Artificial intelligence-based attenuation correction; closer to clinical reality?

Robert J. H. Miller,[a,b,c] and Piotr J. Slomka[c]

[a] Department of Cardiac Sciences, University of Calgary, Calgary, AB, Canada
[b] Libin Cardiovascular Institute, Calgary, AB, Canada
[c] Department of Imaging, Medicine, and Biomedical Sciences, Cedars-Sinai Medical Center, Los Angeles, CA

Received Jun 21, 2021; accepted Jun 22, 2021
doi:10.1007/s12350-021-02724-5

See related article, pp. 2235–2250

Artificial Intelligence (AI) has been increasingly applied to nuclear cardiology to improve image segmentation,[1] disease diagnosis, and risk prediction.[2,3] When applied to image segmentation, AI can be used to automate processes which normally require tedious manual adjustments.[1] In risk prediction, the major advantage of AI is the ability to objectively integrate multiple potential parameters[4-6] or directly predict the outcome of interest from images while explaining predictions.[7] Additionally, AI has been used to facilitate automated structured clinical reporting.[8]

AI techniques have also been applied extensively to improve image reconstruction, resulting in better image quality, reduced radiation exposure, or both.[2], [3] Convolutional autoencoders, a type of deep-learning algorithm, are structured with hidden inner layers with fewer dimensions compared to the input or output layers. Convolutional autoencoders are frequently tasked with copying an image from the input to output layer, but the reduced inner dimensions force the algorithm to identify only the most critical aspect of images to carry forward. This can be applied to provide image noise reduction as a specialized post-processing technique. Ramon et al demonstrated the feasibility of denoising single photon emission computed tomography (SPECT) using stacked autoencoders designed to predict full-dose images from low-dose image reconstructions.[9] In simulations, images with as little as 1/16th of the clinical dose de-noised with stacked autoencoders achieved similar quality to images with 1/8th of the dose reconstructed with standard methods.[9] Other approaches have also been applied. For example, Shiri et al integrated a deep residual neural network to predict full time and projection acquisitions from either half-time acquisitions or half of the projections.[10] Using 10-fold cross-validation in 363 patients, the residual network was able to generate images resulting in similar automatic quantitation of perfusion (stress total perfusion deficit) and function (volume, eccentricity, and shape index) compared to full acquisition studies.[10]

Another important application of AI to image reconstruction is to provide automated attenuation correction (AC). Nguyen et al developed a generative adversarial network (GAN) to simulate AC images from non-AC data with data from 491 patients for training and 112 for testing.[11] The generator network, based on the UNet architecture which is a specialized convolutional autoencoder, simulated AC images while the discriminator network was tasked with differentiating the simulated images from actual AC images.[11] The goal of such architecture is to make the images indistinguishable. The UNet-GAN achieved structural similarity index of 0.946 compared to true AC images and outperformed UNet alone.[11] In this issue, Chen et al present a novel method to incorporate multiple imaging parameters within the reconstruction process.[12] The proposed dual squeeze-and-excitation residual dense network (DuRDN) incorporates gender, body mass index (BMI), and images from 3 scatter windows together with non-AC images in order to predict AC images.[12] The authors demonstrate that the predicted AC images from DuRDN more closely matched the actual AC images compared to UNet, with normalized mean

Reprint requests: Robert J. H. Miller, Department of Imaging, Medicine, and Biomedical Sciences, Cedars-Sinai Medical Center, Los Angeles, CA ; *robert.miller@ahs.ca*
J Nucl Cardiol 2022;29:2251–3.
1071-3581/$34.00

square error of 2.01% vs 2.23%.[12] Additionally, the images generated by DuRDN, on a segmental basis, were quantitatively similar compared to actual AC images while those generated using UNet were not.[12] Lastly, the authors show that the addition of each element (incorporating gender/BMI, incorporating scatter window images, and the addition of the dual-squeeze block) incrementally improved model performance.[12] Establishing the value of the components is important since each increases the computational complexity which may be a barrier to clinical implementation.

While the study by Chen et al represents a step forward in the application of AI to image reconstruction, there are a few important considerations. The study was performed in a relatively small patient population, imaged with a single camera system, with final testing performed using only 42 datasets. A larger study will be needed to evaluate this approach more robustly. Critically, while demonstrating that DuRDN-generated images are quantitatively similar to AC images is an important step, most physicians would have more interest in the diagnostic and prognostic accuracy of the approach. To date there is no evidence that simulated AC images can offer equivalent improvements in diagnostic performance of risk stratification as the actual AC images.[13]

Another consideration is that the anatomic information available from computed tomographic (CT) AC imaging carries significant independent diagnostic and prognostic information.[14-18] Therefore, centers with existing SPECT/CT scanners may decide that the added diagnostic and prognostic information more than outweighs the minimal increase in radiation exposure. While synthetic CT datasets have been generated using convolutional neural networks;[19] it is unlikely that information regarding coronary calcification could be obtained with this technique. Therefore, the simulated AC imaging, if indeed proven viable, is more likely to be implemented in centers without SPECT/CT systems (which is the majority of centers). Nevertheless, in spite of these considerations, the work presented by Chen et al represents a potentially promising future application of AI, although further investigations are needed to more conclusively demonstrate the feasibility of this approach.

References

1. Wang T, Lei Y, Tang H, He Z, Castillo R, Wang C et al. A learning-based automatic segmentation and quantification method on left ventricle in gated myocardial perfusion SPECT imaging: A feasibility study. J Nucl Cardiol 2020;27:976-87
2. Slomka PJ, Moody JB, Miller RJH, Renaud JM, Ficaro EP, Garcia EV. Quantitative clinical nuclear cardiology, part 2: Evolving/emerging applications. J Nucl Cardiol 2021;28:115-27
3. Shrestha S, Sengupta PP. Machine learning for nuclear cardiology: The way forward. J Nucl Cardiol 2019;26:1755-8.
4. Hu LH, Miller RJH, Sharir T, Commandeur F, Rios R, Einstein AJ et al. Prognostically safe stress-only single-photon emission computed tomography myocardial perfusion imaging guided by machine learning: report from REFINE SPECT. Eur Heart J Cardiovasc Imaging 2021;22:705-14
5. Haro Alonso D, Wernick MN, Yang Y, Germano G, Berman DS, Slomka P. Prediction of cardiac death after adenosine myocardial perfusion SPECT based on machine learning. J Nucl Cardiol 2019;26:1746-54
6. Eisenberg E, Miller RJH, Hu L, Rios R, Betancour J, Azadani P et al. Diagnostic safety of a machine learning-based automatic patient selection algorithm for stress-only myocardial perfusion SPECT. J Nucl Cardiol 2021; Epub ahead of print.
7. Otaki Y, Singh A, Miller RJH, Kavanagh P, Sharir T, Fish M et al. Clinical deployment of explainable deep learning to improve myocardial perfusion imaging. JACC Cardiovasc Imaging 2021; Epub ahead of print.
8. Garcia EV, Klein JL, Moncayo V, Cooke CD, Del'Aune C, Folks R et al. Diagnostic performance of an artificial intelligence-driven cardiac-structured reporting system for myocardial perfusion SPECT imaging. J Nucl Cardiol 2020;27:1652-64
9. Ramon AJ, Yang Y, Pretorius PH, Johnson KL, King MA, Wernick MN. Initial Investigation of Low-Dose SPECT-MPI via Deep Learning. 2018 IEEE Nucl Sci Symp Med Imaging Conf 2018;1-3
10. Shiri I, Sabet KA, Arabi H, Pourkeshavarz M, Teimourian B, Ay MR et al. Standard SPECT myocardial perfusion estimation from half-time acquisitions using deep convolutional residual neural networks. J Nucl Cardiol 2020; Epub ahead of print.
11. Nguyen TT, Chi TN, Hoang MD, Thai HN, Duc TN. 3D unet generative adversarial network for attenuation correction of SPECT images. IEEE Conf Advanc Sig Proc Telecomm Comput 2020;93-7.
12. Chen XC, Zhou B, Shi LY, Liu H, Pang YL, Wang R et al. CT-free attenuation correction for dedicated cardiac SPECT using a 3D dual squeeze-and-excitation residual dense network. J Nucl Cardiol 2021; Epub ahead of print.
13. Arsanjani R, Xu Y, Hayes SW, Fish M, Lemley M Jr, Gerlach J et al. Comparison of fully automated computer analysis and visual scoring for detection of coronary artery disease from myocardial perfusion SPECT in a large population. J Nucl Med 2013;54:221-8
14. Commandeur F, Slomka PJ, Goeller M, Chen X, Cadet S, Razipour A et al. Machine learning to predict the long-term risk of myocardial infarction and cardiac death based on clinical risk, coronary calcium, and epicardial adipose tissue: A prospective study. Cardiovasc Res 2020;116:2216-25
15. Pyslar N, Doukky R. Myocardial perfusion imaging and coronary calcium score: A marriage made in heaven. J Nucl Cardiol 2019; Epub ahead of print.
16. Trpkov C, Savtchenko A, Liang Z, Feng P, Southern DA, Wilton SB et al. Visually estimated coronary artery calcium score improves SPECT-MPI risk stratification. IJC Heart Vasc 2021;35:100827.
17. Hacker M, Becker C. The incremental value of coronary artery calcium scores to myocardial single photon emission computer tomography in risk assessment. J Nucl Cardiol 2011;18:700-11; quiz 12-6.
18. Mouden M, Ottervanger JP, Timmer JR, Reiffers S, Oostdijk AHJ, Knollema S et al. The influence of coronary calcium score on the

interpretation of myocardial perfusion imaging. J Nucl Cardiol 2014;21:368-74

19. Shi L, Onofrey JA, Liu H, Liu YH, Liu C. Deep learning-based attenuation map generation for myocardial perfusion SPECT. Eur J Nucl Med Mol Imaging 2020;47:2383-95