AUTOMATIC TBI LESION SEGMENTATION

in Anisotropic CT using Convolutional Neural Networks

E Ferrante[1], K Kamnitsas[1], S Cooke[2], JP Coles [2]
VFJ Newcombe[2], DK Menon[2], D Rueckert[1], B Glocker[1]

[1] BioMedIA, Imperial College London
[2] Department of Medicine, University of Cambridge

Motivation

Accurate image-based lesion quantification is essential for diagnosis, monitoring and understanding TBI from a clinical perspective.

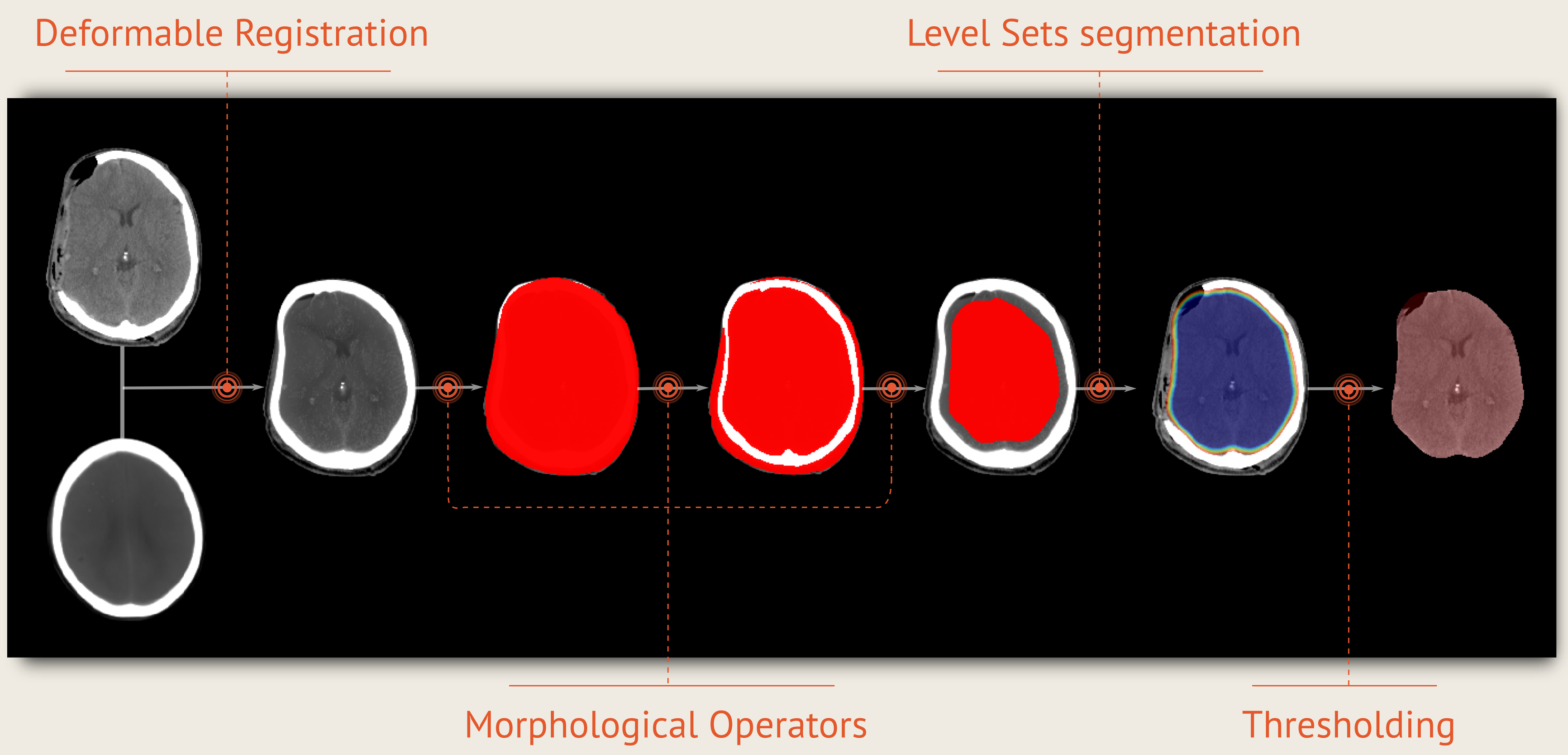
Although CT is the most common image modality for rapid detection of TBI lesions, computational methods have been mostly proposed for lesion segmentation on MRI, given its higher definition.

Deep learning methods like Convolutional Neural Networks (CNN) have shown promising results for TBI MRI [1], but its potential has not been evaluated on CT images yet.

Methods

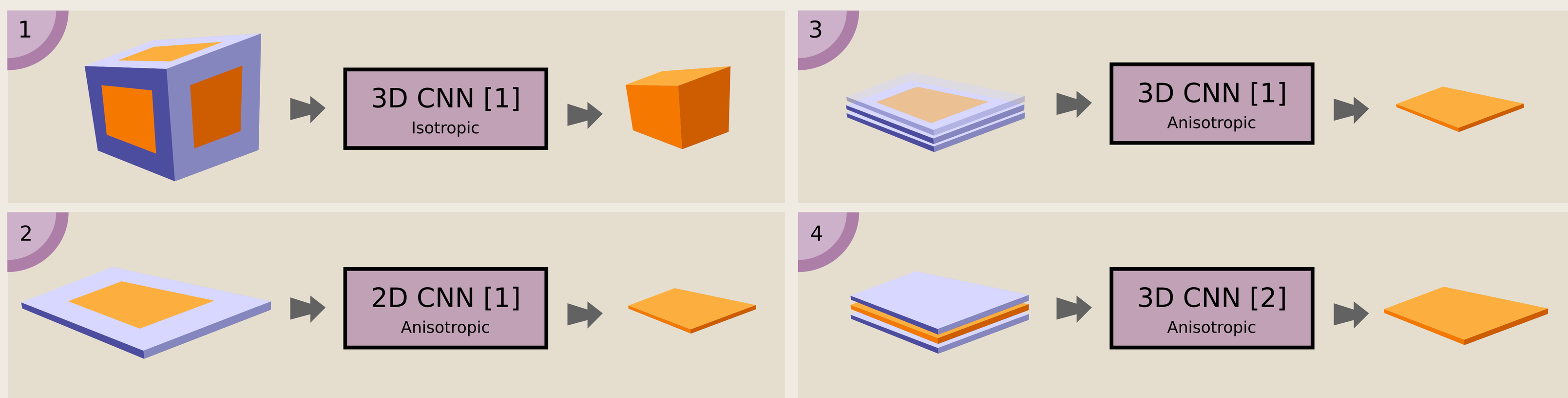
SKULL STRIPING

We removed the skull to isolate the brain tissue and simplify the segmentation task. Our method can deal with extreme cases including displaced skull fractures, craniotomy holes and decompressive craniectomy sites.



ALTERNATIVE CNN ARCHITECTURES

In our preliminary experiments, we aimed to understand the influence of the slice thickness and 3D context in TBI lesion segmentation on CT.



In terms of slice thickness, model 1 was trained on isotropic (1mm3) resampled images (using trilinear interpolation) while models 2, 3 and 4 considered anisotropic (1mm2 x Original Res) volumes. Regarding the 3D context, model 1 used full 3D context, model 2 considered only single 2D slices, and models 3 and 4 a reduced 3D context given the two adjacent slices.

Method 1 outperformed the others resulting in an average of 0.43 DSC, versus 0.36 (Method 2), 0.41 (Method 3) and 0.39 (Method 4).

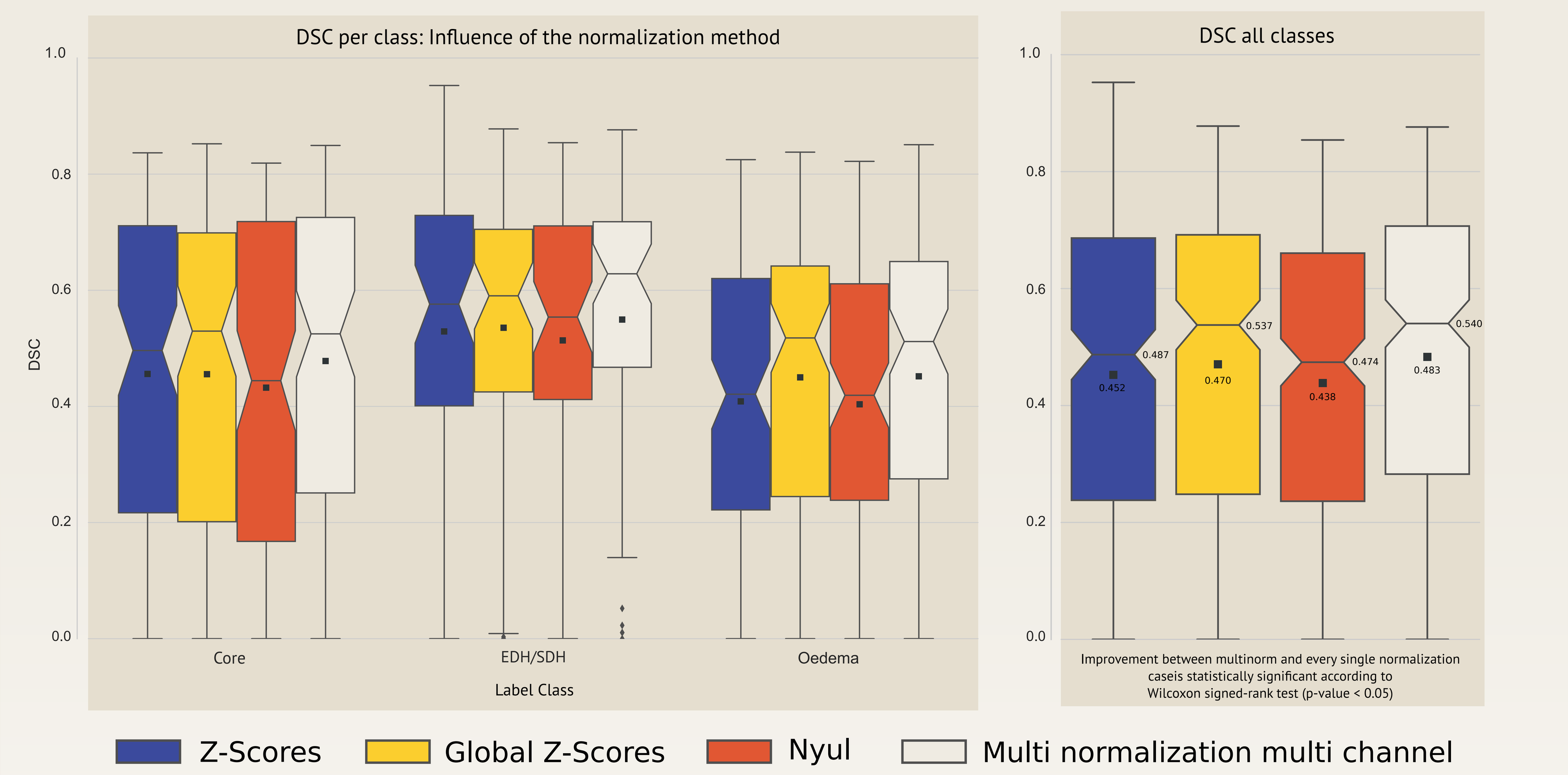
MULTIPLE NORMALIZATIONS

We considered alternative intensity normalization schemes. A single channel version of the best performing architecture (Model 1) was trained with data normalized with the alternative schemes.
A multichannel version was also trained, considering the 3 normalizations as 3 channels.

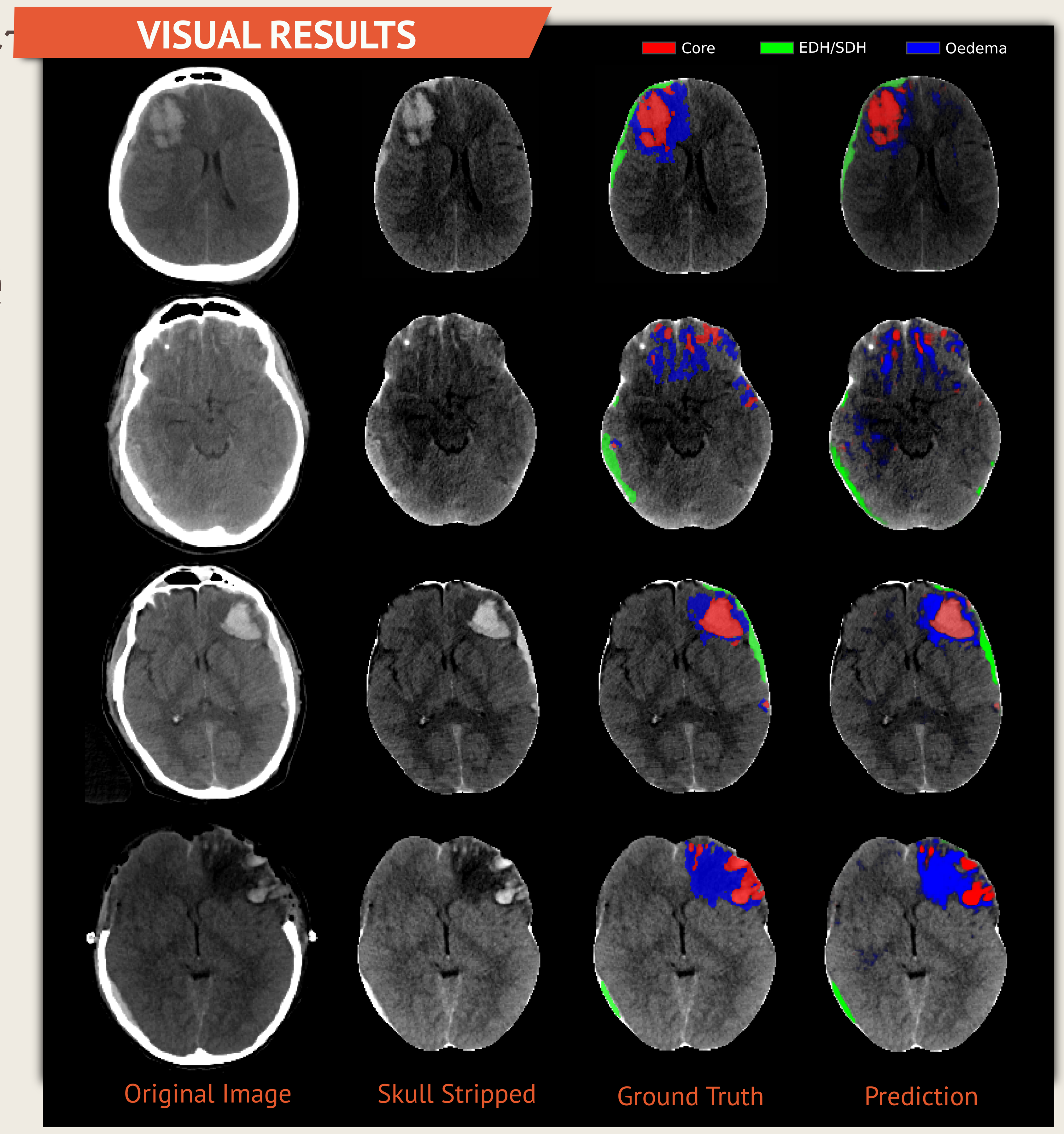
Z-scores	$I_i(x) = \frac{I_i(x) - \mu_i}{\sigma_i}$
Global Z-scores	$I_i(x) = \frac{I_i(x) - \hat{\mu}}{\hat{\sigma}}$
Nyul's Method [3]	A linear piece-wise normalization function is learned from data

Results

We used 110 CT images (~0.4x0.4x5mm resolution) of 25 patients with different degrees of TBI lesions, manually annotated by medical experts, including: contusions divided in their core and surrounding oedema, and extra cerebral blood (EDH and SDH) combined into one ROI.



VISUAL RESULTS



Conclusions

- Our preliminary experiments confirmed the importance of 3D context for TBI lesion segmentation on CT using CNNs.
- Multi-channel CNNs using multi-normalized data seem to significantly improve the quality of the segmentation results when compared to single channel CNNs trained with CT data.

SOURCE CODE

The source code will be soon available at **https://github.com/eferrante/tbi-ct-cnn**

References

[1] Kamnitsas K, Ledig C, Newcombe V, Simpson J et al. (2016) Efficient Multi-Scale 3D CNN with Fully Connected CRF for Accurate Brain Lesion Segmentation. Medical Image Analysis
[2] Ronneberger O, Fischer P, Brox T (2015) U-Net: Convolutional Networks for Biomedical Image Segmentation. MICCAI 2015
[3] Nyúl, László G., and Jayaram K. Udupa. "On standardizing the MR image intensity scale" Magn Reson Med. (1999) Dec;42(6):1072-81.

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