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 clue [2]. With the histo-images where muscle and fibrosis are stained red and blue, it is hence 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 in due to the scarce of manual annotated training sets. In our work, on the one hand we implement original u-net [3] by taking great K-Means segmentations as training set, on the other hand 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 of methods show better 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 [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.

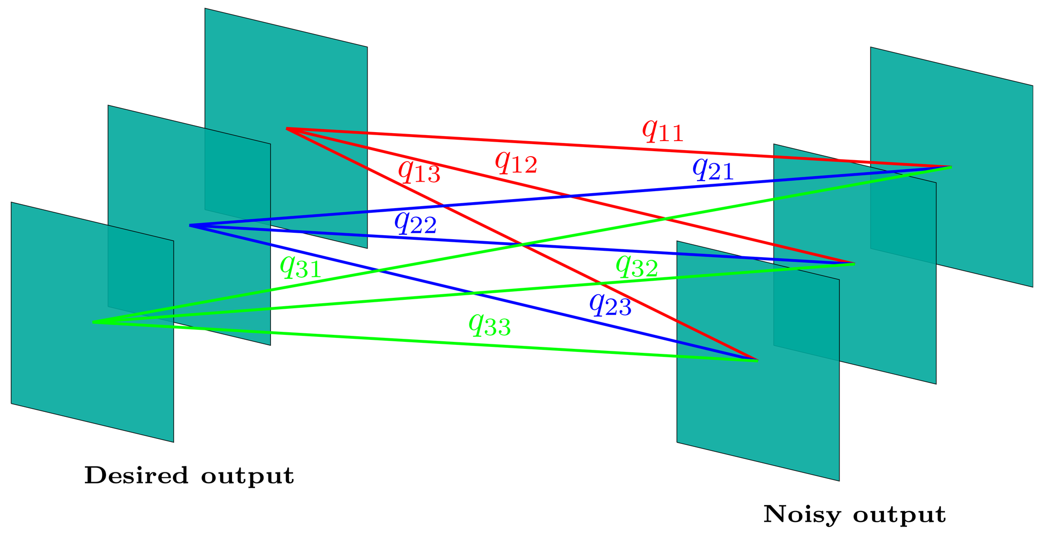


Figure 1: Illustration of the "noise-tolerant" layer

Model

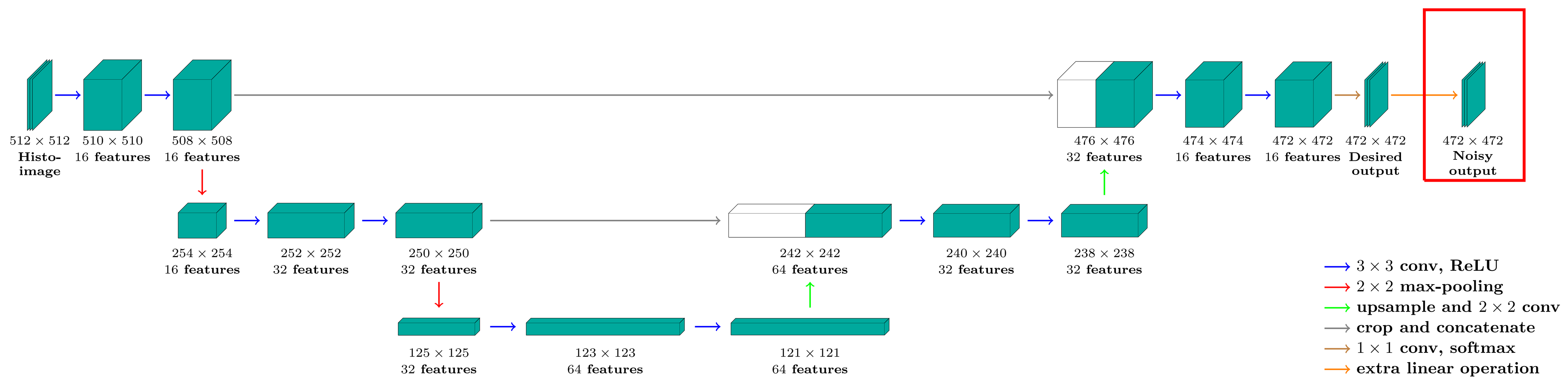


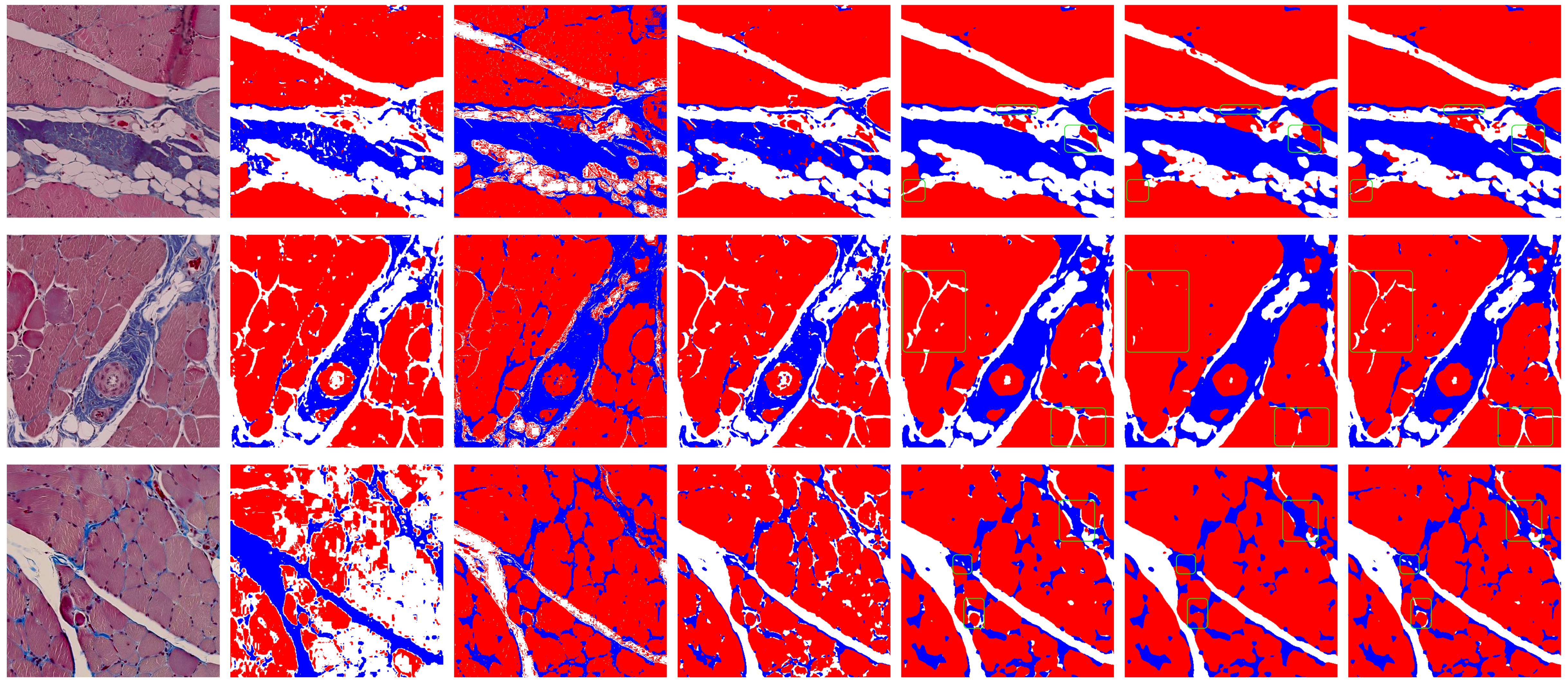
Figure 2: Schematic illustrations of u-net (without the extra linear layer in the red box) and our noise-tolerant u-net (with the extra layer). The sizes of input images or feature maps with the corresponding numbers of features are denoted under each box.

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:

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

where K is the total number of pixels in X and i and j are label class.

Segmentation Results



(a) Original (b) K-Means (c) Otsu (d) u-net¹ (e) u-net² (f) u-net³ (g) NTNU

Figure 3: Segmentation results. u-net¹: u-net trained with ten "clean" segmented images. u-net²: u-net trained with one "clean" segmented image. u-net³: u-net trained with one "noisy" segmented image. NTUN: Noise-tolerant u-net trained with one "noisy" segmented image.

Both of u-net and NTUN perform better than K-Means and Otsu's method, moreover NTUN outperforming 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 L*a*b* 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 are outperforming all the other methods for comparison. Again, even without manual segmentations for training, our proposed NTUN can achieve good histo-image segmentation for further analysis.

Conclusion

We have proposed 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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