Abstract #44 | Oral or Poster presentation

Segmentation of Multiple Tissue Types in Regenerating Wounds

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Introduction

In wound histology, manual annotation and subsequent analysis of whole slide images (WSI) is extremely labour intensive, often hampering research progress. We believe that the application of deep learning (DL) methods can greatly improve analysis and may result in identification of new features and mechanisms involved in skin regeneration. Existing DL methods have not been extensively applied to wound histology; thus, this work has the potential to produce a first-in-class tool to significantly augment skin regeneration research.

Methods

Our proposed framework consists of a UNet-based[1] architecture, employing a supervised approach with WSI and accompanying segmentation masks from our own database (Figure 1). We employ data augmentation and transfer learning to boost performance. Training is conducted using full WSI as well as using patches extracted from associated WSI to capture the global context of the wound, the intricacy of the tissue type borders and the less prevalent features within the wound. Our framework is optimised to segment 14 classes (12 key tissue types, slide artefacts and background) from haematoxylin & eosin (H&E) stained slides, a common immuno-histochemistry staining type widely employed to analyse wound healing.

Results/Discussion

Preliminary data (Figure 2) demonstrates that our framework is able to accurately segment dominant tissue types, as seen in the table and confusion matrix. Strong initial performance was achieved despite limited WSI (N=6). Further optimisation is required to segment the less prevalent tissue types. Our data also shows that excessive augmentation can reduce performance and suggests that the level of data augmentation requires a careful consideration. We also believe that patch size and extraction method is a significant factor impacting performance. Currently, patches of size 256x256 are extracted sequentially from associated WSI. This may cause contextual information to be lost during training. Hence, further optimisation is required. To improve performance, we propose to increase patch size and employ random patch extraction and to adapt the framework further. We believe this will allow retention of global context and local fine detailed information.

Conclusions

We demonstrate that our framework functions accurately for dominant tissue types of the wound. Further optimisation work is required to enhance its performance, particularly for less dominant tissue types. We apply DL methods for the first time in wound healing research to analyse tissue holistically. Leveraging the DL framework for wound parameter analysis presents strong groundwork for future development of wound healing research.

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Disclosure

I or one of my co-authors have the following financial interest or relationship(s) to disclose regarding the subject matter of this presentation concerning research support from T. J. Smith and Nephew Limited.

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References

[1] Ronneberger, Olaf, Philipp Fischer, and Thomas Brox (May 2015). "U-Net: Convolutional Networks for Biomedical Image Segmentation". In: arXiv:1505.04597 [cs]. arXiv: 1505.04597 version: 1. url: http://arxiv.org/abs/1505.04597

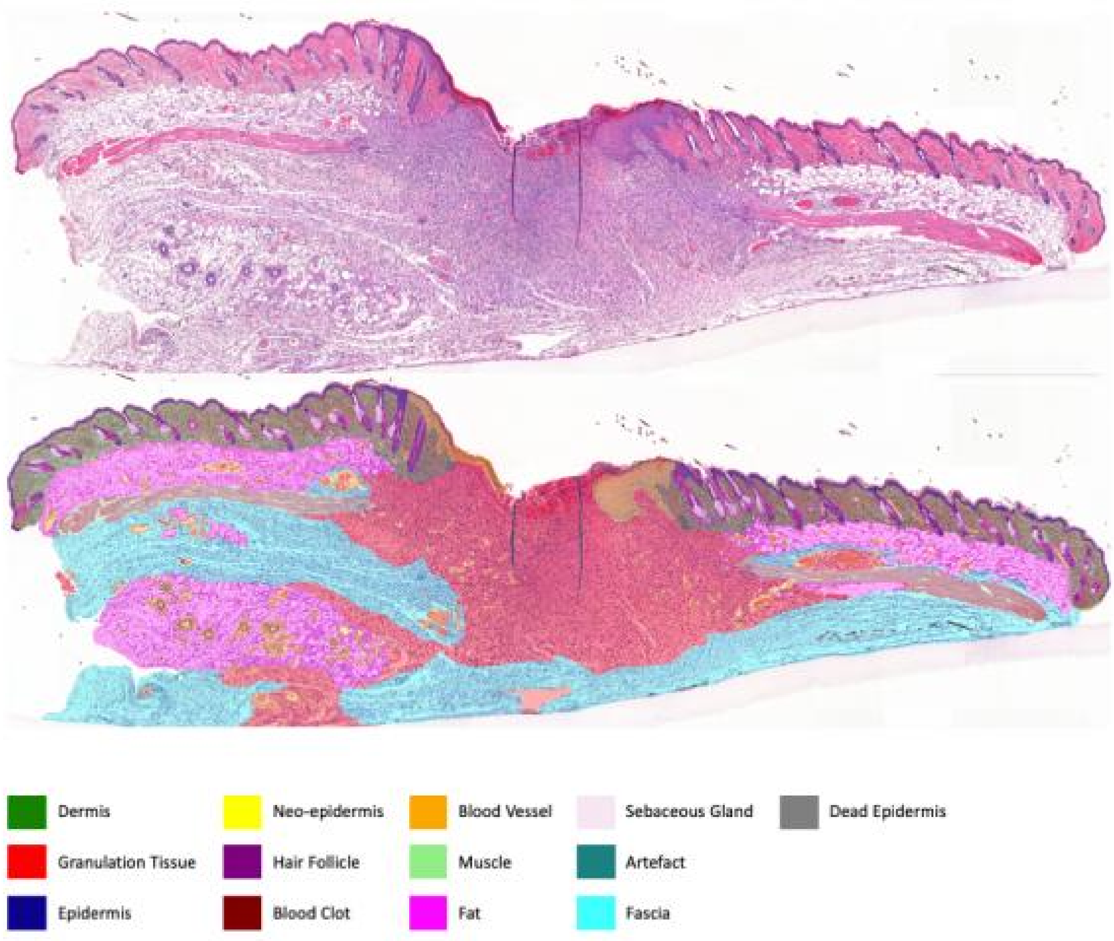
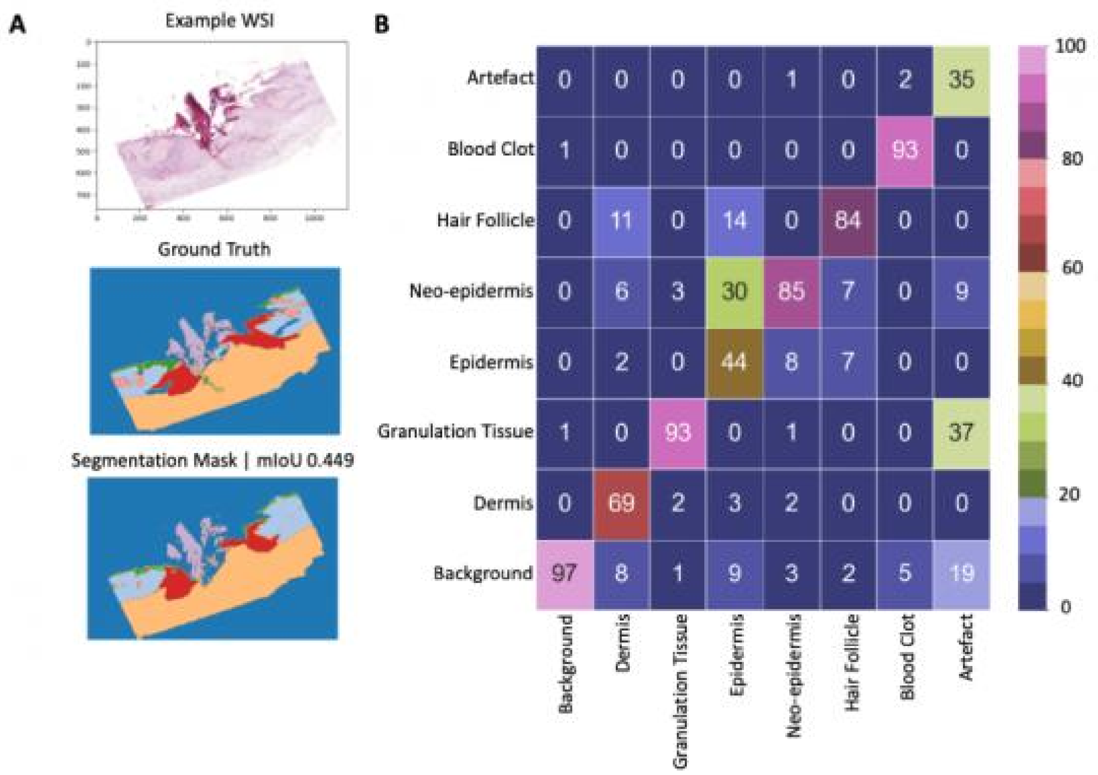


Figure 1. Example H&E stained WSI with accompanying manually created segmentation mask.
Figure 1. Example H&E stained WSI (top) with accompanying manually created segmentation mask (bottom) depicting 12 classes of tissue typically found in a wound. Please note that each tissue type may not be present in every WSI, for example, the blood clot.



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Class	Dermis	Granulation Tissue	Epidermis	Neo-epidermis	Hair Follicle	Blood Clot	Artefact
IoU Score	0.632	0.885	0.256	0.621	0.127	0.756	0.197

Figure 2. Accurate segmentation of dominant tissue types by the framework.

Figure 2. A) Test output of our framework showing an example WSI (top), Ground Truth (middle) and Segmentation Mask (bottom) produced by the model with a mean intersection over union score (mIoU) of 0.449 (including background); B) The confusion matrix produced by our framework demonstrating that dominant tissue types (dermis, granulation tissue, neo-epidermis and blood clot) are most accurately segmented and classified (>60%). Scale: percentage of pixels classified; C) Table of intersection over union (IoU) scores per class, for dominant tissue types and artefact, exlcuding background.