Comparing U-Net convolutional network with mask R-CNN in Nuclei Segmentation

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Summary
Deep Learning is used nowadays in Nuclei segmentation. While recent developments in theory and open-source software have made these tools easier to implement, expert knowledge is still required to choose the exemplary model architecture and training setup. We compare two popular segmentation frameworks, U-Net and Mask-RCNN, in the nuclei segmentation task and find that they have different strengths and failures. we compared both models aiming for the best nuclei segmentation performance. Experimental Results of Nuclei Medical Images Segmentation using U-NET algorithm Outperform Mask R-CNN Algorithm.

Key words:
U-Net, Mask R-CNN, Nuclei Segmentation.

1. Introduction

Biomedical imaging can apply Modern Deep Learning algorithms. The current use of convolutional neural networks for segmentation has Important applications in the medical field. Computer Vision systems can replace these tasks. Nowadays, deep neural networks have increased use in biomedical and medical areas. Automated nuclei instance segmentation from microscopy images is an essential step due to the subjectivity of manual segmentations. Classical computer vision methods such as watershed have been used in nuclei segmentation. However, neural networks with enough training data outperform these systems by a significant margin [1] With the increasingly large amount of free and open-source software libraries, they have become viable for everyday use in laboratories. More Accurate segmentation requires expert-level knowledge. Also, images must be labeled by hand because they may contain tens of thousands of nuclei. U-Net [2] and Mask-RCNN [3] are available as open-source libraries, often packaged with pre-trained models for segmentation and detection. Still, tuning these networks to get acceptable results in different domains requires expert knowledge. This paper compares U-NET and Mask R-CNN to know where everyone excels and fails.

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2. Algorithms

2.1 Mask R-CNN

Mask R-CNN as in Fig (1) is used in instance segmentation to determine the real object using classification part, also locate the bounded box around the real object with the help of mask to separate the real object from the background for more information check [4].

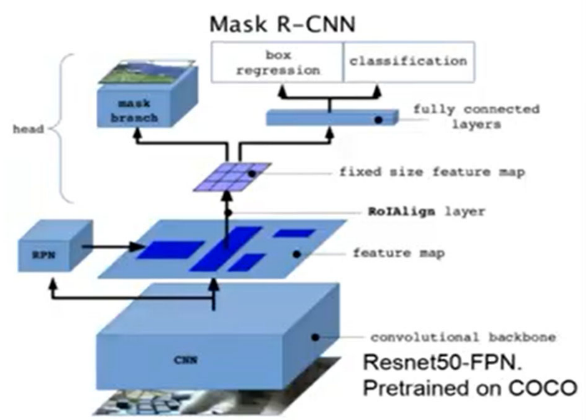

Fig (1)

2.2 U-NET

U-Net is an encoder-decoder architecture based on convolution networks with skip connections between the same layers in encoder and decoder. The encoder computes the representation of the image as lower features vector, and then the decoder decodes the vector to a full resolution image; the architecture shares information between parts in

the encoder-decoder. The model uses a deep learning network such as ResNet[5]. The model can use pre-trained ResNet such as ImageNet or CoCo[4] to initialize the algorithm. Using pre-trained models is important when there are a few images for training. Choosing this architecture is not the only important factor to get high performance but also the choice of the components of U-NET. Instance segmentation can be done using U-NET.
U-NET as in Fig (2). For more information [6][7][8].

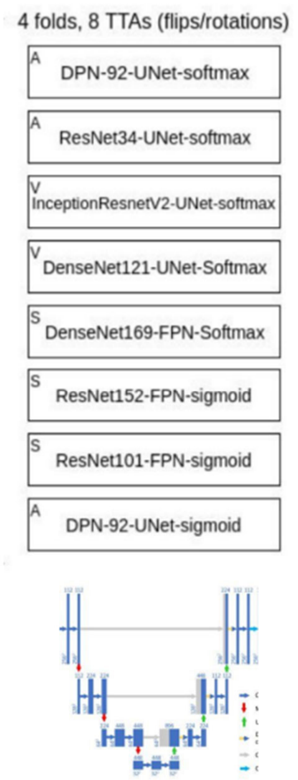

Fig (2)

3. Experiments and Results

Nuclei images used in this experiment have different modalities (brightfield vs. fluorescence) and cell types.

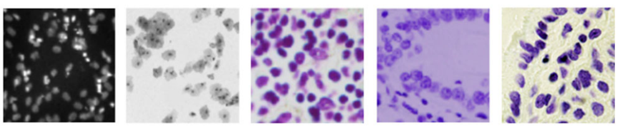

Fig (3) different modalities and cell types.

The evaluation metrics used are the mean average precision(mAP) at a different intersection over union (IoU) thresholds. Other metrics used, precision, recall and Dice.

Creation of Accurate segmentation masks determined using the values of the Dice metric. U-NET is better than Mask R-CNN to Create proper segmentation masks. The difference between mAP values is slight. Precision and Recall is good for Mask R-CNN; this means that it can detect nuclei accurately.

Table 1: Performance Metrics

For all	**mAP**	**Precision**	**Recall**	**Dice**
U-NET	0.495	0.650	0.554	0.630
Mask R-CNN	0.490	0.793	0.578	0.490

4. Conclusion

U-NET algorithm and Mask R-CNN algorithm are good in nuclei segmentation, but U-NET is better than Mask R-CNN in nuclei segmentation. In future work, hybrid algorithm from both uses their power in nuclei segmentation.

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