**Purpose:** Automatic identification of consistently defined body regions in medical images is vital in many applications. In this paper, we describe a method to automatically demarcate the superior and inferior boundaries for neck, thorax, abdomen, and pelvis body regions in computed tomography (CT) images.

**Methods:** For any 3D CT image I, following precise anatomic definitions, we denote the superior and inferior axial boundary slices of the neck, thorax, abdomen, and pelvis body regions by NS(I), NI(I), TS(I), TI(I), AS(I), AI(I), PS(I), and PI(I), respectively. Of these, by definition, AI(I) = PS(I), and so the problem reduces to demarcating seven body region boundaries. Our method consists of a two-step approach. In the first step, a convolutional neural network (CNN) is trained to classify each axial slice in I into one of nine categories: the seven body region boundaries, plus legs (defined as all axial slices inferior to PI(I)), and the none-of-the-above (NOTA) category. This CNN uses a multi-channel approach to exploit the inter-slice contrast, providing the neural network with additional visual context at the body region boundaries. In the second step, to improve the predictions for body region boundaries that are very subtle and that exhibit low contrast, a recurrent neural network (RNN) is trained on features extracted by CNN, limited to a flexible window about the predictions from the CNN.

**Results:** The method is evaluated on low-dose CT images from 442 patient scans, divided into training and testing sets with a ratio of 70:30. Using only the CNN, overall absolute localization error for NS(I), NI(I), TS(I), TI(I), AS(I), AI(I), and PI(I) expressed in terms of number of slices (nS) is (mean ± SD): 0.61±0.58, 1.05±1.13, 0.31±0.46, 1.85±1.96, 0.57±2.44, 3.42±3.16, and 0.50±0.50, respectively. Using the RNN in tandem improved the accuracy of AI(I) and TI(I) to: 0.61±0.58, 1.05±1.13, 0.31±0.46, 1.35±1.71, 0.57±2.44, 2.83±2.75, and 0.50±0.50, respectively. This model outperforms the results achieved in our previous work by 2.4, 1.7, 3.1, 1.1, and 2 slices, respectively for TS(I), TI(I), AS(I), AI(I) = PS(I), and PI(I) classes with statistical significance. The model trained on low-dose CT images was also tested on diagnostic CT images for NS(I), NI(I) and TS(I) classes; the resulting errors were: 1.48±1.33, 2.56±2.05, and 0.58±0.71, respectively.

**Conclusions:** Standardized body region definitions are a pre-requisite for effective implementation of quantitative radiology, but the literature is severely lacking in the precise identification of body regions. The method presented in this paper significantly outperforms earlier works by a large margin, and the deviations of our results from ground truth are comparable to variations observed in manual labelling by experts. The solution presented in this work is critical to the adoption and employment of the idea of standardized body regions, and clears the path for development of applications requiring accurate demarcations of body regions. The work is indispensable for automatic anatomy recognition, delineation, and contouring for radiation therapy planning, as it not only automates an essential part of the process, but also removes the dependency on experts for accurately demarcating body regions in a study.

**Novelty and Significance**

* This work fills two significant gaps that exist in medical image analysis: lack of standardized body region definitions; lack of a methodology to automatically recognize each major body region in given 3D scans.
* An effective formulation of the problem with two key innovative elements: (i) A standardized, clinically meaningful, and computationally effective definition of the 4 body regions. (ii) Formulating the body region recognition problem as a classification task that is suitable to be effectively implemented by deep learning networks.
* Design of a CNN-RNN tandem architecture, CNN for handling the problem of detecting region boundary slices that are conspicuous, and RNN for detecting boundary slices characterized by very subtle features.
* An automatic methodology that works irrespective of the type of input – low-dose CT or diagnostic CT, of whole body or specific body regions. High accuracy of body region recognition that falls within the variation observed in manual recognition by experts.