Deep learning-based attenuation map generation and correction; could it be useful clinically?

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Deep learning (DL) is a branch of machine learning characterized by a multi-layered learning approach. Convolutional neural networks (CNNs) are an example of DL which are commonly applied to imaging data.^{1,2} DL models are particularly well suited to direct image analysis and image manipulation because each input image pixel can be mapped to one neuron in the first layer of the network. Since neurons are only connected to nearby neurons in the following layer, the structural relationships within the image are preserved through the model layers.

DL models are being increasingly applied to single photon emission computed tomography (SPECT) image reconstruction and segmentation, with one widely used model architecture being U-Net.³ In the U-Net model architecture, there is an initial down-sampling network similar to many other convolutional autoencoders.³ However, high-resolution features from the down-sampled network are combined with the up-sampled network.³ In simpler terms, some image features are carried across the model to allow the model to generate more precise output.

Shi et al.⁴ used a conditional generative adversarial network⁵ to generate synthetic imaging data. The algorithm consists of two sub-networks. The generator (a modified 3D fully convolutional U-net) generates the synthetic attenuation correction (AC) images from photopeak window and scatter window SPECT images.⁴ The discriminator a CNN is the “adversarial” network that attempts to correctly differentiate the synthetic and real AC images. In 25 testing subjects, the normalized mean absolute error (NMAE) between CTAC and synthetic AC maps was $3.60 \pm 0.85\%$.⁴ SPECT images reconstructed with the synthetic AC maps demonstrated even lower NMAE ($0.26\% \pm 0.15\%$) when compared to SPECT images reconstructed with CTAC images.⁴ While this may be a clinically useful application, it was necessary to transfer the synthetic AC maps back into vendor-specific software for the SPECT reconstructions which was a potentially time-consuming process.

In this issue of the journal, Liu et al. modify this approach to potentially simplify clinical implementation.⁶ In the proposed post-reconstruction AC (PRAC) approach, non-AC SPECT images are forwardly projected using a slice-by-slice rotation-based projector.⁶ These reprojections, along with the synthetic AC maps generated with the previously developed DL approach, can then be used to reconstruct synthetic AC SPECT images.⁶ The PRAC approach, tested in 30 patients, was able to generate images similar to scanner-generated AC images, with global NMAE $1.1 \pm 0.6\%$ and structural similarity index measure of 0.90 ± 0.06 .⁶ The most novel aspect of the proposed approach is that it removes the requirement for vendor-specific software from the reconstruction process. Additionally, since non-AC images are used during forward projection, the approach still benefits from vendor- and camera-specific resolution recovery algorithms.⁷

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The degree to which the work by Liu et al. will advance the field of image reconstruction with DL is not clear. Firstly, although the proposed approach removes the need for transferring synthetic CT images back to the vendor-specific reconstruction software, it may be even more clinically advantageous to have the synthetic AC maps generated automatically during the initial reconstruction. For example, Shiri et al. integrated a deep residual neural network within the reconstruction process to predict full time and projection acquisitions from either half-time acquisitions or half of the projections.⁸ This would potentially provide a more elegant solution by avoiding the need for image transfer and taking advantage of vendor-specific algorithms, but also removing errors related to the forward projection process.

Secondly, the comparisons between reconstructed image datasets were previously demonstrated in the work by Shi et al. and both studies were tested in small populations. To obtain highly accurate synthetic images it would be ideal to have larger training and testing sets, ideally representing camera systems to ensure generalizability. Additionally, although the distribution of visual interpretation was similar, it remains to be demonstrated whether these approaches improve physician interpretation or diagnostic accuracy compared to non-AC or scanner-generated AC images. Demonstrating these more clinically relevant outcomes will be critical given that similar approaches to generating synthetic AC images have been demonstrated previously.^{9–11} Previous studies have shown that scanner-generated AC images improve the area under the receiver operating characteristic curve for obstructive CAD by 0.01 to 0.08 compared to non-AC images,^{12,13} so much larger studies would be needed. These approaches would also need to be compared with DL-based approaches for direct image interpretation. For example, we recently demonstrated that an explainable DL model had higher diagnostic accuracy for obstructive coronary artery disease compared to physician interpretation or quantitative analysis.¹⁴

Lastly, the potential reduction in radiation from using DL will need to be balanced against the potentially useful information which can be gained from CT AC imaging.¹⁵ Knowledge regarding coronary artery calcium (CAC) can change physician interpretation of myocardial perfusion in up to 31% of patients, with significant reduction in the proportion of scans interpreted as equivocal.¹⁶ Additionally, CAC and epicardial adipose tissue volume and attenuation can potentially be leveraged to improve risk stratification.^{17–19} Most importantly, CAC can be used to appropriately direct medical therapy in patients with normal myocardial perfusion,²⁰ which may ultimately improve long-term

patient outcomes. Given how quickly the field of artificial intelligence applications to cardiovascular imaging is advancing, it seems to be time to raise standards for evaluation. Until studies demonstrate that these methods can be applied during clinical practice to improve diagnosis and ultimately management and patient outcomes, it's unlikely that DL will have enough momentum to overcome clinical inertia.

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