Deep Learning-based Spine Segmentation in DXA scans

De Guio, François, fdeguio@medimapsgroup.com, Medimaps, Canéjan (Orateur)
Ahmed, El Hassen, eahmed@medimapsgroup.com, Medimaps, Canéjan
Michelet, Franck, fmichelet@medimapsgroup.com, Medimaps, Canéjan

Thème 6 : Intelligence Artificielle : Robotique, Réseaux de Neurones, Deep Reinforcement, Automatique, Chatbot

Summary : *(6 lines)*

Spine segmentation in DXA scans is crucial as it directly impacts the computation of scores related to bone quantity/quality which are important for the diagnosis and prognosis of patients at risk of osteoporotic fractures. We implemented and optimized a deep learning method to automatically segment the spine. Our network showed a very good accuracy compared to experts, above existing automatic segmentation. Our method was found to be relevant in a clinical cohort, showing excellent agreement in bone scores by comparison to experts while being fully automated.

Key words : *(maximum 6)* deep learning; CNN; medical imaging; X-ray; segmentation; bone

1. Introduction

Dual-energy X-ray absorptiometry (DXA) is an imaging technique used routinely worldwide to measure the Bone Mineral Density (BMD). In many countries, every woman over the age of 65 is getting a DXA scan. As defined by the World Health Organization, BMD computed from DXA scans is typically used to diagnose and monitor osteoporosis.

While BMD is a marker of bone quantity, another score was developed from same DXA scans to assess the bone quality: the Trabecular Bone Score (TBS), a texture score that has been related to bone microarchitecture. In clinical practice, both BMD and TBS are used to evaluate patients bone health. BMD and TBS are independently predicting the incidence of future fractures and therefore are important metrics for osteoporosis management.

After DXA acquisition, a prior step before BMD and TBS computation is the segmentation of the spine. This is the process of defining pixel-wise where is the bone in order to compute BMD and TBS in that specific region to obtain meaningful values. This is currently done by DXA manufacturers which provide an automatic segmentation. However, as this segmentation is rough and inaccurate, DXA technicians have to spend additional time to manually edit the bone contour. This manual intervention leads to an added variability in bone scores due to inter-operator variability and may lead to inaccuracies due to difficult challenges in spine bone segmentation. Indeed, spine segmentation can be a challenging task given the amount and variability of noise in the image and the inter-patient variability in bone shape, rotation, presence of osteophytes, etc.

Our objective was to implement and optimize a deep learning method for automatic and accurate spine segmentation in DXA scans. More specifically, we aimed at getting a good agreement between bone scores obtained after expert manual segmentation and scores obtained after deep learning segmentation.

2. Methods

A population-based cohort comprising 1182 anonymized DXA scans of Caucasian women was retrieved and split as follows: 50% for training dataset, 25% for validation dataset, 25% for test dataset.

Rules for accurate spine segmentation were discussed in collaboration with 3 international DXA experts and consensus was reported in a segmentation protocol. Afterwards, fine centralized manual spine segmentation of the whole dataset was performed according to the segmentation protocol.

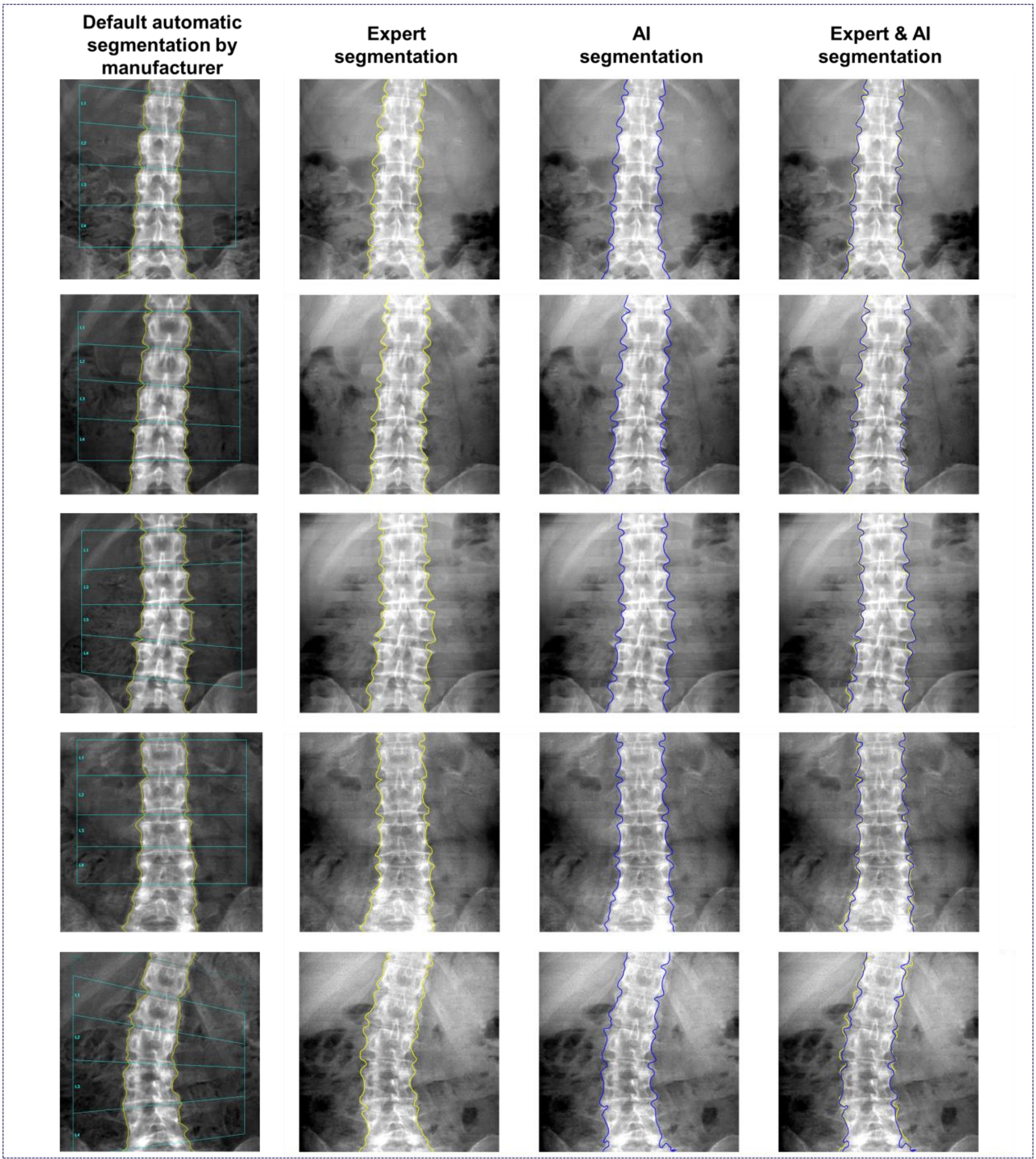
Several convolutional neural networks (CNN) were then tested for this supervised pixel-wise classification task. Metrics for evaluation included Dice Coefficient (DC), Hausdorff distance (max local distance), ASSD (average symmetric surface distance). Different U-Net based networks were compared (Ronneberger et al., 2015), varying number of input images (single energy or dual energy), number of features maps, number of downsampling/upsampling steps, etc. Our final network was inspired by IVD-Net (Dolz et al., 2019), a network built to take as input multiple images that are spatially correlated (we took both low-energy and high-energy images as inputs to predict the bone contour) and enabling connections within and across each path. We used Keras framework with TensorFlow backend with ReLU activation function, ADAM optimizer and minimization of Dice Coefficient as loss function. Post-processing steps included small clusters filtering and hole filling.

3. Results

Our network showed high accuracy with DC > 0.97 in the test dataset:

Dataset	Metrics					
	DC		Hausdorff (mm)		ASSD (mm)	
	Mean	SD	Mean	SD	Mean	SD
Validation	0.973	0.007	5.906	2.071	0.032	0.018
Test	0.973	0.011	5.684	2.201	0.033	0.032

Expert and deep learning (AI) segmentation were visually very close and coherent:



Finally, there was a good agreement between BMD or TBS values after expert or AI segmentation by comparison to manufacturer segmentation:

	Medimaps AI segmentation	Manufacturer segmentation
Correlation coefficient BMD - BMDexpert	0.996	0.994
RMSD BMD – BMDexpert (%)	0.028 (2.56%)	0.040 (3.70%)
Correlation coefficient TBS - TBSexpert	0.989	0.960
RMSD TBS – TBSexpert (%)	0.017 (1.31%)	0.034 (2.55%)

with RMSD = Root Mean Squared Deviation

Deviations (RMSD) from the expert values were 1.4 (BMD) and 1.9 (TBS) times worst for Manufacturer vs. AI segmentation.

4. Originality / perspectives

Despite being widely and extensively used for osteoporosis diagnosis, DXA scans do not yet have a proper bone segmentation. We propose here a deep learning-based segmentation that performs better than the segmentation proposed by the DXA manufacturer. This segmentation enables a quick (3s), reproducible and accurate bone mask to get clinically meaningful bone scores.

Perspectives include validation in another independent cohort acquired on a different DXA device.

References

Ronneberger et al., U-Net : *Convolutional Networks for Biomedical Image Segmentation*, MICCAI, 2015.

Dolz et al., IVD-Net *: Intervertebral disc localization and segmentation in MRI with a multi-modal UNet*, LNCS, 2019.