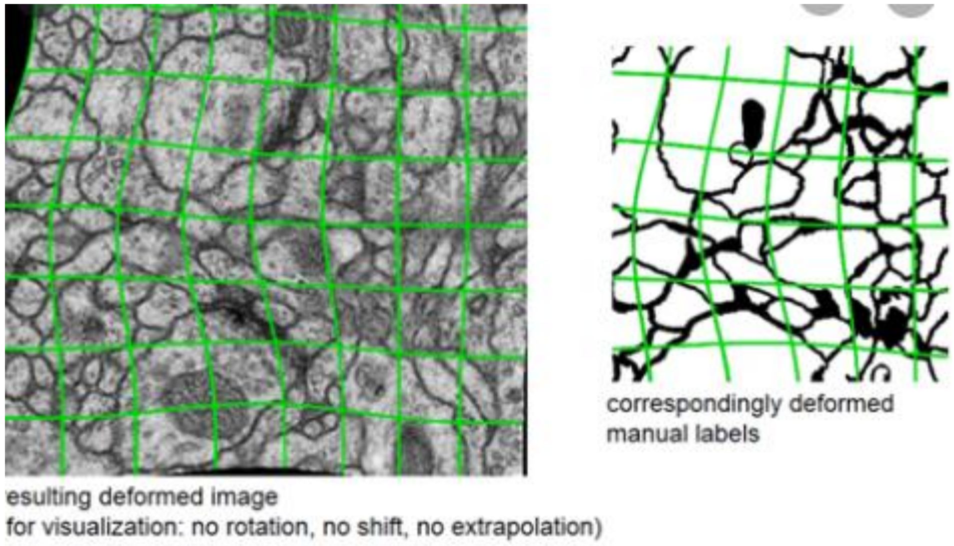
Mirroring extrapolatation



https://medium.com/@msmapark2/u-net-%EB%85%BC%EB%AC%B8-%EB%A6%AC%EB%B7%B0-u-net-convolutional-networks-for-biomedical-image-segmentation-456d6901b28a

Training - Data Augmentation



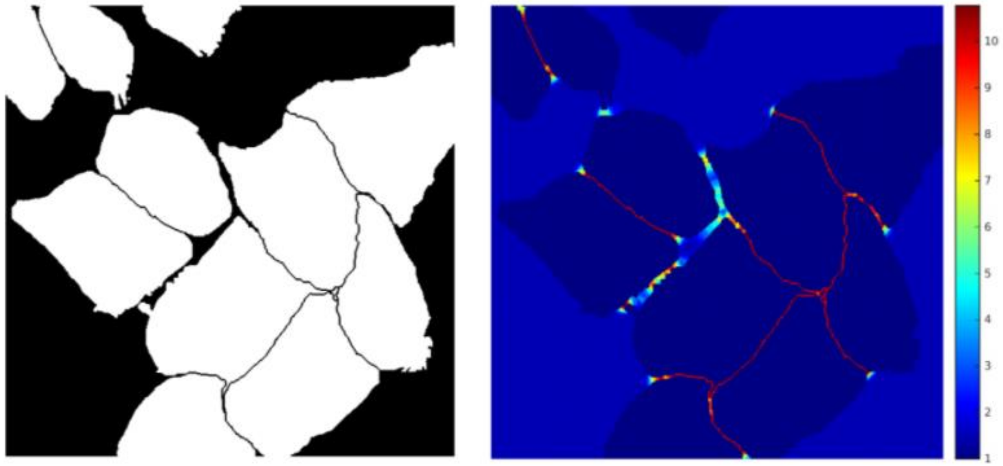


적은 데이터로 충분한 학습을 하기위해 data augmention 사용

Elastic Deformation : 세포 조직의 실질적인 변형과 유사

Image : https://joungheekim.github.io/2020/09/28/paper-review/

Training - Weight Loss



분할 이미지 Weight Map 시각화

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

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

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

$d_1(x)$: 픽셀 x로부터 가장 가까운 셀 경계까지의 거리

$d_2(x)$: 픽셀 x에서 두 번째로 셀 경계까지의 거리

$w_{(x)}$ **: 픽셀 x와 경계의 거리가 가까우면 큰 값을 갖게 됨**
➔ 해당 픽셀의 Loss 비중이 커짐

이미지 : https://joungheekim.github.io/2020/09/28/paper-review/

Training

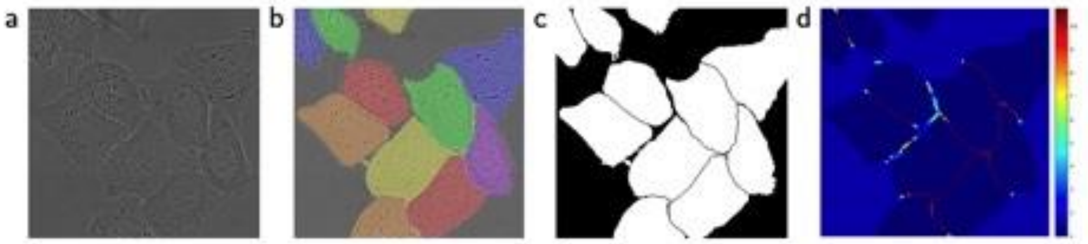


Fig. 3. HeLa cells on glass recorded with DIC (differential interference contrast) microscopy. (**a**) raw image. (**b**) overlay with ground truth segmentation. Different colors indicate different instances of the HeLa cells. (**c**) generated segmentation mask (white: foreground, black: background).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

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

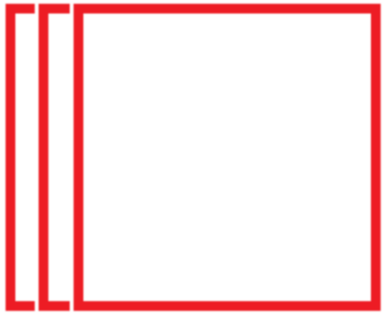
$$E = \sum_{\mathbf{x} \in \Omega} w(\mathbf{x}) \log(p_{\ell(\mathbf{x})}(\mathbf{x}))$$

$a_k(x)$: 픽셀 x가 Class k일 값 (픽셀 별 모델의 output)
$p_k(x)$: 픽셀 x가 Class k일 확률(0 -1)
$l(x)$: 픽셀 x의 실제 Label

Image ：https://joungheekim.github.io/2020/09/28/paper-review/

U-Net의 개선점

1. 속도와 연산



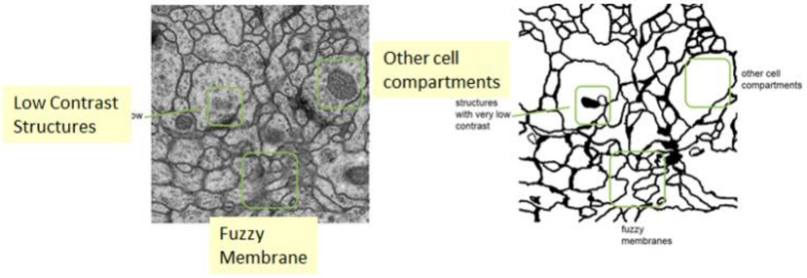
기존의 sliding window

U-Net의 patch

2. Context인식과 localization의 trade-off 해결

Experiments

1. EM segmentation challenge(2015) , 현미경 이미지



EM 이미지의 일부 어려운 부분

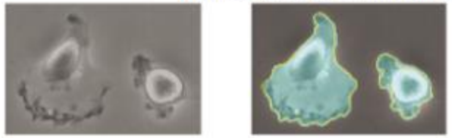
Rank	Group name	Warping Error	Rand Error	Pixel Error
	** human values **	0.000005	0.0021	0.0010
1.	u-net	**0.000353**	0.0382	0.0611
2.	DIVE-SCI	0.000355	0.0305	0.0584
3.	IDSIA [1]	0.000420	0.0504	0.0613
4.	DIVE	0.000430	0.0545	**0.0582**
⋮				
10.	IDSIA-SCI	0.000653	**0.0189**	0.1027

Warping Error : 객체 분할 및 병합이 잘 되었는지에 대한 segmentation error

2. ISBI cell tracking challenge

PhC-U373

Cyan: U-net
Yellow border: Ground truth



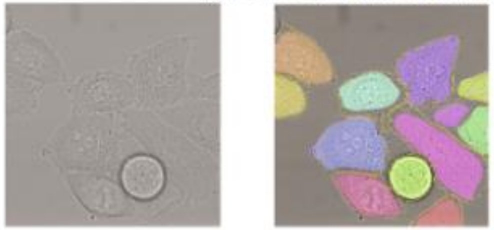
IoU

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**

92% IOU Score

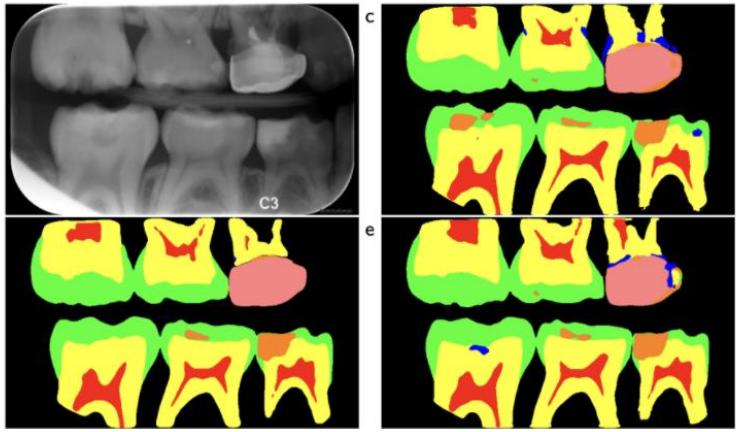
DIC-HeLa

Colors: U-net
Yellow border: Ground truth



77.5% IOU Score

Conclusion



U-Net은 Fully Connected Networds보다 확장된 개념의 Up-sampling과
Skip Architecture를 적용한 모델을 제안했다.

결과적으로 U-Net의 구조는 아주 적은 양의 학습 데이터만으로 Data Agmentation을 화룡하여 많은 training image를 필요로하지 않는다
여러 Biomedical Image Segmentation문제에서 우수한 성능을 보여주었습니다.

Contracting path에서 포착한 피쳐맵의 컨텍스트와 결합하여 더 정확한 로컬라이제이션을 한다.

참고한 사이트 및 이미지 출처

https://joungheekim.github.io/2020/09/28/paper-review/

https://medium.com/@msmapark2/u-net-%EB%85%BC%EB%AC%B8-%EB%A6%AC%EB%B7%B0-u-net-convolutional-networks-for-biomedical-image-segmentation-456d6901b28a

https://mylifemystudy.tistory.com/87

https://velog.io/@goe87088/%EB%85%BC%EB%AC%B8-U-Net-Convolutional-Networks-for-Biomedical-Image-Segmentation

https://m.blog.naver.com/9709193/221979612209

https://everyday-image-processing.tistory.com/58

https://medium.com/@codecompose/u-net-174d1bc7627c

http://www.affineanalytics.com/blog/data-augmentation-for-deep-learning-algorithms/

감사합니다