Noise-tolerant Deep Learning for Histopathological Image Segmentation

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Introduction

To assess the progression of disease Duchenne Muscular Dystrophy (DMD), the proportion of fibrosis has been considered an important biomarker to provide prognostic information [2]. In the histo-images, muscle and fibrosis are stained in red and blue. it is critical to have accurate segmentation for muscle and fibrosis in histo-images. While the classical K-Means and Otsu are unable to provide satisfactory results, the popular supervised deep learning method is also difficult to be applied due to the scarcity of manually annotated training sets. In our work, we implement the original u-net [3] by taking great K-Means segmentations as training set. More importantly we innovatively modify the u-net [3] to a noise-tolerant u-net (**NTUN**) so that the training with noisy segmentations such as those from Otsu is possible. Both methods show improved performance than the K-Means and Otsu.

Objectives

- Apply deep learning in histo-image segmentation with noisy training sets.
- Relieve doctor from manual segmentation.

Innovation

Motivated by the work in [4], we innovate a noise-tolerant layer (Figure 1) to the output layer of a deep learning image segmentation framework u-net (Figure 2), which alleviates the requirement of accurately segmented training images and enables "unsupervised" histo-image segmentation by taking noisy segmentation results of traditional image segmentation algorithms as the training outputs.

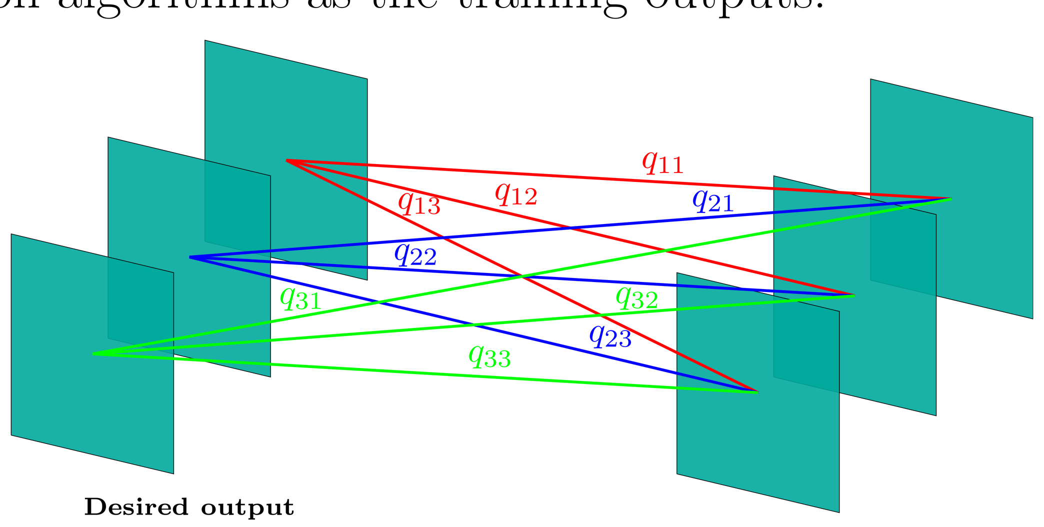


Figure 1: Illustration of the "noise-tolerant" layer

Model

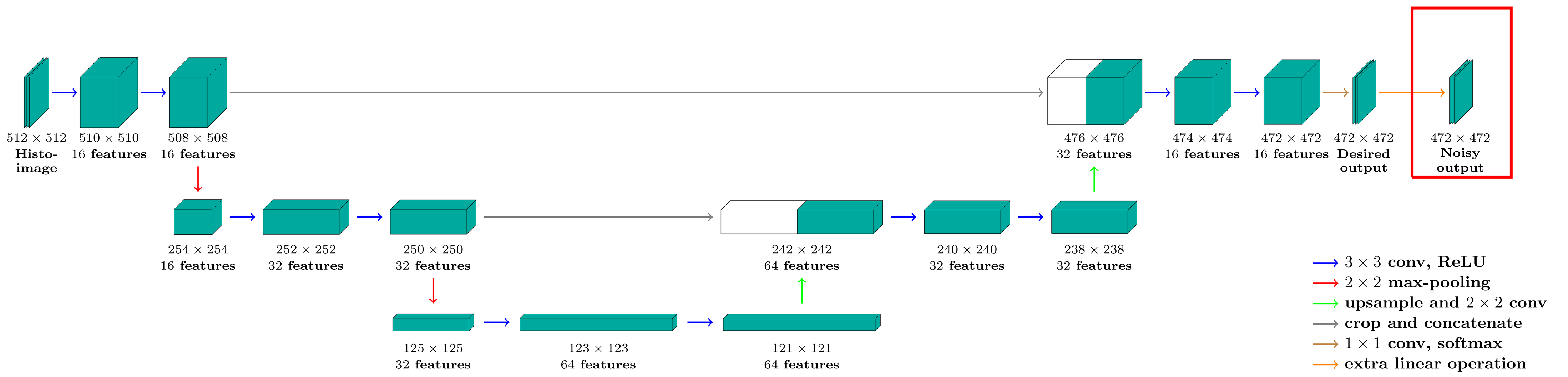


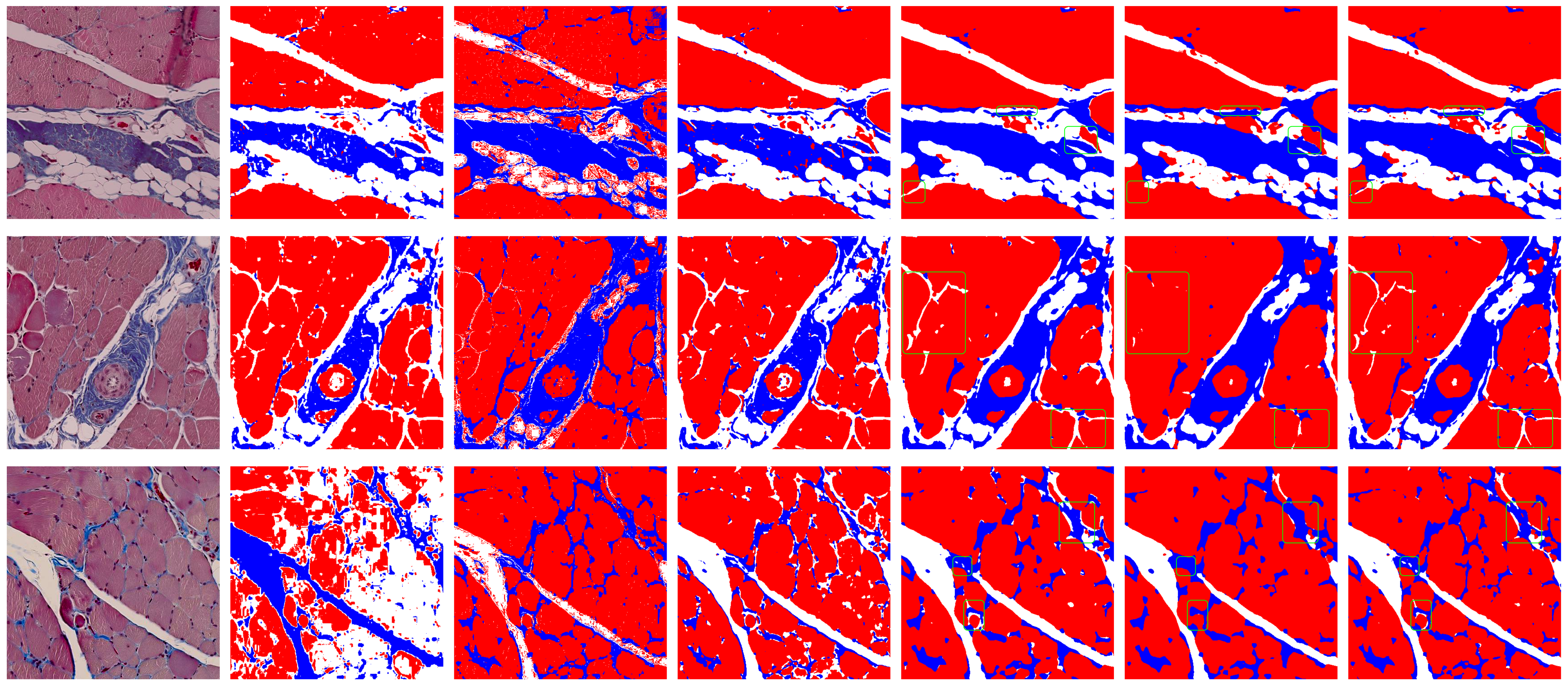
Figure 2: Schematic illustrations of u-net (without the extra linear layer in the red box) and our noise-tolerant u-net (with the extra layer). The sizes of input images or feature maps with the corresponding numbers of features are denoted under each box.

Given w training images $X = \{X_1, \ldots, X_w\}$ and the corresponding noisy segmentation Y_n, we aim to recover clean segmentations Y_s. With the probabilistic model $Pr(Y_n) = \left[\sum_{Y_s} Pr(Y_n|Y_s)Pr(Y_s|X)\right]$, we can construct the loss function:

$$L = -\frac{1}{K}\sum_{k=1}^{K} log\left[\sum_{i=1}^{3} Pr(Y_n^k = j|Y_s^k = i)Pr(Y_s^k = i|X)\right] = -\frac{1}{K}\sum_{k=1}^{K} log\left[\sum_{i=1}^{3} q_{ij}Pr(Y_s^k = i|X)\right], \qquad (1)$$

where K is the total number of pixels in X and i and j are class of a pixel for $i, j = 1, 2, 3$. Minimization of L is carried out using backpropagation combined with weight decay for noise-tolerant layer.

Segmentation Results



(a) Original (b) K-Means (c) Otsu (d) u-net[1] (e) u-net[2] (f) u-net[3] (g) NTUN

Figure 3: Segmentation results. u-net[1]: u-net trained with ten "clean" segmented images. u-net[2]: u-net trained with one "clean" segmented image. u-net[3]: u-net trained with one "noisy" segmented image. NTUN: Noise-tolerant u-net trained with one "noisy" segmented image. The training was performed using a different image.

Both u-net and NTUN perform better than K-Means and Otsu's method. Moreover, NTUN outperforms the u-net without the noise-tolerant layer, especially at the places marked in green boxes. The segmentation results by NTUN, when trained with "noisy" segmentation, are in fact consistent with the results by the u-net trained with "clean" segmentation.

Statistical Results

We quantitatively evaluate segmentation results based on the uniformity within clustered regions and disparity across regions in Lab color space following [1, 5] since we do not have the ground-truth.

	1	2	3	4	5
KM	0.1240	**0.1426**	0.2141	0.1876	0.1317
OS	**0.1081**	0.1735	0.2450	0.1932	0.1660
UN	**0.0983**	**0.1425**	**0.1908**	**0.1724**	**0.1241**
UN*	0.1059	0.1611	**0.1993**	0.1857	0.1649
NTUN	**0.0976**	**0.1429**	**0.1870**	**0.1731**	**0.1315**

Table 1: Performance comparison by E for five groups. KM: K-Means; OS: Otsu; UN: u-net trained with K-Means segmentation; UN*: u-net trained with Otsu segmentations; and NTUN: NTUN trained with Otsu segmentation.

Clearly, NTUN with noisy training samples and u-net with clean training samples outperform all the other methods. Even without manual segmentations for training, our proposed NTUN can achieve acceptable histo-image segmentation for further analysis.

Conclusion

We have developed a noise-tolerant version of the u-net, which enables "unsupervised" deep learning for reliable segmentation of histo-images. Our preliminary experimental results show clear advantages of NTUN over the u-net and other traditional histo-image segmentation algorithms.

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References

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