Abstract

Image segmentation is a fundamental technique utilized in neuroscience for precise detection of anatomical structures in biological images. It involves the partition of images into multiple segments of interest. As manual segmentation is tedious, automated methods are pursued to increase consistency and efficiency. The semantic segmentation algorithms assign structured semantic labels to individual pixels in images. U-Net, a deep learning algorithm, has been proven to be effective in bio-medical image segmentation. It has a u-shaped architecture with contracting and expanding paths that are more or less symmetric. This encoder-decoder neural network makes it efficient in handling both local and global context within medical images. Moreover, the architecture includes skip connections to retain spatial information. The skip connection can help propagate the spatial information that gets lost during the pooling operation to help recover the full spatial resolution through the encoding-decoding process. These connections alleviates the vanishing gradient problem and hence improves the optimization convergence speed. Moreover, U-Net can work efficiently with limited training samples. Here we aim to dissect the U-Net architecture and explore the properties that make it an effective and proficient segmentation tool. In our study, we experimented with the varying architectures of U-Net and their effect on model performance. We expect that decreasing the number of convolutional steps in encoder and decoder paths would decrease the model performance. Whereas, the addition of skip connections should boost the performance. Moreover, choosing an optimal kernel size for convolution would result in optimal performance.

Evaluating the role of UNet architecture on image segmentation accuracy

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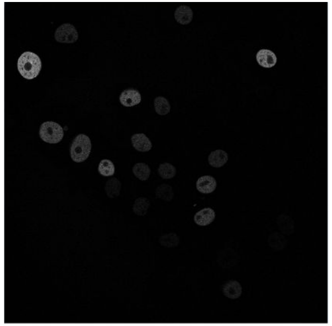
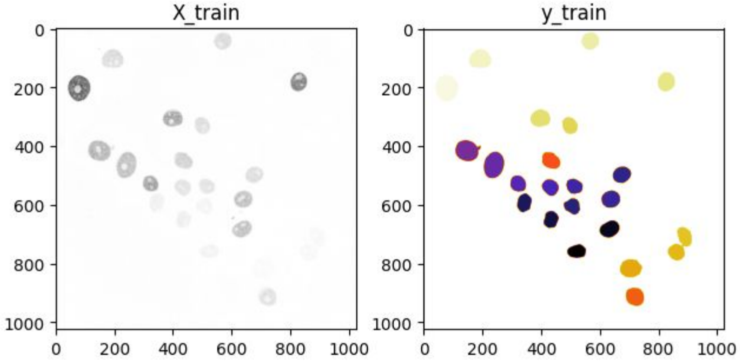
neuromatch academy

How do specific components of the UNet architecture contribute to image segmentation accuracy?

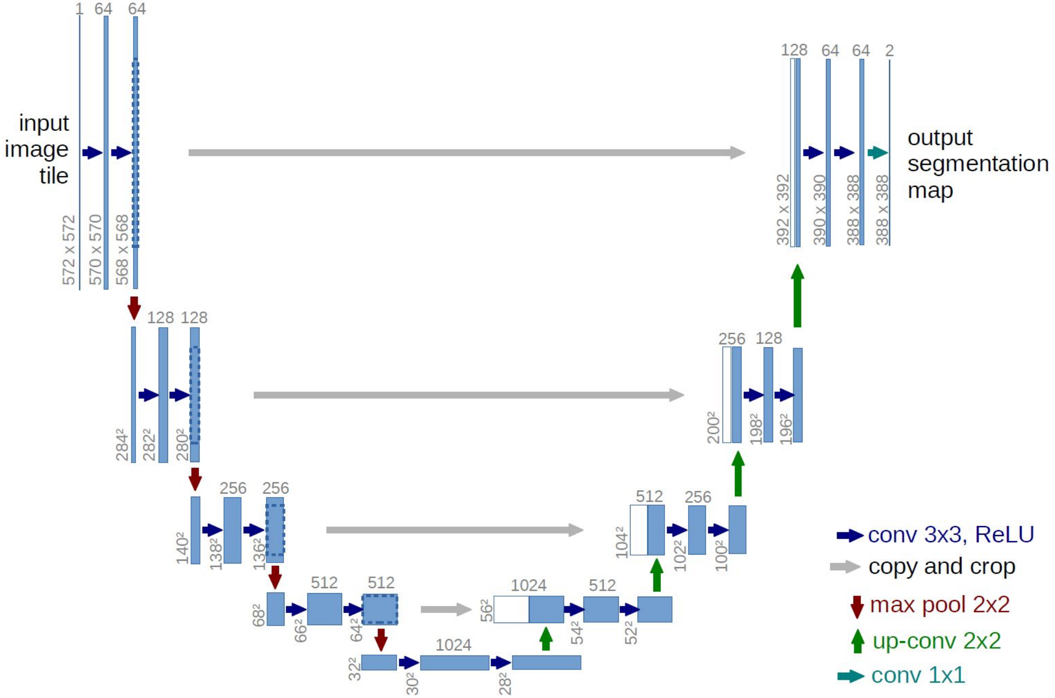
Introduction

Cell Tracking Challenge





U-net



Effect of Kernel Size on Model Performance

Loss: Measure of the error of reconstruction

Kernel: a convolutional matrix

Optimal kernel size helps in:

- Spatial information preservation
- Computational efficiency
- Generalization capability

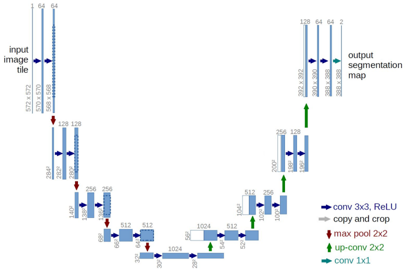
3 × 3 kernel size optimal in this case!

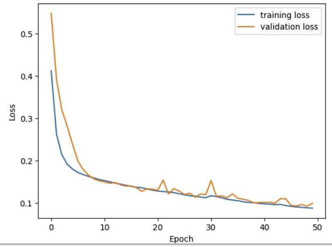
Effect of removing Convolutional Layers

Epoch 1

Epoch 100

Validation Loss: 0.098

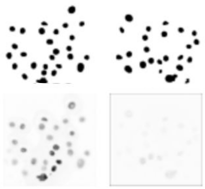




Train Val

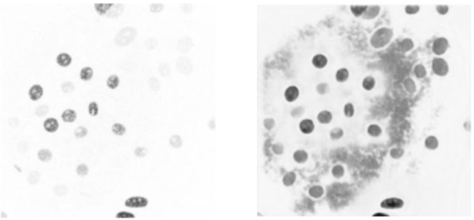
label

Output

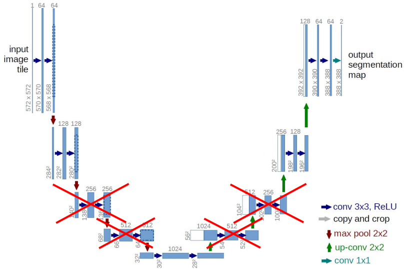


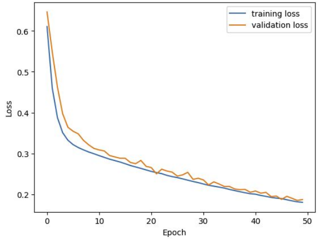
Test

Image Output



Validation Loss: 0.187

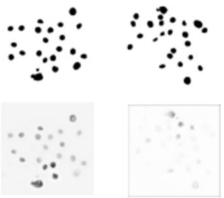




Train Val

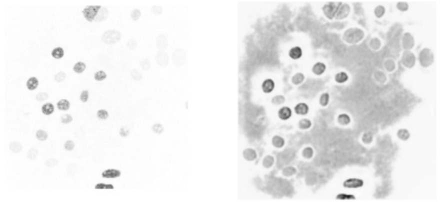
label

Output

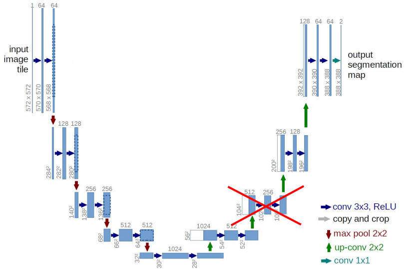


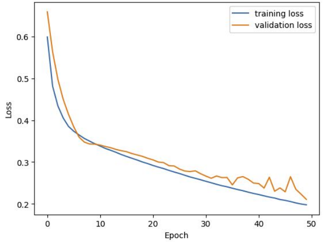
Test

Image Output



Validation Loss: 0.211

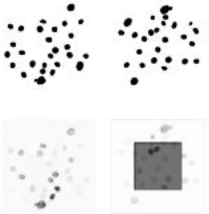




Train Val

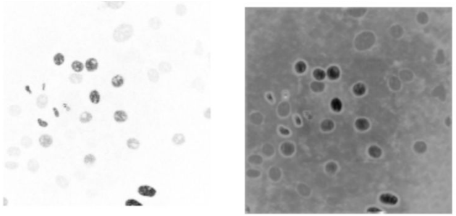
label

Output

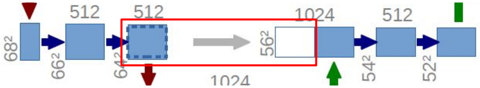


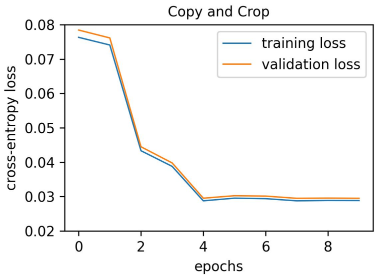
Test

Image Output

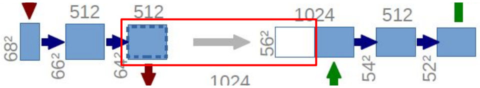


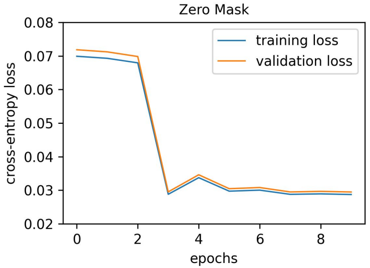
Effect of **Skip Connections** on U-Net Performance



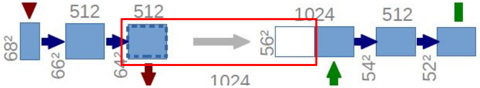


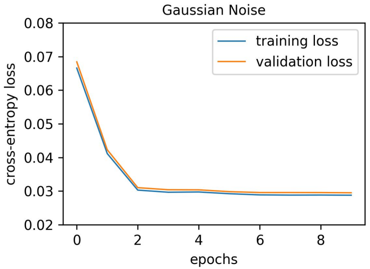
Copy and crop: original U-Net implementation of skip connections



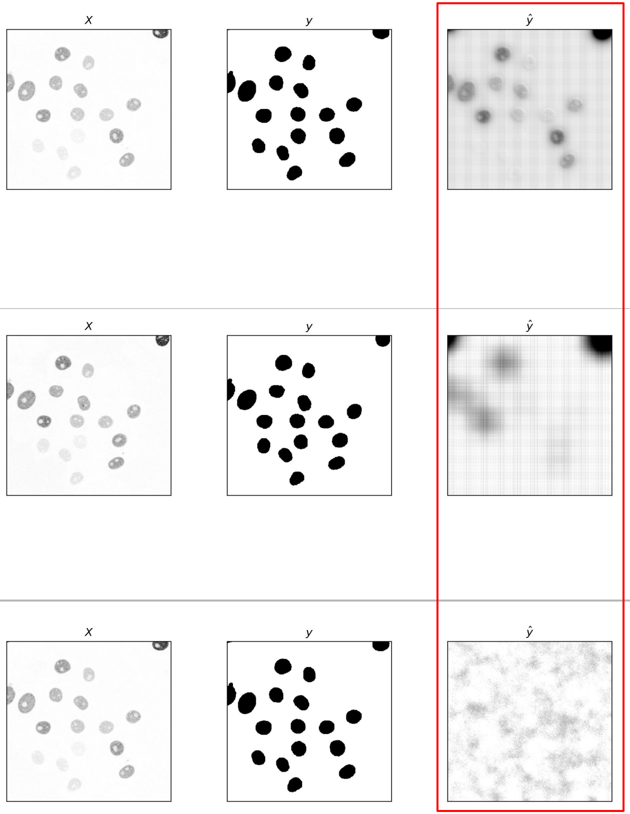


Zero mask: replacing skip connections with zero-filled images





Gaussian noise: replacing skip connections with random N(0,1) images



after 10 epochs of training

Our Conclusions

- Kernel size has huge impact on the model performance. A 3x3 kernel is the optimal size to detect high detail borders between cells and background.
- The number and symmetry of convolutional layers has little effect on training or validation loss, but significantly changes the ability of the model to generalize to test images.
- Skip connections have little influence on cross-entropy loss, but greatly enhance localization of cell boundaries.