

# U-Net과 앙상블

기초심화CV1팀

조윤주 김서진 박경준 박성현

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## Overlap-tile strategy

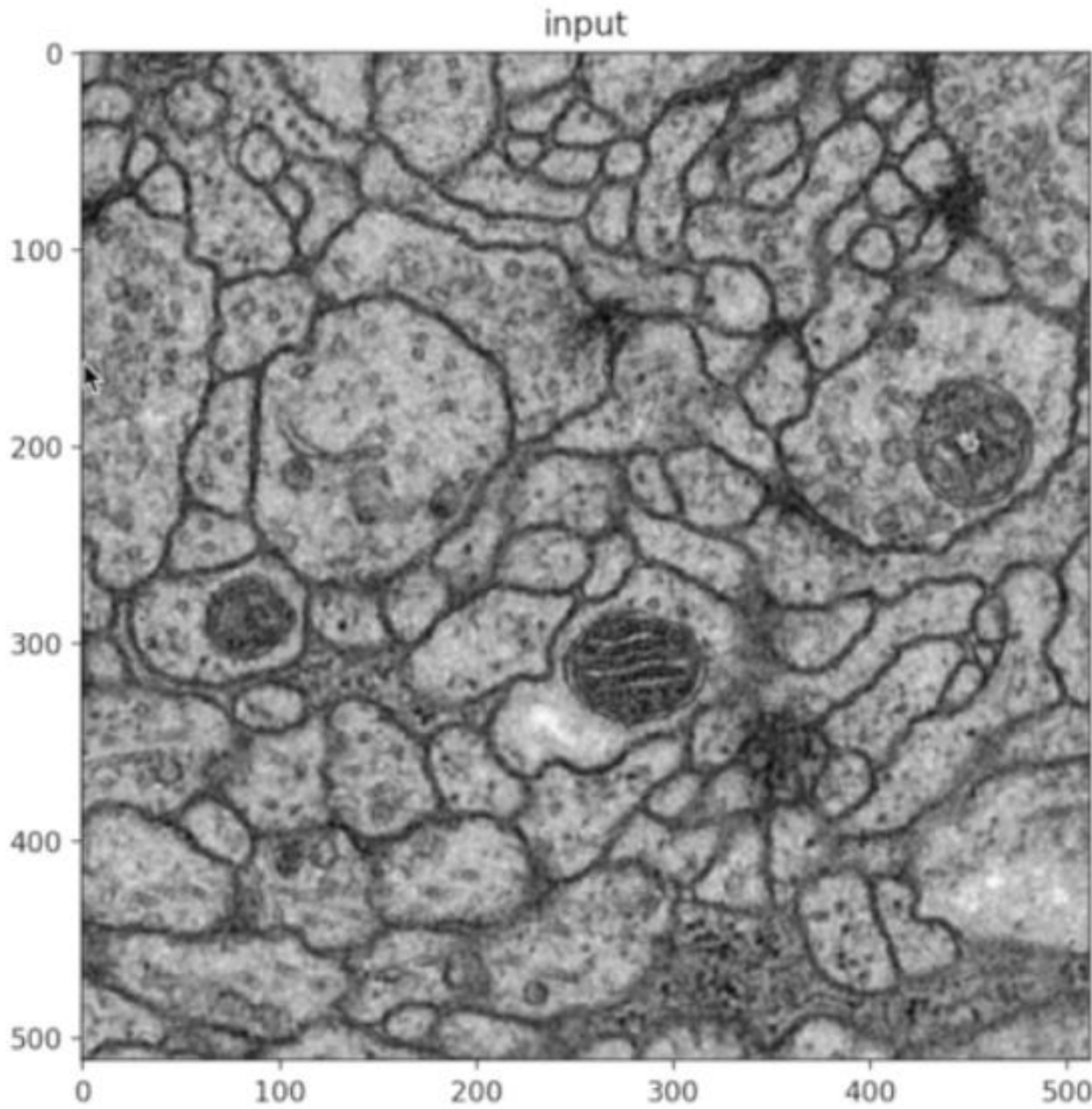
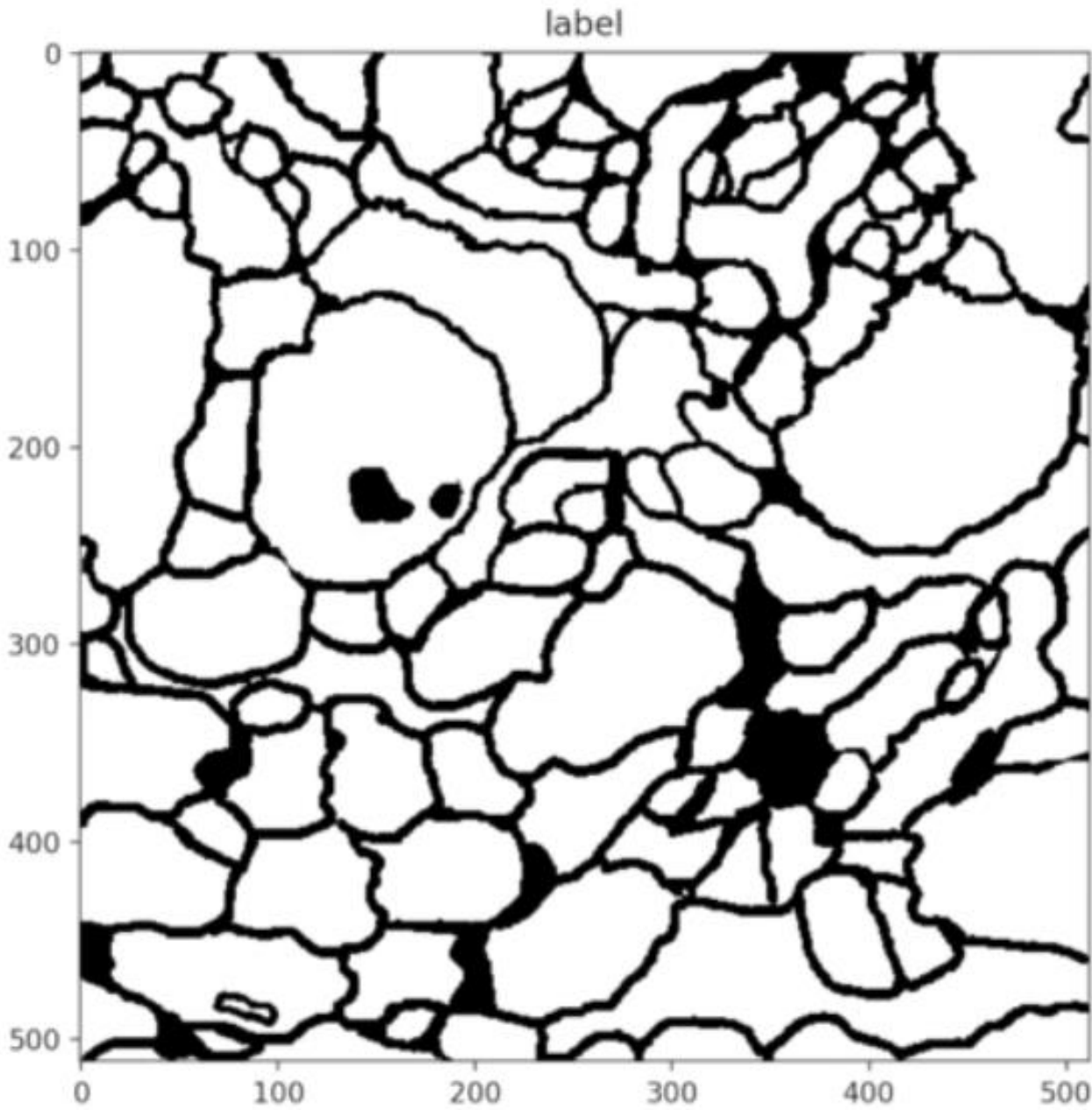
부족한 데이터 수를 해결하기 위해 다양한 기법 사용

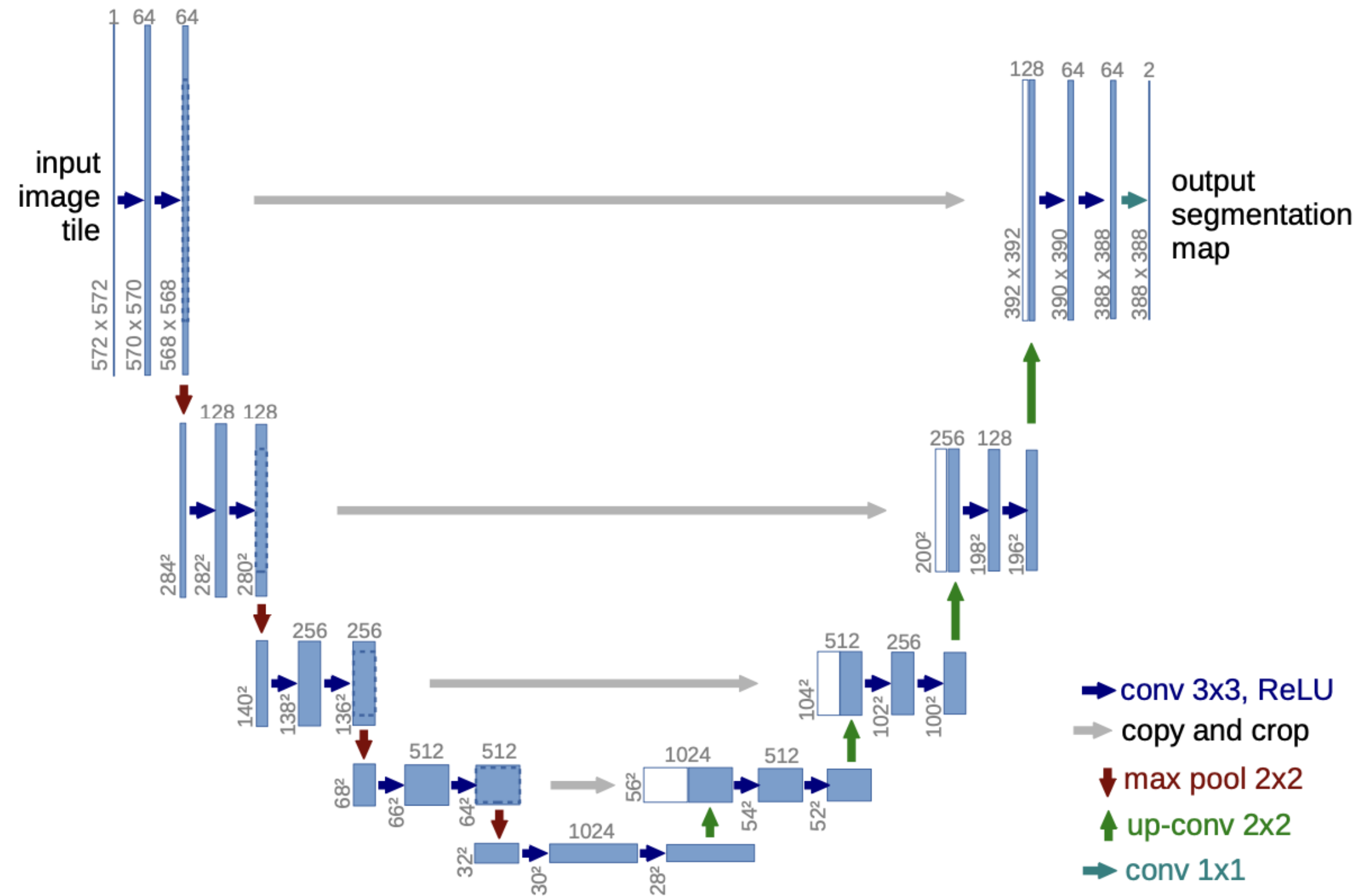
## Skip Architecture

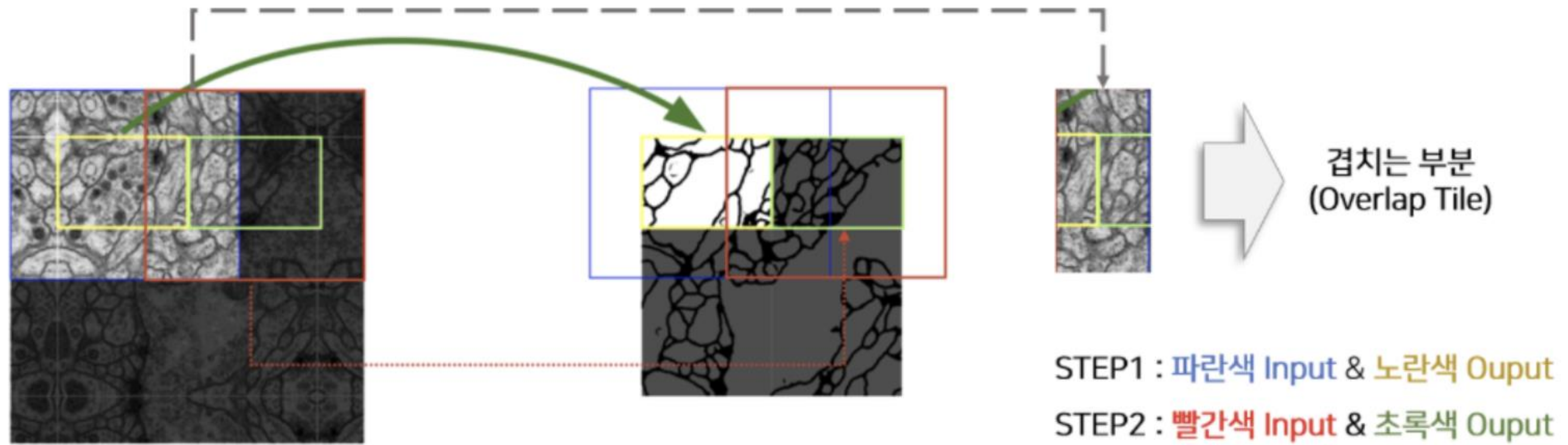
인코더의 피처맵을 디코더의 피처맵에 Concat 하여 위치정보 전달

## Loss function

세포의 경계선 라인에 대해 더 강한 학습을 시키기 위해 경계선 픽셀에는 더 큰 손실값을 줌

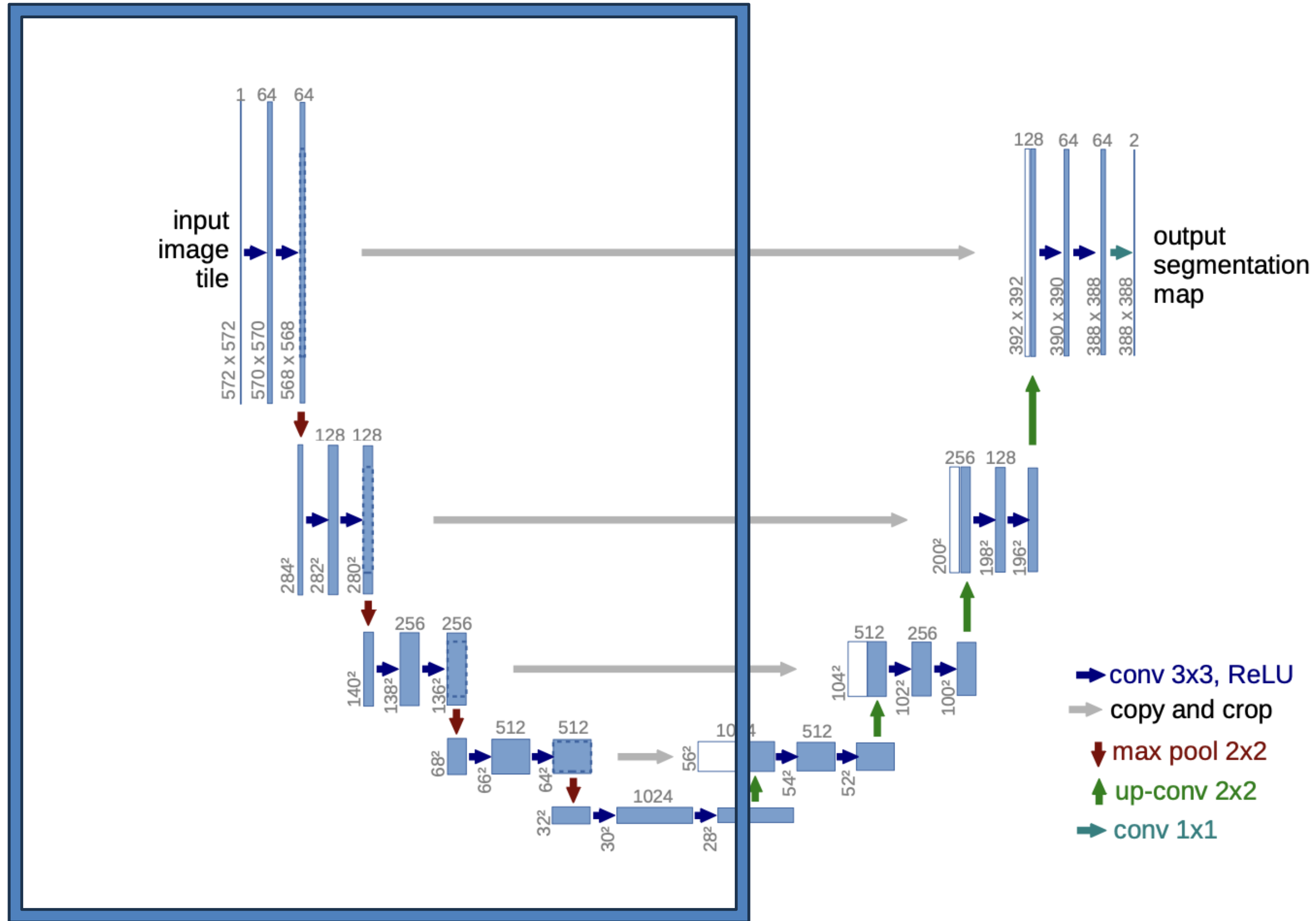




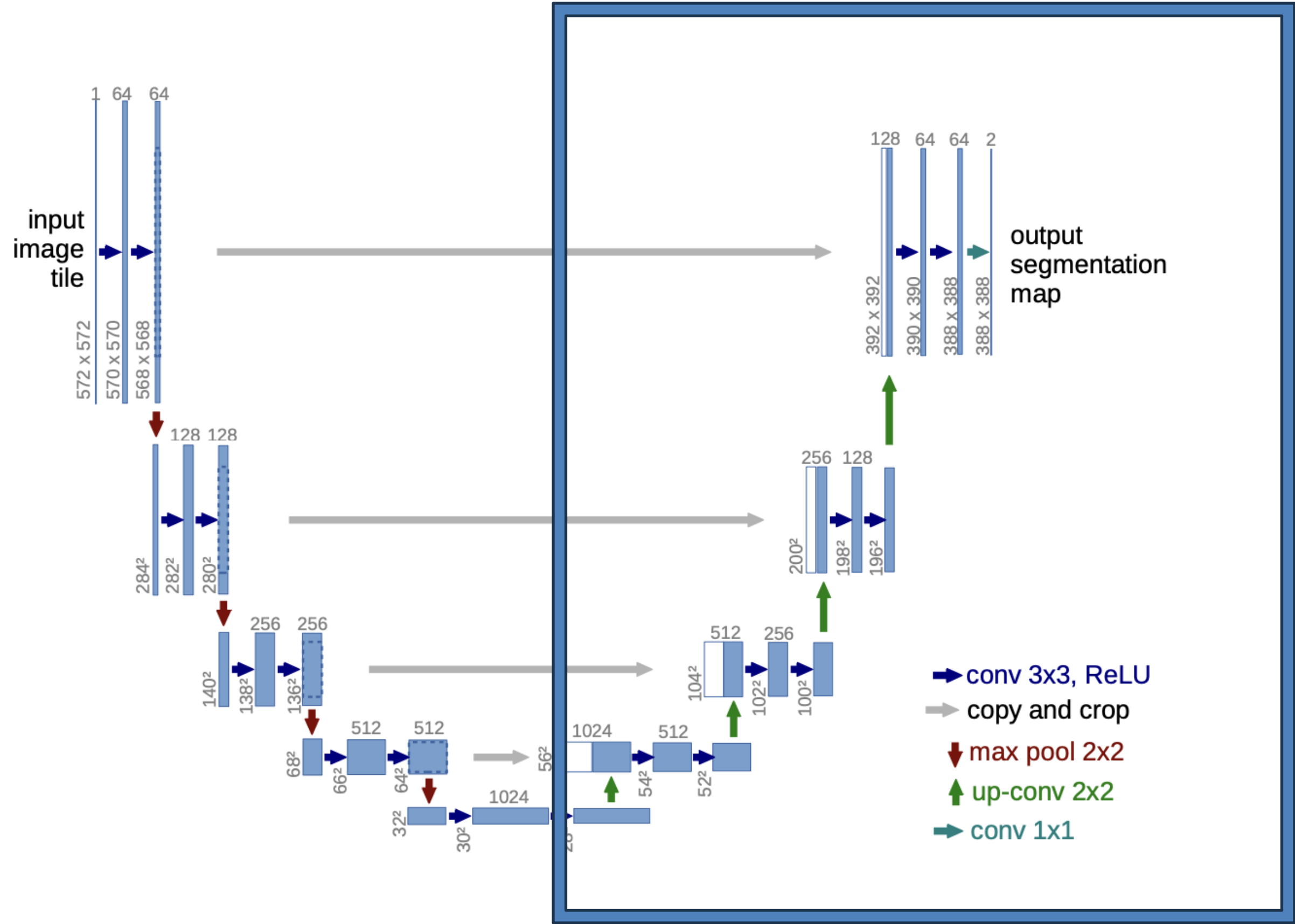


# Contracting Path

02



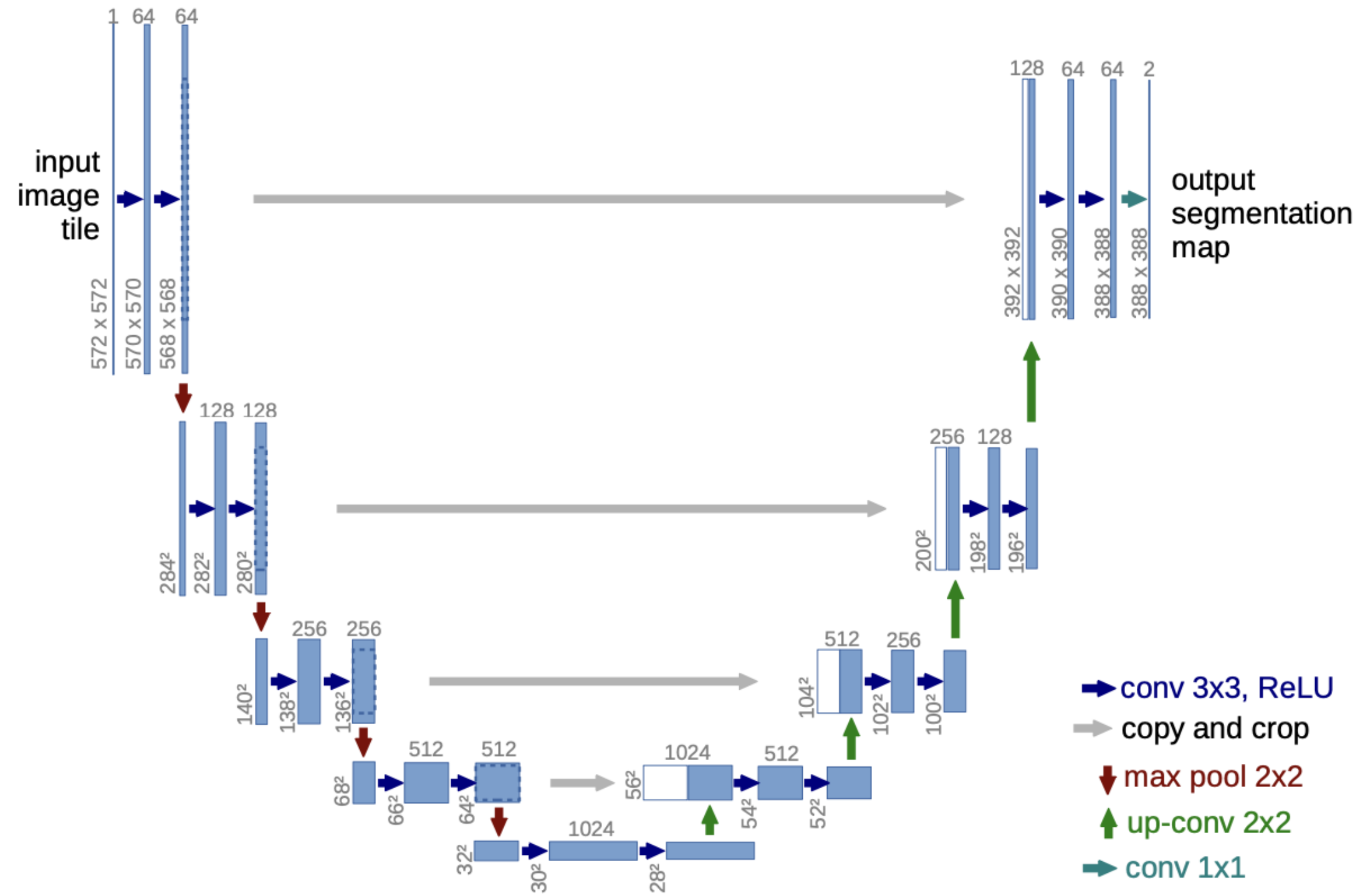






# Skip Architecture

03



## pixel-wise cross-entropy loss

$$p_k(x) = \frac{\exp(a_k(x))}{\sum_{k'=1}^K \exp(a_{k'}(x))}$$

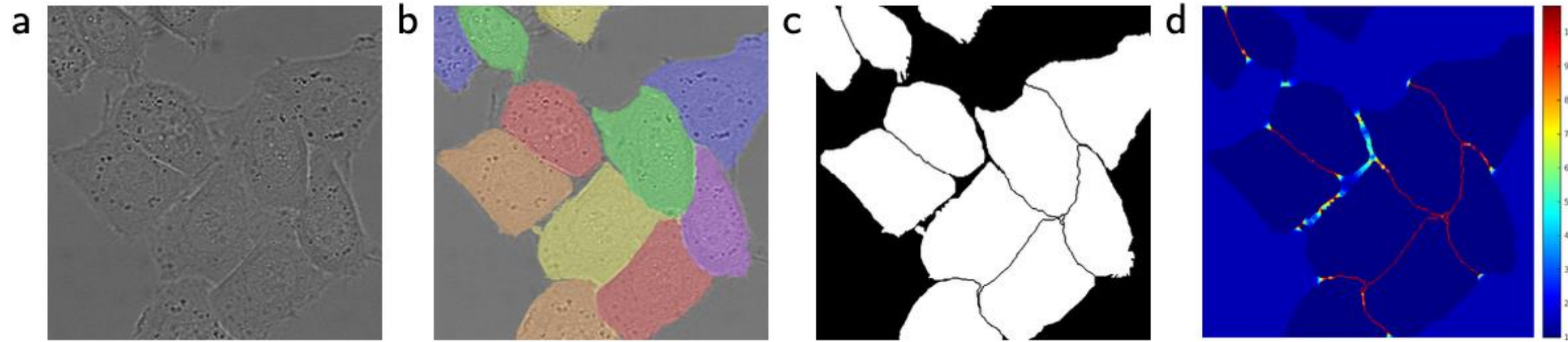
$$w(x) = w_c(x) + w_0 \cdot \exp\left(-\frac{(d_1(x) + d_2(x))^2}{2\sigma^2}\right)$$

d1: The distance to the border of the nearest cell

d2: The distance to the border of the second nearest cell

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

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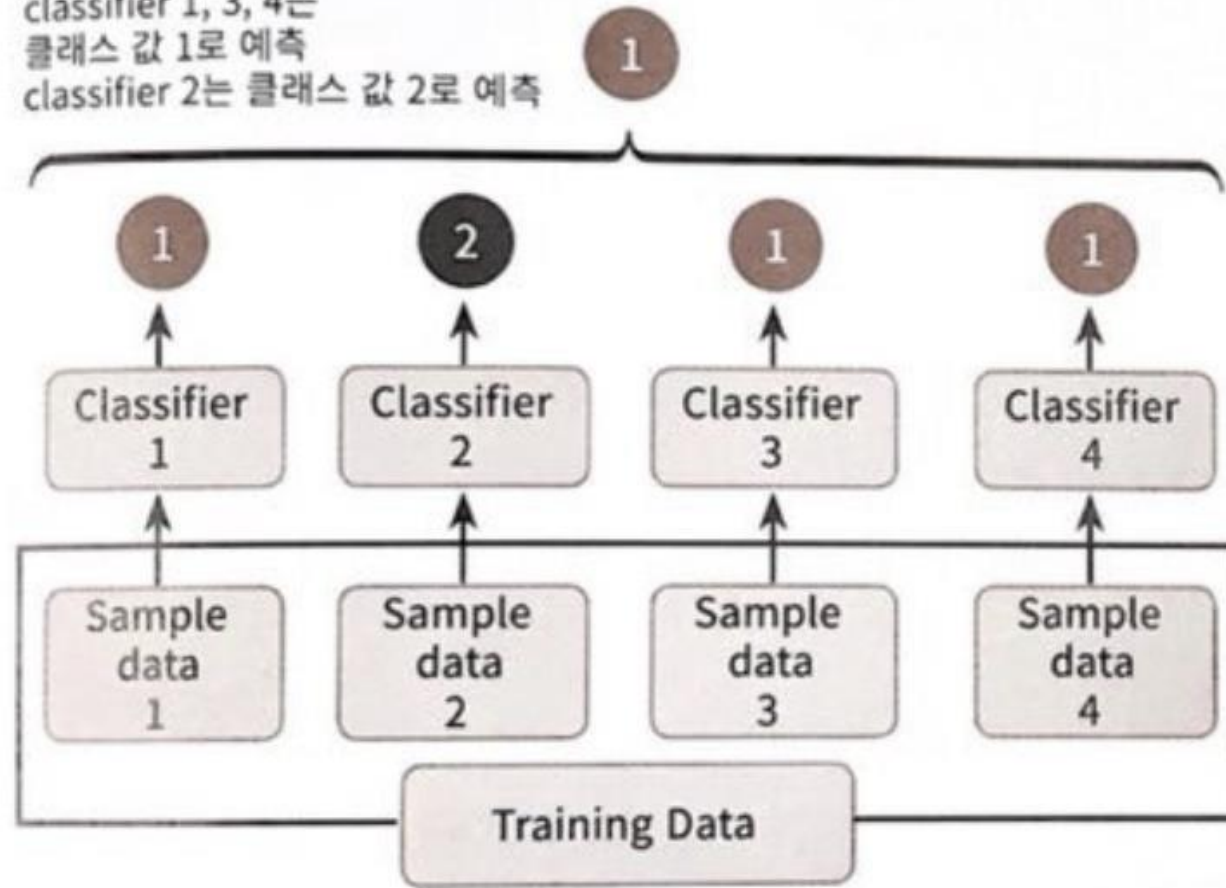


**Fig. 3.** HeLa cells on glass recorded with DIC (differential interference contrast) microscopy. (a) raw image. (b) overlay with ground truth segmentation. Different colors indicate different instances of the HeLa cells. (c) generated segmentation mask (white: foreground, black: background). (d) map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

# 앙상블 기법

Hard Voting은 다수의 classifier 간 다수결로 최종 class 결정

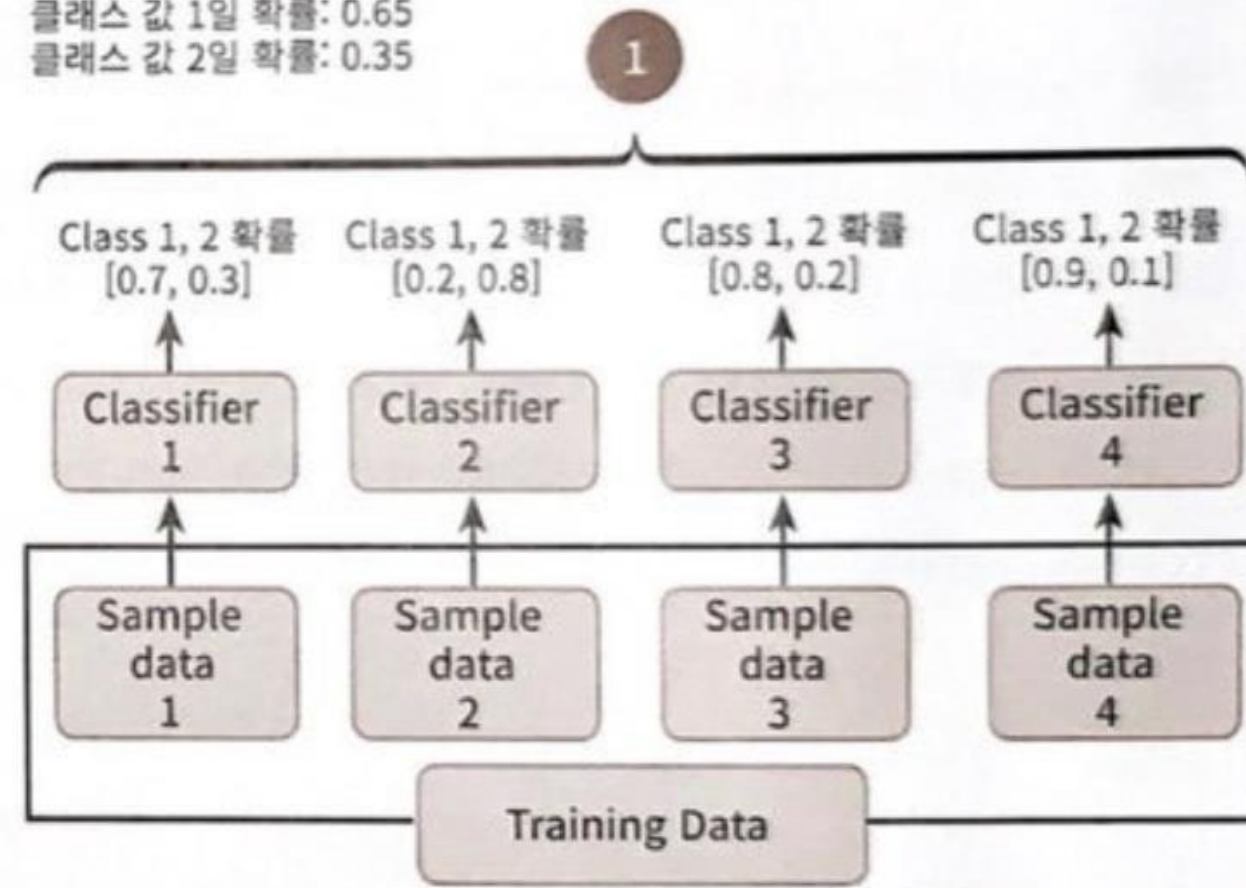
클래스 값 1로 예측  
classifier 1, 3, 4는  
클래스 값 1로 예측  
classifier 2는 클래스 값 2로 예측



<하드 보팅>

Soft Voting은 다수의 classifier 들의 class 확률을 평균하여 결정

클래스 값 1로 예측  
클래스 값 1일 확률: 0.65  
클래스 값 2일 확률: 0.35



<소프트 보팅>

