

# X-ray Bones Extraction and Enhancement Based on Deep Learning

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**INTRODUCTION:** Bones on X-ray of low dose or spinopelvic part often suffer from issues such as soft tissue obscuration and contrast interference, making it challenging for physicians to identify and assess accurately. The CT localizer radiograph, also known as scanogram, scout and surviw, is obtained at the start of a CT in a lateral and/or a frontal projection. One of the key roles of the localizer radiograph is to ensure that the CT acquisition covers the correct anatomy. This study aims to develop a deep learning-based method that utilizes CT localizer images as input to extract bones voxels while generating Digital Radiographic Radiograph (DRR) projection X-ray images from CT voxels as output, thereby eliminating soft tissue image and retaining clear bones images.

**METHODS:** The study has been reviewed and approved by the ethics board of Shanghai Tongji Hospital. 1) A dataset of 5000 cases including cervical, thoracic, abdominal, and pelvic CT data with corresponding localizer images was collected from Shanghai Tongji Hospital. Localizer images were cropped based on CT voxel to serve as input. 2) Bones segmentation was performed on CT voxels using Hounsfield Unit (HU) values (400-800). Non-bone voxels were set to zero, and DRR projection was applied to obtain X-ray images preserving only bones, serving as output. 3) A novel U-Net architecture neural network was introduced to capture complex intricate features. It took original DRR projection images, mimicking real X-ray samples, learned to generate DRR projections with only bones imaging. The network encoded features from input images, decoded enhanced bones images, and optimized its parameters using reconstruction error and perceptual similarity. Evaluation metrics included Root Mean Square Error (RMSE), Structural Similarity Index (SSIM), Multi Scale Structural Similarity Index Measure (MS-SSIM) and Peak Signal-to-Noise Ratio (PSNR) to quantitatively assess image similarity between the ground truth and prediction. 4) An external dataset including 200 X-ray images was employed for model validation. Multiple expert radiologists evaluated extracted and enhanced X-ray bones images to assess the efficacy and the reliability of the method.

**RESULTS SECTION:** After comprehensive training and validation, our neural network model demonstrated a considerable performance in X-ray bones extraction predication and enhancement phase was synthesized from original and extraction phases. On the test data set, the soft tissue images were removed, and the clear bones images were retained by inputting CT localizer images, which results in RMSE: 22.86; PSNR: 21.17; SSIM: 0.49; MS-SSIM: 0.77. On an external dataset, assessed by multiple experts in radiology, it was determined that 95% of the images exhibited favorable extraction and enhancement results, concurrently demonstrating a high level of reliability.

**DISCUSSION:** Our deep learning method showcases the successful extraction and enhancement of bones structures from X-ray images. Complex anatomical structures with overlapping bones or intricate joint configurations challenge the accuracy, and its robustness in real-world clinical scenarios necessitates further investigation.

**SIGNIFICANCE/CLINICAL RELEVANCE:** Clearer bones images facilitate more accurate identification of fractures, lesions, and abnormalities, enabling clinicians to make more informed decisions. In surgical planning, our method could provide surgeons with sharper, more detailed images of bones structures, aiding in preoperative assessments and improving the precision of surgical interventions.

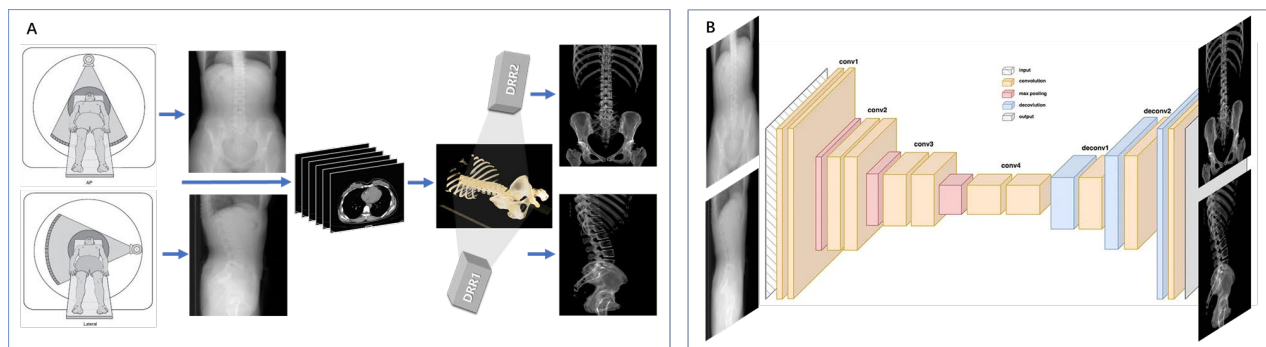


Fig 1. A) Schematic of the dataset built; B) Schematic of the U-net neural network architecture.

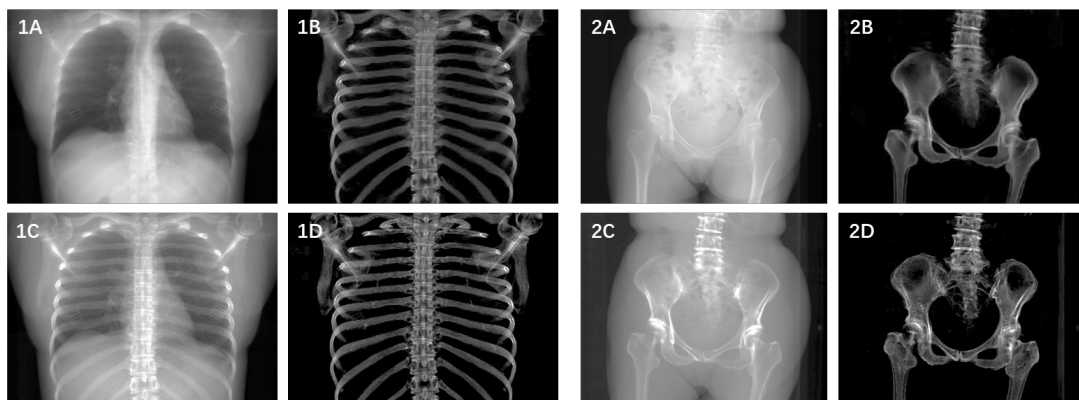


Fig 2. Examples of the neural network performance: 1) Chest X-ray Processing Results; 2) Pelvic X-ray Processing Results; A) Original X-ray; B) DRR image from CT; C) Synthesized bone-enhanced X-ray image; D) Bone-extracted X-ray image predicted from the neural network.