Automatic Deep learning based calculation of water equivalent diameter from 2D CT localizer image

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INTRODUCTION

Computed Tomography (CT) is one of the highest dose procedures in medical imaging, which has many indications and offers valuable diagnostic data. The easiest way for evaluation of the radiation dose in CT is CT Dose Index (CTDI) and Dose Length Product (DLP), presenting the exposure output of the scanner. To gain a more specific dose quantity, AAPM introduced Size-specific Dose Estimate (SSDE) in 2011, described the measurement and calculation method on report 220[1] by considering the effective diameter (DEff). To consider the contribution of patients' habitus into the absorbed dose, the SSDE was updated by water equivalent diameter later. Accurate DW can be calculated from 3D CT images as described in the previous studies[2]. Furthermore, the localizer images can be used to estimate the SSDE before the spiral (or sequential) scans. It can be more accessible, needs less calculation burden, and overcomes the truncation artefact problems in 3D CT images. Besides, the localizer scan length in Z-Axis is usually more than axial images, so size and DW are for larger body parts. This study aimed to establish an automatic pipeline to calculate the DW and patient's DEff from localizer images using machine learning.

METHODS

Data Acquisition:

We included 10836 chest CT images performed for various ranges of indications. As described in figure 1, the axial CT images in DICOM format were processed employing MatLab software.

The patient's bed was removed, and the body contour was segmented. The DW and DEff were calculated on axial images for all the slices and averaged over slices for each patient. Two dimensional (2D) lateral projections were calculated using 3D axial images and considered as localizer. Also, the 3D axial images were segmented by thresholding into five classes of air (ρe=0.001), lung (ρe=0.38), fat (ρe=0.95), soft tissue (ρe=1.05), and bone (ρe=1.8) according to Hounsfield unit values and water attenuation coefficient. This image was named CTAX,Gth. After the bed removal and body contour extraction phase, the 3D axial images were reoriented to the sagittal plane, matching the lateral localizer field of view. This image was named CTSAG,Gth. the images were cropped to body contour and resized to 128×112×56 matrix size. A U-NET network was used to predict the CTSAG,Gth images from a 2D localizer image. The network was trained using the MatLab deep learning (DL) toolbox on RTX 2080 TI GPU by splitting the data to train (8000 cases) and validation (1400 cases) groups. The network was tested on 1436 external test groups, untouched during the training phase. After post-processing the ratio of electron densities for all pixels in axial images of CTAX,Deep and CTAX,Gth. (Eq.1). Besides, the AP, Lateral, and DEff were measured on CTAX,Deep images. The linear regression was used to evaluate the correlation between AA and DW.

Eq1: $AA = \sum_{n=1}^{number\ of\ pixels}(pixel.\ \rho e)$.

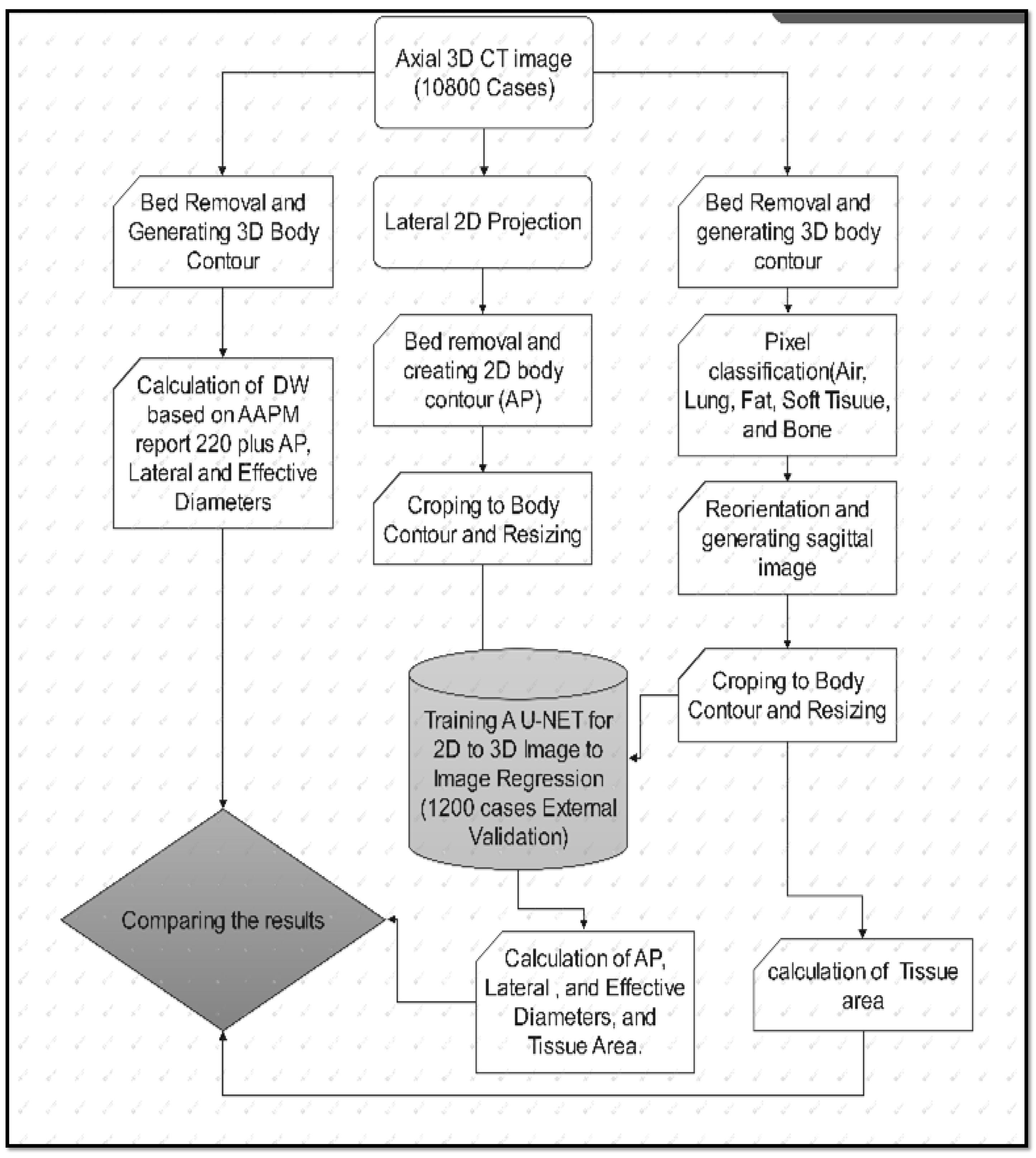

Figure 1: the flowchart describing the whole process. Left: calculation of D_w, Attenuating area and training process.

RESULTS

A good agreement between the AA calculated from $CT_{AX,Deep}$ and $CT_{AX,Gth}$, where the average absolute error was 4.04% (10 percentile: 0.73% , 90 percentile : 7.49%). Figure 2 shows an example slice of $CT_{AX,Deep}$ and $CT_{AX,Gth}$ and the error box.

A strong correlation between AA calculated from $CT_{AX,Deep}$ and D_W was revealed and line up well (R^2~0.95). The AP, Lateral and D_{Eff} calculated from $CT_{AX,Deep}$ images were in good agreement with axial CT images. The average error was 4.43 % (10 percentile: 0.53, 90 percentile: 9.7%).

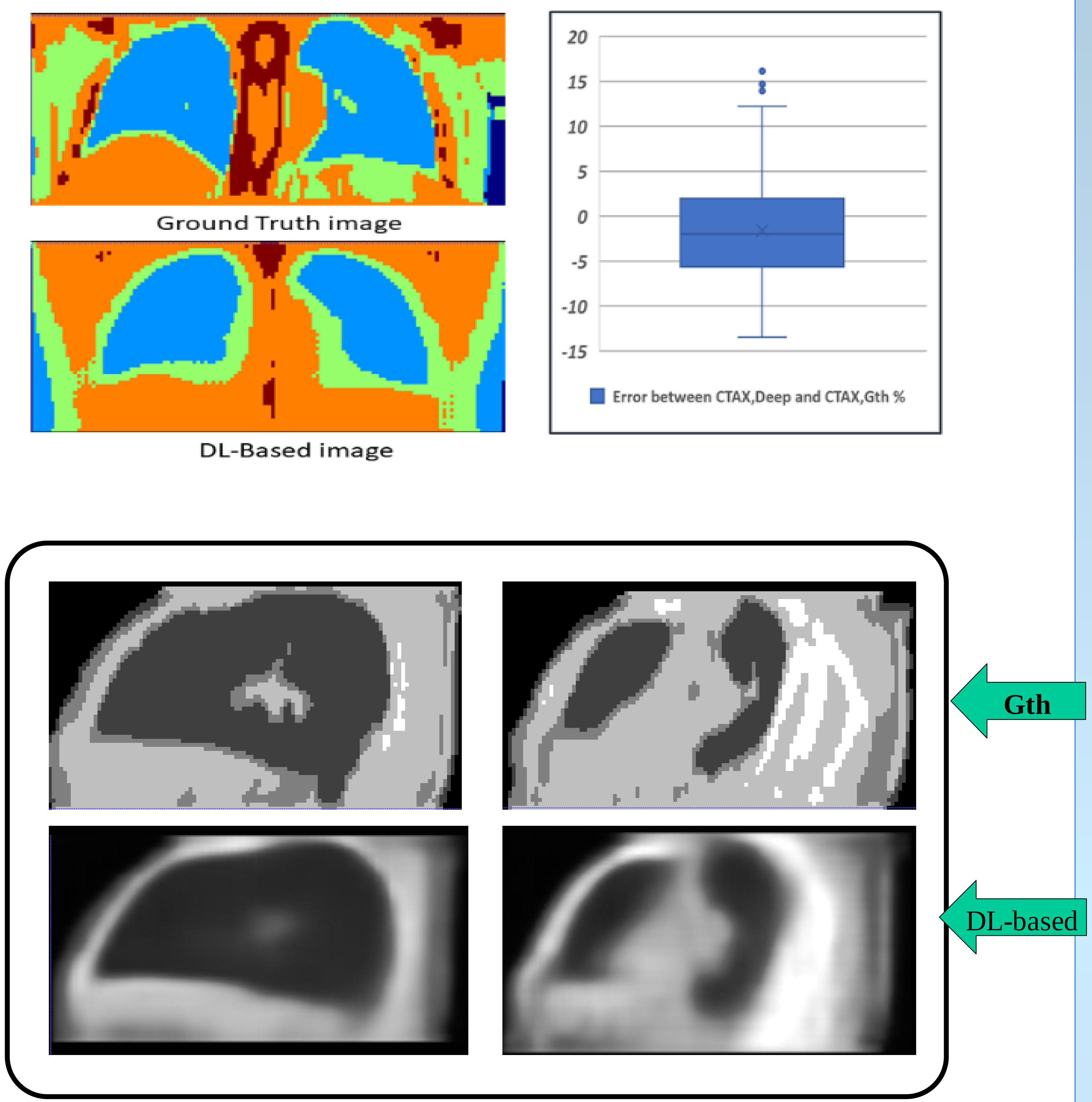

Figure 2: an example of coronal slice from deep network output vs ground truth. The boxplot shows AA error calculated from the predicted image compared to the ground truth data.

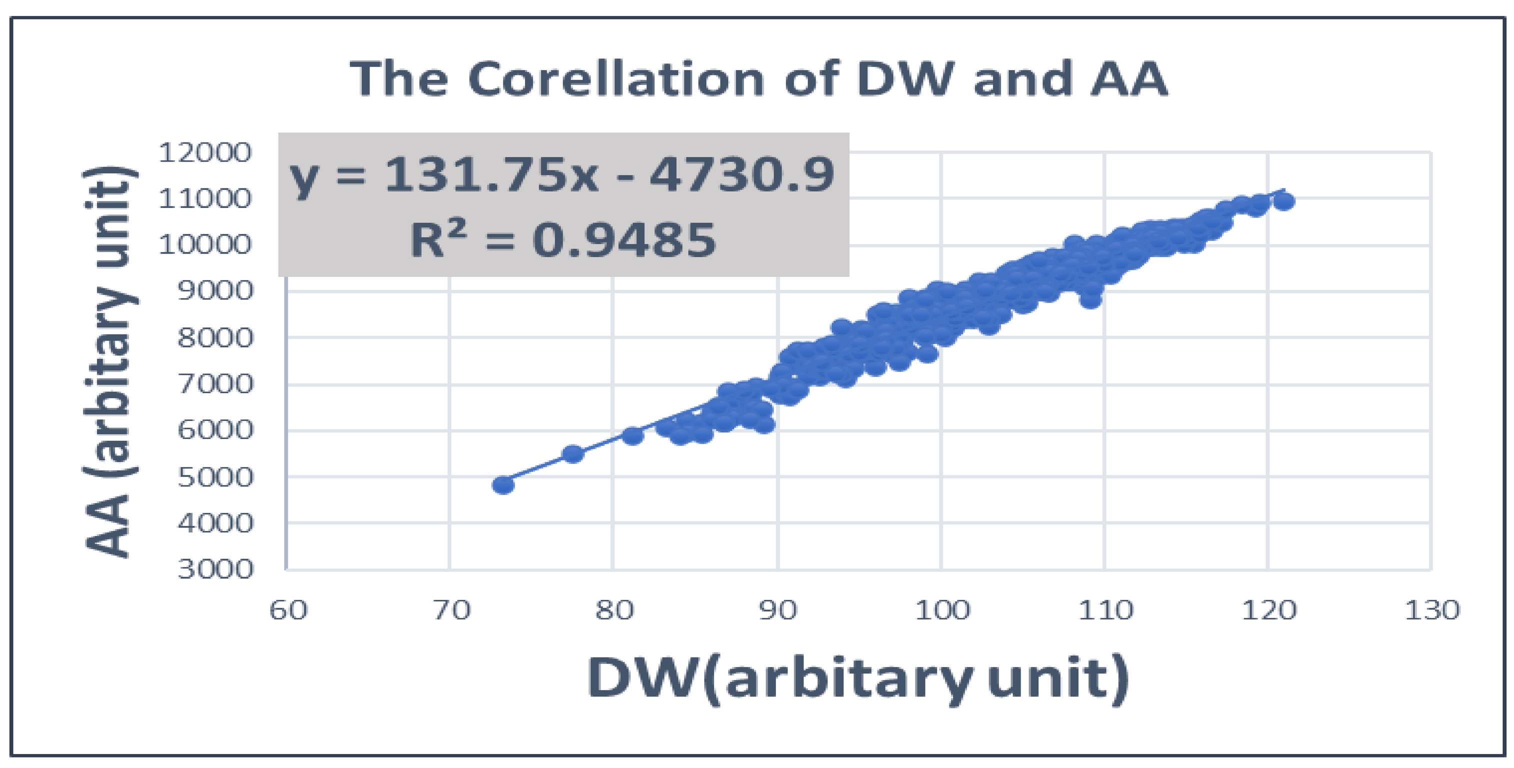

Figure 3: the correlation of AA calculated from predicted images and DW calculated from CT HU images. the units were the same for each patient.

CONCLUSION

In this study, we proposed a DL-based 2D to 3D image regression method to measure the D_W from the lateral localizer image, enabling the SSDE calculation prior to the spiral scan. Our method with the acceptable agreement (R^2~0.95) outperformed the study done by Mihailidis et al.[3] on 16 patients and was comparable with Anam et al.[4] report on a cylindrical phantom. Besides, we could measure the effective diameter by means of localizer image with reasonable accuracy of 4.43 % compared to Burton[5] study on 573 CT images. These simple 3D axial images with a limited number of pixel values extracted from localizer images can be good criteria for protocol selection and optimizing the radiation dose based on body habitus.

In order to optimize the computational burden and maintaining the resolution, we cropped the images to body contour and the area, and D_W units were in pixel sizes kept the same for ground truth and DL output images. Also, we used the localizer projection instead of AP to eliminate the effect of the bed.

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