XNet: A CNN for X-Ray Image Segmentation

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1. Introduction

Medical X-Ray image enhancement regularly requires the segmentation of images into 3 categories: **open beam**, **soft tissue** and **bone**. Current methods rely heavily on a complex system of classical image processing techniques, however, utilising machine learning offers several advantages over these traditional methods since: (i) it naturally addresses noise, (ii) it generalises well to different body parts, and (iii) the segmented regions have continuous boundaries.
Driven by the requirements of IBEX Innovations Ltd. we design and implement a neural network for such segmentation, with the aim of minimising false positives in the soft tissue category.

2. Methods

Dataset:

- 150 X-Ray images.
- No scatter correction.
- 20 human body part classes.
- Highly imbalanced.
- Artificially augmented to a balanced dataset composed of over 7000 images.

Network Architecture:

- Built on a typical encoder-decoder **Convolutional Neural Network (CNN)**.
- Additional feature extraction stage, with weight sharing across some layers.
- Fine and coarse feature preservation through concatenation of layers.
- **L2 regularisation** at each of the convolutional layers, to decrease overfitting.
- Post-processing by applying probability thresholding and pixel dilation to reduce soft tissue false positives.

3. Network Architecture

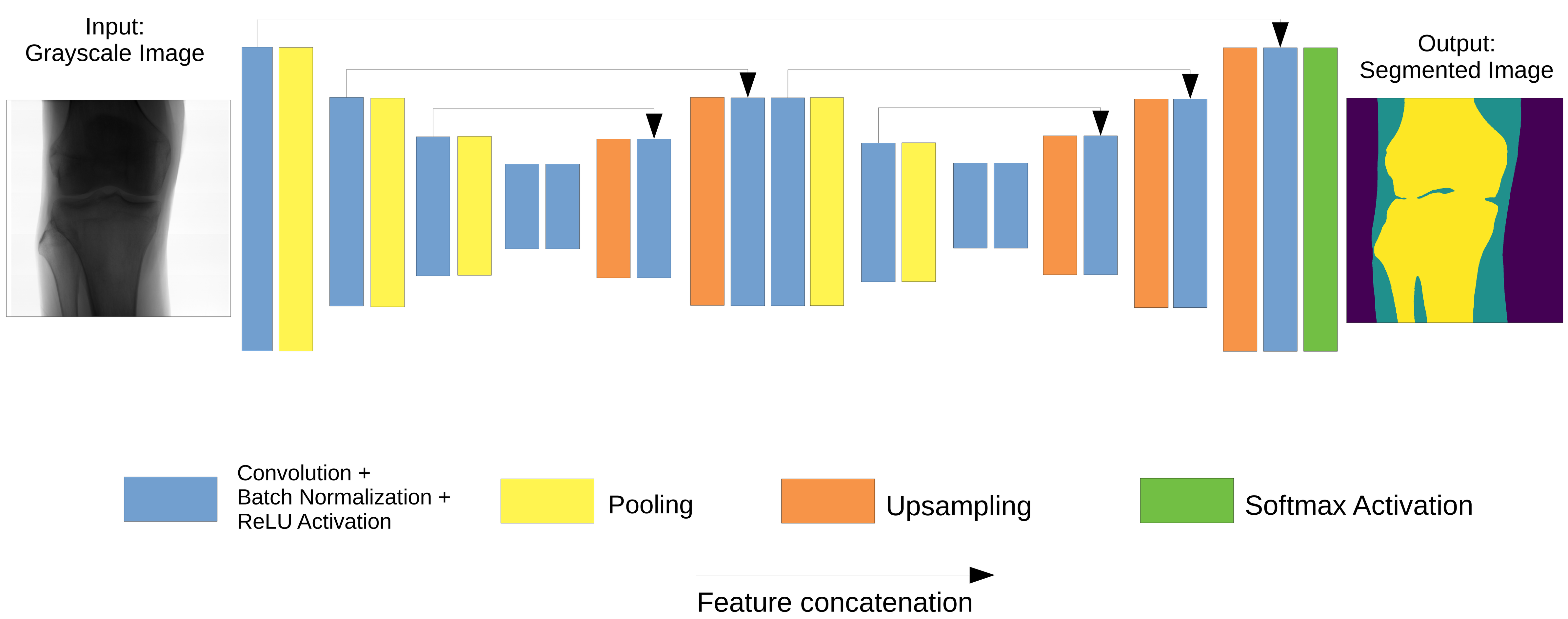

Figure 3: The XNet architecture with input images of size 200x200 pixels producing a segmentation mask of the same size.

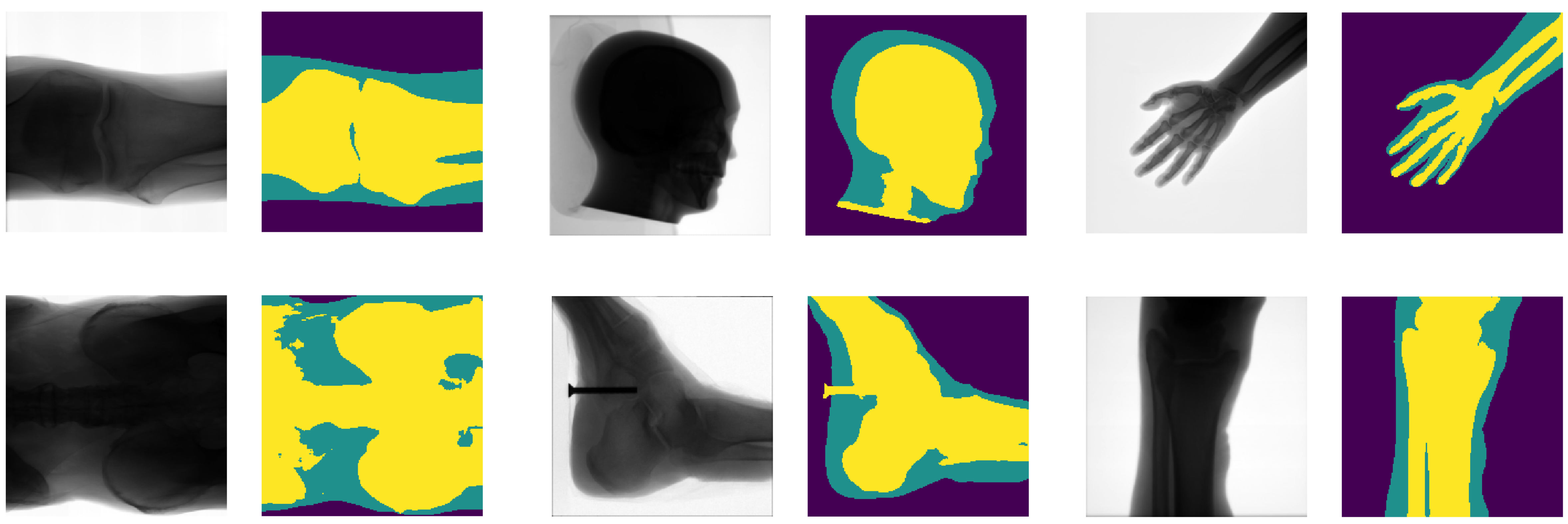

Figure 4: Predictions from the network. Open beam in purple, soft tissue in green and bone in yellow.

4. Results

The output of our network achieves an overall accuracy score of 93%, before post-processing, and has an area under the ROC curve of 0.98 (Fig. 1). This accuracy demonstrates a significant improvement upon results from previous work that rely on traditional segmentation techniques.

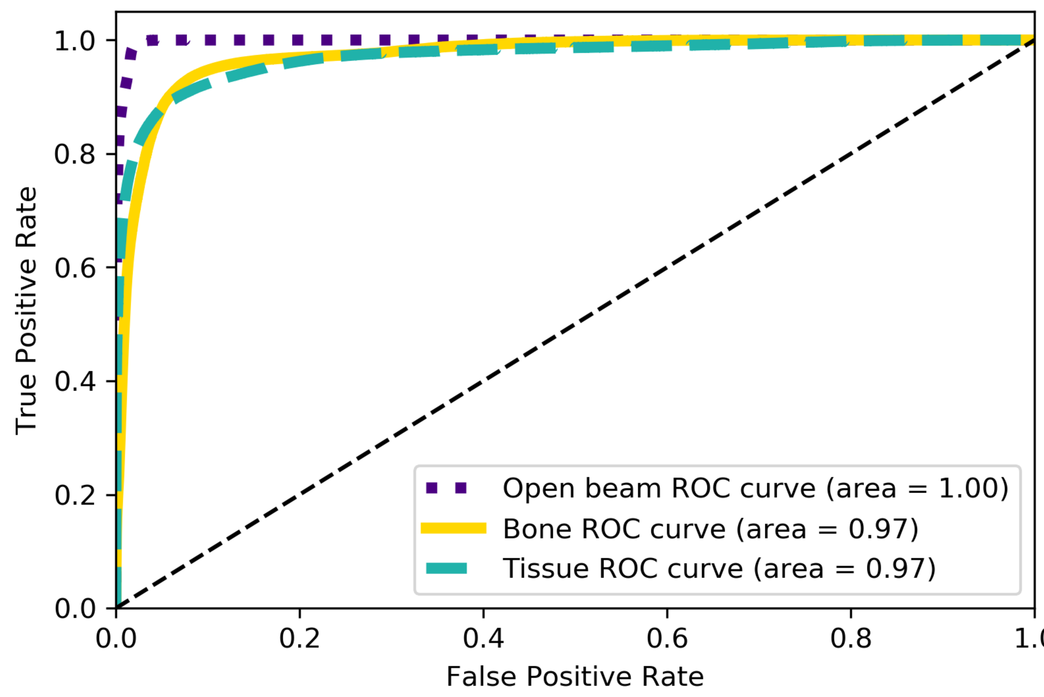

Figure 1: ROC curve showing XNet performance.

The per-category performance of our classifier is shown in the confusion matrix (Fig. 2).

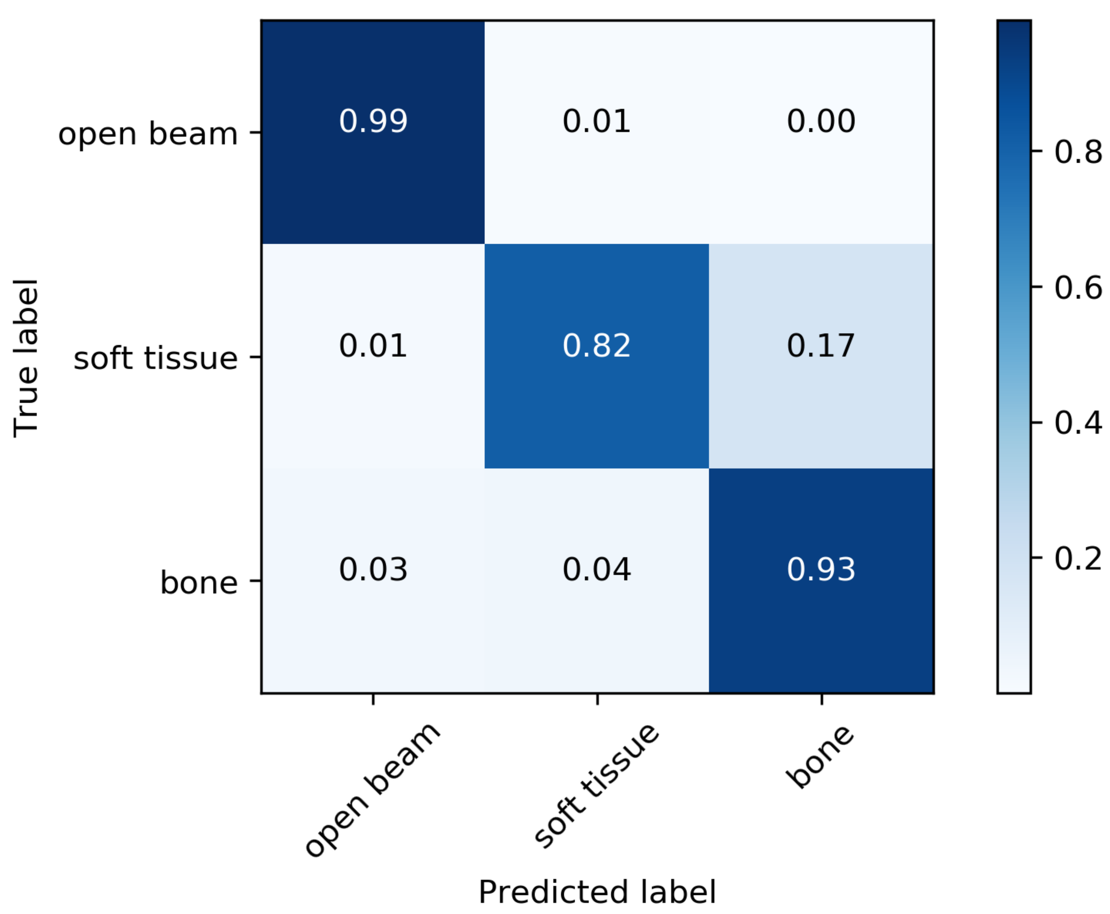

Figure 2: Normalized confusion matrix

Furthermore, our post-processing techniques can be used to either reduce false positives or false negatives in any of the segmented categories. Indeed, we reduce the soft tissue false positive rate from 5% to 0.5%.

5. Conclusions

The imbalanced nature of our dataset is comparable to that of a hospital, or other medical institution. Similarly, since each image requires manual segmentation for network training purposes, having such a small dataset is representative of that manageable by a non-specialist organisation. Due to its performance on a representative dataset, we believe our end-to-end methodology for segmenting medical images serves as an important contribution to the field of X-Ray image enhancement.

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