**Deep Learning Based Vertebral Body Segmentation for Bone Marrow Fat Fraction Quantification**

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**Introduction**

Significant associations have been found between bone marrow fat (BMF) fraction and biochemical changes in the adjacent intervertebral disc (IVD), the degeneration of which is often considered a primary cause of chronic low back pain (CLBP), one of the most common health problems worldwide [1]. As such, characterizing CLBP provides specific targets for intervention and reducing the risk of prescribing medications with high abuse potential (e.g. opioids) unnecessarily. Recent advances in magnetic resonance imaging (MRI) have facilitated quantitative analysis of vertebral BMF and biochemical composition of the IVD, including a qualitative rating scheme (Modic changes) of bone marrow using clinical T1‐ and T2‐weighted MR images [2]. BMF fraction maps can be obtained with high resolution and high accuracy from chemical shift encoding‐based water–fat MRI [3]. However, manual identification of vertebral bodies in MR images can be laborious and time consuming. This study aimed to develop a fully automated deep learning pipeline to segment and quantify BMF fraction of the lumbar vertebrae with future applications of identifying vertebral biomarkers of CLBP that would act as a radiology assist in image interpretation.

**Methods**

The dataset used in this study consisted of 46 subjects (CLBP=34, Controls=16) imaged using a Discovery MR 750 3 T scanner with an 8‐channel phased‐array spine coil (GE Healthcare, Waukesha, WI). The water–fat MRI protocol consisted of a 3D SPGR sequence with six echoes and iterative decomposition of water and fat with echo asymmetry and least‐squares estimation (IDEAL) reconstruction algorithm with TR = 7 msec, TE = 2.1 msec, flip angle = 3°, rBW = ±83.3 kHz, FoV = 22 cm, in‐plane resolution = 1.3 mm, and slice thickness = 4 mm.

The deep learning portion of the segmentation and fat quantification pipeline was implemented in Python using Keras with Tensorflow backend. A U-Net (Jaccard distance loss, Adam optimizer, learning rate=1e-4, batch size=4) [4] was trained on 33 subjects, with a 20% validation split during the training process, to segment lumbar vertebrae. Twenty slices of size 256x256 from each subject were input to the U-Net with four channels corresponding to the water, fat, fat fraction, and R2\* images. The ground truth segmentation used was created manually on water images. The U-Net performance on a hold-out validation set (CLBP=7, Controls=1) was measured using Dice coefficients and receiver operating characteristic (ROC) curve analysis. Resulting predicted segmentations were binarized with a threshold of 0.5 and used to create Bland-Altman plots of the fat fractions in each vertebral region of interest (ROI).

**Results**

The network was trained for 100 epochs and achieved an AUC of 0.98 (training) and 0.90 (validation) on classification of pixels as vertebrae. A sensitivity of 0.77 and specificity of 1.0 were achieved for the validation dataset. Comparing manual and automatic segmentations on fat fraction maps using Bland-Altman analysis results in a bias of only -0.214 and agreement limits of -2.258 and 1.830.

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| **Figure 1:** Automatic vertebrae segmentation and fat quantification pipeline. All IDEAL images (water, fat, fat fraction, and R2\*) are fed in as multichannel input to a trained U-Net [4], which outputs a predicted segmentation map. Each ROI corresponding to lumbar vertebrae was analyzed on fat fraction maps to yield mean BMF values. | **Figure 2:** **A)** Receiver operating characteristic (ROC) for training (blue) and validation (orange) datasets. Chance performance is shown by the dotted green line. **B)** Bland-Altman plot of mean bone marrow fat fraction (BMF) values as determined by manual segmentation compared to automatic segmentation for each lumbar vertebra. |

**Discussion**

Overall, the current trained model can automatically segment vertebrae with high specificity and AUC. Bland-Altman analysis shows that the automatic segmentation method when used for BMF fraction quantification is comparable with the manual segmentation. However, the datasets used for training and evaluation can be considered “unbalanced”, where more pixels are representative of the “not vertebra” class and only 2% of pixels make up the “vertebra” class, making it more difficult to train a neural network with high sensitivity. We aim to improve the performance of the neural network by utilizing data augmentation and exploring alternative networks (e.g. 3D networks). In the future, we also plan to implement these segmentations in an automated pipeline for investigating associations with biomarkers of CLBP, including Modic changes.

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