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First PACS-integrated artificial intelligence-based software tool for rapid and fully automatic analysis of body composition from CT in clinical routine

Nick Lasse Beetz[1,2]*, Christoph Maier[1], Laura Segger[1], Seyd Shnayien[1], Tobias Daniel Trippel[2,3], Norbert Lindow[4], Khaled Bousabarah[4], Malte Westerhoff[4], Uli Fehrenbach[1] & Dominik Geisel[1]

[1]*Department of Radiology, Charité – Universitätsmedizin Berlin, corporate member of Freie Universität Berlin and Humboldt-Universität zu Berlin, Berlin, Germany;* [2]*DZHK (German Centre for Cardiovascular Research), partner site Berlin, Berlin, Germany;* [3]*Department of Internal Medicine – Cardiology, Charité – Universitätsmedizin Berlin, corporate member of Freie Universität Berlin and Humboldt-Universität zu Berlin, Berlin, Germany;* [4]*Visage Imaging GmbH, Berlin, Germany*

Abstract

Background To externally evaluate the first picture archiving communications system (PACS)-integrated artificial intelligence (AI)-based workflow, trained to automatically detect a predefined computed tomography (CT) slice at the third lumbar vertebra (L3) and automatically perform complete image segmentation for analysis of CT body composition and to compare its performance with that of an established semi-automatic segmentation tool regarding speed and accuracy of tissue area calculation.
Methods For fully automatic analysis of body composition with L3 recognition, U-Nets were trained (Visage) and compared with a conventional image segmentation software (TomoVision). Tissue was differentiated into psoas muscle, skeletal muscle, visceral adipose tissue (VAT) and subcutaneous adipose tissue (SAT). Mid-L3 level images from randomly selected DICOM slice files of 20 CT scans acquired with various imaging protocols were segmented with both methods.
Results Success rate of AI-based L3 recognition was 100%. Compared with semi-automatic, fully automatic AI-based image segmentation yielded relative differences of 0.22% and 0.16% for skeletal muscle, 0.47% and 0.49% for psoas muscle, 0.42% and 0.42% for VAT and 0.18% and 0.18% for SAT. AI-based fully automatic segmentation was significantly faster than semi-automatic segmentation (3 ± 0 s vs. 170 ± 40 s, $P < 0.001$, for User 1 and 152 ± 40 s, $P < 0.001$, for User 2).
Conclusion Rapid fully automatic AI-based, PACS-integrated assessment of body composition yields identical results without transfer of critical patient data. Additional metabolic information can be inserted into the patient's image report and offered to the referring clinicians.

Keywords Artificial intelligence; AI; Image segmentation; Body composition; Sarcopenia; Sarcopenic obesity; Computed tomography; CT

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**Correspondence to: Dr. Nick Lasse Beetz, Department of Radiology, Charité – Universitätsmedizin Berlin, corporate member of Freie Universität Berlin and Humboldt-Universität zu Berlin, Department of Radiology, Augustenburger Platz 1, 13353 Berlin, Germany. Phone: +49-30-450657278, Fax: +49-30-4507527911, Email: nick-lasse.beetz@charite.de*
Uli Fehrenbach and Dominik Geisel contributed equally to this work and share the last authorship.

Introduction

Body composition describes the percentages of muscle, bone and water in the human body and has long been used as a measure of physical fitness.[1,2] The reason why body composition is widely considered to be a better indicator of physical fitness than body mass index (BMI) or body weight is obvious: Both BMI and body weight reflect the combined weight of all body tissues but do not measure the relative proportions of the different tissue types contributing to a person's overall weight. Thus, two patients of the same sex and age may have the same weight, whereas their body composition and relative amounts of different tissues such as fat and muscle might be different.[3] In terms of body composition, a basic distinction is made between body fat and lean mass including muscle, organs and bones.[4,5]

For initial assessment of obesity in clinical routine, anthropometric measures such as BMI and waist circumference are often sufficient.[6] However, more sophisticated measurement techniques are required if a discordance between BMI and adiposity is suspected (e.g. in body builders or patients with sarcopenia and normal BMI) or if analysis of the relative proportions of body fat and lean mass in the body is desired.

Increasingly, analysis of body composition has been used to identify and monitor patients at risk for sarcopenia and/or obesity, which have been identified to be important indicators of outcome in several diseases.[7–9] In diseases, the psoas muscle area at the level of the third lumbar vertebra (L3) might predict outcome of patients undergoing transcatheter aortic valve replacement (TAVR), and abdominal obesity appears to be highly predictive of coronary heart disease.[10,11] More recently, the focus has shifted to oncologic patients as several studies suggest that pre-therapeutic sarcopenia is associated with poorer overall outcome.[12–14]

A conventional method to determine a patient's body composition is the compartment model in which the density and proportion of fat, muscle, bone and water are calculated by underwater weighing and chemical dilution.[15,16] More commonly used methods for determining body composition are dual-energy x-ray absorptiometry (DEXA), which uses a very low dose of radiation and provides an accurate estimation of body fat percentage, and bioelectrical impedance analysis measurement, which estimates the body fat percentage from water impedance.[17–19]

Modern imaging techniques allow reliable analysis of body composition from a single axial image acquired at the L3 level with either computed tomography (CT) or magnetic resonance imaging (MRI). Patients prone to obesity and sarcopenia often undergo CT examinations for various reasons: Cardiovascular patients need CT angiography for pre-treatment evaluation of aortic stenosis, and cancer patients need CT for staging and monitoring of the treatment response. In these settings, CT allows straightforward analysis of body composition and quantification of sarcopenia without additional radiation dose or examination time for the patient.[20,21]

As manual segmentation of CT datasets is time consuming, CT-based analysis of body composition has not yet been used in larger patient populations. In the medical and scientific community, there is a growing need for artificial intelligence (AI)-based automated tissue segmentation in order to dramatically decrease post-processing time of these datasets.[22] Semi-automatic image segmentation techniques have already been established; however, these solutions demand extra external software and require an expert reader for correct segmentation.[23,24] A commonly used software tool for semi-automatic image segmentation is sliceOmatic, which uses pixel thresholding with region growing and has been shown to allow reliable assessment of body composition in studies.[25]

The purpose of this study is to externally evaluate a new AI-based workflow, which we trained to automatically detect a predefined CT slice at the third lumbar vertebra (L3) and automatically perform complete image segmentation for analysis of body composition, and to compare its performance with that of an established threshold-based semi-automatic segmentation method in terms of speed and accuracy of tissue area calculation. The new AI-based software tool for assessment of body composition is fully integrated into the interface of a widely used picture archiving and communications system (PACS).

Material and methods

Study design

In this single-centre study, we analysed body composition twice with a semi-automatic software tool and a fully automatic, PACS-integrated software tool using a retrospective dataset of patients who underwent a full abdominal CT scan. The study was approved by the institutional review board.

Patient population and patient characteristics

The first and randomly selected patients diagnosed with acute abdomen at the Emergency Department of the Charité University Hospital who were referred to the Department of Radiology between 15 December 2020 and 15 January 2021 were considered for inclusion in this study, if they underwent abdominal CT imaging. Patients with additional CT scans of non-abdominal body regions were not included. Another exclusion criterion was foreign material at the third vertebral level causing relevant beam-hardening artefacts. Pre-existing conditions or a history of surgery were no exclusion criteria to this real-world patient population.

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Image acquisition

All patients referred to the Department of Radiology were examined on one of two 64-row CT scanners (Revolution EVO or GSI, General Electric, Milwaukee, USA). Two patients underwent unenhanced CT. All other patients were administered an intravenous bolus injection of iodinated contrast medium, followed by a full abdominal helical scan in the portal venous phase in 14 cases and in the venous phase in four cases. Adequate opacification was ensured by bolus tracking using SmartPrep (General Electric, Milwaukee, USA).

Semi-automatic analysis of body composition

First, the 5-mm-thick DICOM slice files at the mid-L3 level of the randomly selected CT scans were extracted from the department's PACS. After anonymization, the mid-L3 level data files were transferred to a conventional image segmentation software for semi-automatic analysis of body composition (sliceOmatic v5.0, TomoVision, Canada). Semi-automatic image segmentation was performed twice by two experienced radiologists (L.S. and N.L.B.). In all cases, semi-automatic image segmentation was manually adjusted to ensure correct differentiation of psoas muscle, skeletal muscle, visceral adipose tissue (VAT) and subcutaneous adipose tissue (SAT). Random presentation and the anonymization of the datasets ensured blinding of the users to clinical data and patient information.

Fully automatic AI-based analysis of body composition with L3 recognition

After a 6-week interval, the two users were instructed to independently repeat tissue segmentation with the AI-based image segmentation software using the same CT datasets. Again, users were blinded to clinical data and patient information. The results of the first round of image segmentation were not revealed.

A PACS-integrated, fully automatic software tool (Visage Imaging GmbH, Berlin, Germany) was used for AI-based analysis of body composition. A neural network with U-Net architecture was trained using 200 axial CT images from the L3 level. Thirty CT datasets were withheld for validation. The neural network consists of nine blocks: four downsampling blocks, four upsampling blocks and one in between. A softmax layer returns the segmentation as five-channel output, one channel per tissue plus background. Each block consists of two convolutional layers using the same number of 3 × 3 kernels in combination with batch normalization for each layer. For the nine blocks, we used 32, 64, 128, 256, 256, 256, 128, 64 and 32 kernels per layer. All convolutional layers applied leaky rectified linear unit activations. For downsampling, max pooling was used, which halved the image resolution in each dimension. For upsampling, bilinear interpolation was applied. Each downsampling block was concatenated to the corresponding upsampling block of the same image dimensions. To improve the generalization of the neural network, image augmentations, including translations, rotations and brightness shifts, were applied during the training. The neural network was optimized with the Adam optimizer and categorical cross entropy as loss function. In case of false tissue segmentation, for example, when hypodense stool in the intestine was misinterpreted as body fat, the software tool allowed manual correction. An illustration of the U-Net is shown in *Figure* 1.

A second U-Net was trained to identify the L3 vertebra along the sagittal direction of the images. The workflow was also embedded into the PACS-based Visage 7 platform (Visage Imaging GmbH, Germany). For evaluation of correct identification of the L3 vertebra, the execution of the workflow was supervised by a radiologist to permit correction in case the algorithm would not select the appropriate CT slice.

External evaluation and comparison of AI-based fully automatic image segmentation with L3 recognition with semi-automatic segmentation

For external evaluation of the workflow, the AI-based software was embedded into the PACS-based Visage 7.1 platform at Charité – University Hospital Berlin. The same image series with 5-mm-thick CT slices, used for the extraction of the datasets for semi-automatic image segmentation, was loaded into the Visage viewer.

After automatic L3 recognition, tissue was fully automatically differentiated into psoas muscle, skeletal muscle, VAT and SAT and coded with different colours. Organ tissues including pancreas, spleen, kidney, liver and intestine were not segmented. Manual image correction for false image segmentation was not necessary. The area in square centimetres (cm^2) of each segmented tissue class was automatically calculated by the software. The following parameters were derived from L3 body composition analysis: area (in cm^2) of skeletal muscle, psoas muscle, SAT and VAT.

Accuracy of measurements was compared using the relative difference between the tissue areas calculated with the AI-based workflow and the areas determined by each of the two users. The difference was calculated as $(200|A_s - A_v|)/((A_s + A_v))$, where A_s is an area of a tissue segmented by a user in sliceOmatic and A_v is the corresponding tissue area segmented by the U-Net in Visage. For both methods, the time needed for image segmentation was measured in seconds. An example of semi-automatic and fully automatic AI-based analysis of L3 body composition is shown in *Image* 1.

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Figure 1 Structure of the U-Net used for fully automatic analysis of the body composition.

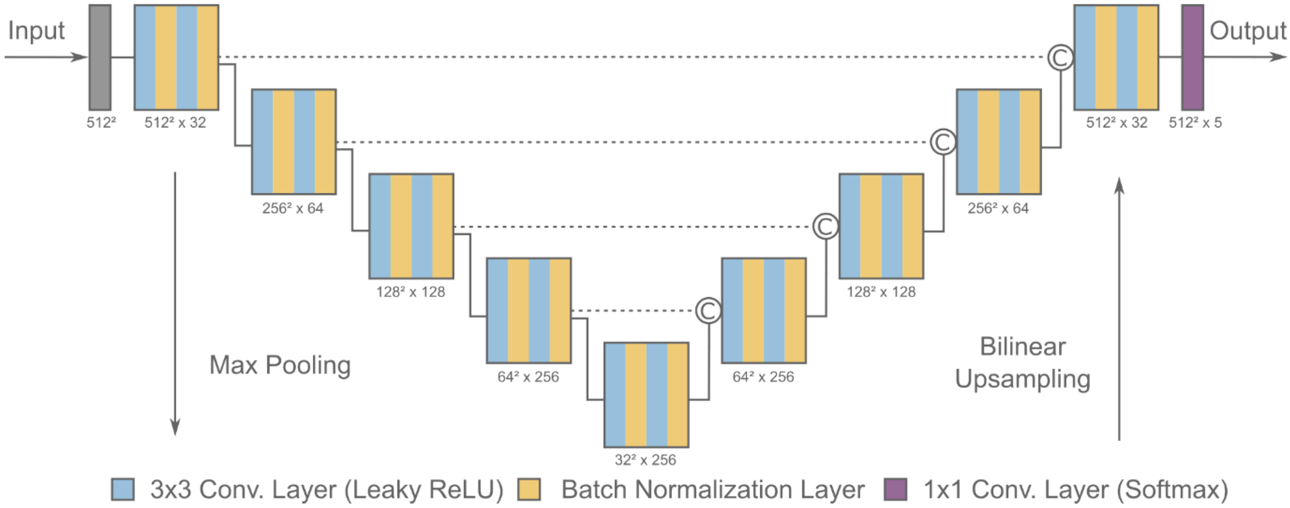
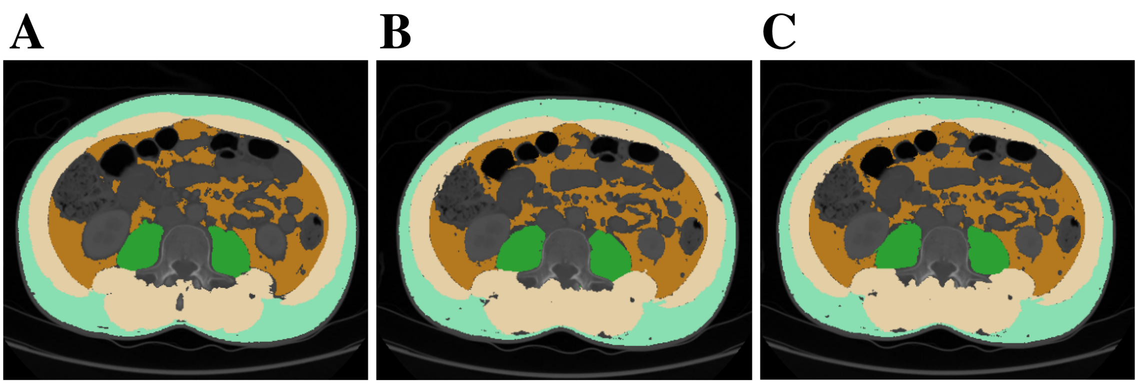


Image 1 Example illustrating results of fully automatic and semi-automatic image segmentation. Each segmented tissue is coded with a different colour: psoas muscle, purple; skeletal muscle (except psoas muscle), green; visceral fat, dark green; subcutaneous fat, blue. Tissue density and area were automatically calculated. (A) Fully automatic AI-based analysis of L3 body composition using Visage. (B) Semi-automatic and manually corrected analysis of L3 body composition using sliceOmatic (User 1). (C) Semi-automatic and manually corrected analysis of L3 body composition using sliceOmatic (User 2).



Statistical analysis

Statistical significance for time differences between the segmentation methods was evaluated using Mann–Whitney *U* test, and a *P*-value ≤ 0.05 was considered significant. Relative differences for areas and the corresponding mean values for each tissue class were calculated. Data analysis was performed using IBM SPSS Statistics Version 27 (IBM, Armonk, New York, U.S.A) and Python Version 3.9.2 (Python Software Foundation, Delaware, USA).

Results

Baseline data

The study included randomly selected patients with acute abdomen referred for CT imaging by the Emergency Department. A total of 20 patients with a mean age of 51 years ranging from 21 to 90 years were included. The mean dose-length product (DLP) was 546 mGy*cm.

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Quality of semi-automatic versus fully automatic AI-based image segmentation

Compared with the semi-automatic segmentation performed by the first user, fully automatic AI-based segmentation of the four tissue areas yielded a relative difference of 0.22% for skeletal muscle, 0.47% for psoas muscle, 0.42% for VAT and 0.18% for SAT. Compared with the second user, the relative differences between the two image segmentation methods were 0.16% for skeletal muscle, 0.49% for psoas muscle, 0.42% for VAT and 0.18% for SAT. The results are illustrated in *Figure* 2.

Speed of semi-automatic and fully automatic AI-based image segmentation

Fully automatic AI-based segmentation was significantly faster than semi-automatic segmentation compared with both User 1 (3 ± 0 s vs. 170 ± 40 sec; $P < 0.001$) and User 2 (3 ± 0 s vs. 152 ± 40 s; $P < 0.001$). There was no significant time difference between User 1 and User 2 ($P = 0.80$). The results are illustrated in *Figure* 3**.**

AI-based recognition of the third lumbar vertebra level

The second neural network, trained for AI-based recognition of the third lumbar vertebra level, had a success rate of L3 recognition of 100%. There was no case in which the supervising radiologist needed to intervene to select the correct slice.

Discussion

In this retrospective study, we analysed CT body composition of randomly selected patients for evaluation of a new AI-based workflow, which we trained to automatically detect a predefined CT slice at the L3 level and automatically perform complete image segmentation. Performance of the AI-based tool in terms of speed and segmentation was compared with that of an established semi-automatic segmentation software. Fully automatic AI-based analysis of body composition with integrated L3 recognition yielded the same results for the body composition parameters investigated and was significantly faster than semi-automatic image segmentation with manual correction.

Body composition analysis can be a useful tool to evaluate undernourishment in cancer patients and detect increased visceral fat as an important risk factor for cardiovascular disease and diabetes mellitus.[3,26–28] Moreover, body composition can identify frail patients, for example, in sarcopenic obesity with normal BMI but reduced muscle mass and severe adiposity.[29,30] As sarcopenia and sarcopenic obesity are associated with a poorer outcome in cancer and cardiovascular patients, knowledge of body composition may make an important contribution to therapy planning in these patients.[11,31–33] As analysis of body composition from CT scans is easily feasible and does not require additional radiation exposure, the tool presented here may be of great interest in many research and clinical settings.

In this study, AI-based fully automatic analysis of body composition was up to 82 times faster than semi-automatic image segmentation. Because the PACS-integrated solution also turned out to allow stable automatic L3 recognition, it eliminates the need for prior extraction of the DICOM slice at the correct level, further shortening processing time tremendously.

The already available semi-automatic software tool sliceOmatic has proven to correctly perform image segmentation in many studies and is widely used. Recently, Feliciano et al. used the same 'manual' threshold-based semi-automatic method to validate a commercially available automatic image segmentation solution. Both methods showed similar associations of body composition parameters and mortality in patients with non-metastatic cancer, demonstrating that automatic image segmentation methods are appropriate and acceptable for outcome analysis in large patient populations.[34]

Although image segmentation of cross-sectional CT for body composition analysis is an accepted reference standard, it is time consuming and therefore often used in small patient populations only.[22,35] The most widely investigated techniques for semi-automatic body composition analysis, such as sliceOmatic, Horos (Horos Project, Horosproject.org) or OsiriX (Pixmeo, Geneva, Switzerland), use pixel thresholding with region growing.[36] Bridge et al.[37] have shown that AI-based segmentation on a single CT slice is feasible with a high level of accuracy. Just recently, Koitka et al.[38] have demonstrated that body composition analysis in routine CT imaging using three-dimensional semantic segmentation convolutional neural networks is possible. However, to our knowledge, we are the first to show that an already PACS-integrated, fully automatic AI-based software tool with automatic L3 recognition can extract valuable metabolic information in addition to providing traditional imaging reports. The areas and radiodensities of psoas muscle, skeletal muscle, VAT and SAT can automatically be measured in the background from abdominal CT scans regardless of the imaging protocol used for acquisition and the patient's clinical indication for CT (e.g. TAVR planning in aortic stenosis or staging in cancer patients).[39,40] Body composition parameters can be inserted into a reporting system and thus provide referring clinicians with additional relevant information. The new AI-based fully automatic and PACS-integrated workflow solution investigated here is very fast and accurate and has great potential to further facilitate and accelerate body

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Figure 2 Accuracy of the new fully automated AI-based image segmentation tool with L3 recognition in measuring the different tissue areas compared with semi-manual image segmentation by Reader 1 and Reader 2.

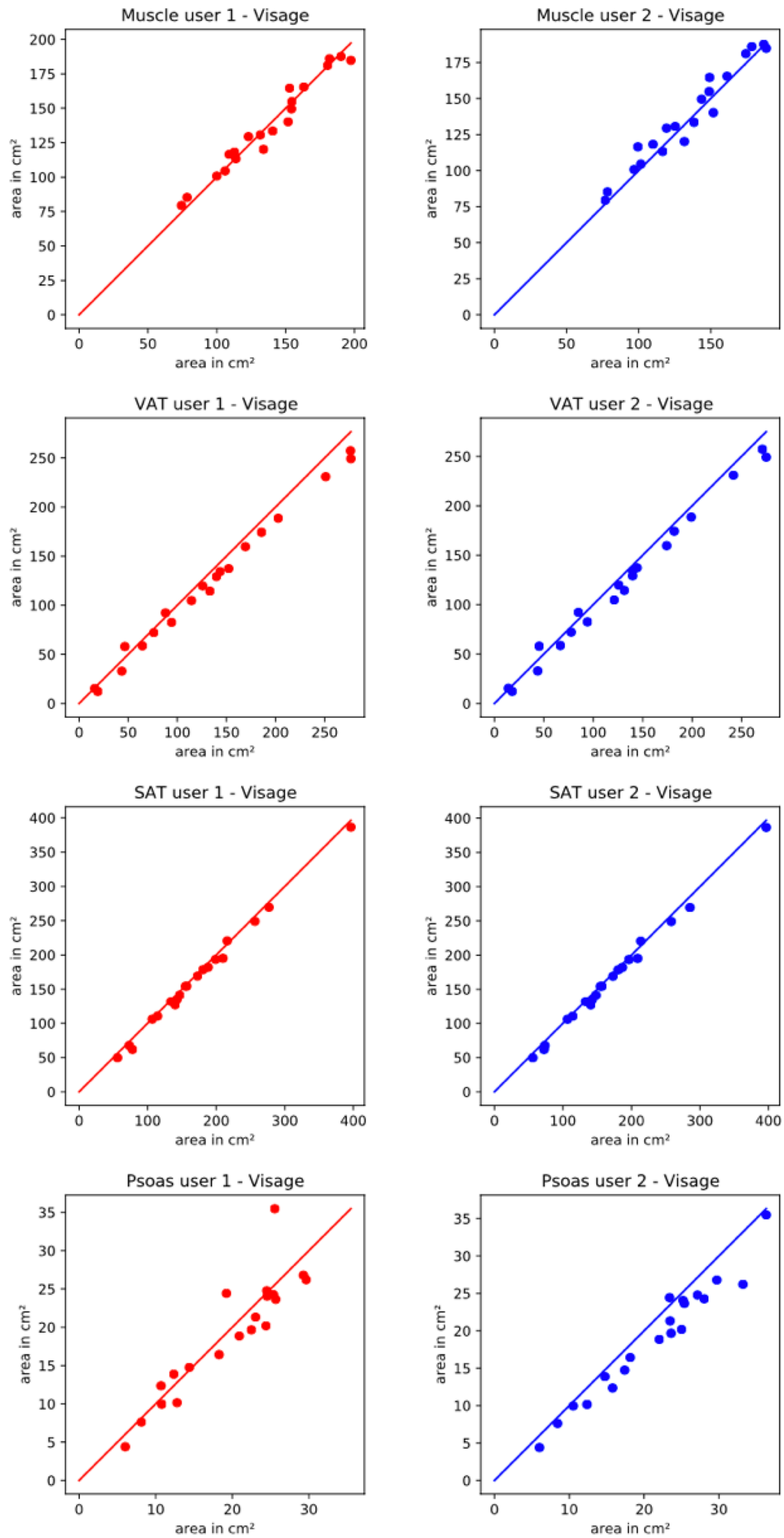

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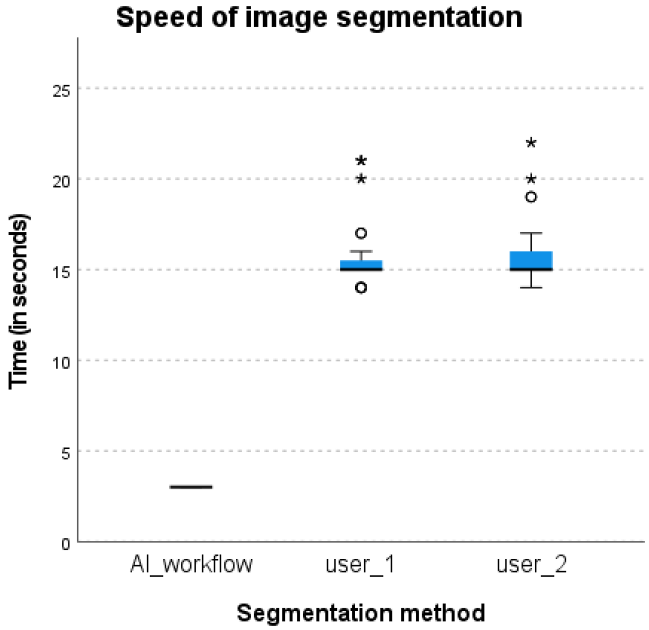
Figure 3 Comparison of segmentation methods shows that image segmentation is significantly faster when the AI workflow is used. AI, artificial intelligence.



composition analysis. As no external software is required for body composition analysis, there is no need for additional protection of patient data, and valuable metabolic information can simply be added to the standard image report.

Limitations

Even though already available, semi-automatic image analysis and the new fully automatic AI-based tool are very representative segmentation methods, there is a small and insignificant proportion of each tissue class that is not completely segmented compared with the real body slice as a hypothetical gold standard. Accuracy of body composition analysis might also be limited in patients with foreign material or severe skeletal deformation. In some cases, severe ascites, oedema and mesenteric fat stranding with altered tissue radiodensity might reduce the capacity of the workflow tool to correctly differentiate tissue classes.

Conclusion

Fully automatic AI-based, PACS-integrated analysis of body composition with L3 recognition is feasible and easily available from CT imaging. Fully automatic AI-based assessment of body composition using Visage yields almost the same results for body composition parameters as conventional semi-automatic image segmentation. This AI-based software solution eliminates the need for external software and does not require any transfer of critical patient data. Without further examinations, it provides valuable metabolic information in addition to traditional imaging reports. Rapid and accurate fully automatic AI-based analysis of body composition may improve risk stratification and patient care.

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Conflict of interest

U.F. reports honoraria and travel expenses for scientific meetings (outside of submitted work) from Bayer, Siemens and General Electrics. N.L., K.B. and M.W. are employed at Visage Imaging. C.M., L.S., S.S., T.D.T. and D.G. declare that they have no conflict of interest.

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