Diagnostic Quality of Machine Learning Algorithm for Optimization of Low-Dose Computed Tomography Data

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Background

In the past 10 years, there has been a rapid increase in applications of artificial intelligence (AI) techniques to computational problems and increasingly to medicine. A variety of medical programs use AI including: IBM's Watson, lung nodule detection, and mammographic screening.

Computed tomography (CT) image reconstruction has long been a topic of research as it is a critical step in the generation of diagnostic images for radiology. Many reconstruction techniques adopt an iterative or statistical optimization approach, or focus on a detailed compensation for characteristics of the imaging chain. While there have been incremental improvements in image quality from many of these techniques, one of the crucial factors determining final image quality has always been the amount of X-ray photons (radiation dose) used to generate the image. As concern for harmful effects from medical ionizing radiation has increased, there has been a surge in ideas and techniques to lower the dose used to generate images, often with the side-effect of increasing quantum mottle and image noise. The need to generate diagnostic images should always be the paramount concern, and doing so with a minimum of radiation is ideal. An analysis of a novel AI technique to improve the image quality of low dose images is presented below.

Case Presentation

A deep machine learning technique was used to build an artificial neural network (ANN) to improve the reconstruction of low dose images. To build the network, the algorithm is shown training pairs of noisy low dose images and high dose reduced noise images. The ANN (Artificial Neural Network) software then learns the correlation between noisy low dose images and corresponding low noise high quality images. The ANN is trained at the pixel level and thus is generalizable and not specific to an anatomic region. Once the ANN is trained, the software is presented with a noisy image and the ANN, using its learned nodes and weights, is able to output a high quality image.

To assess the quality of these images, two surveys were constructed to assess the PixelShine reconstruction algorithm versus conventional techniques requesting users to: (1) rate images as diagnostic or non-diagnostic and (2) whether the image appeared to use low-dose or routine radiation dose technique. Two representative images using different reconstruction techniques from 5 low-dose CT scans were presented to survey respondents. The first of the two images was the conventional reconstruction of the low-dose exam and the second was the PixelShine optimization of the same dataset. The order of the 10 images was randomized to separate the reconstructed images from each other.

Surveys were sent to program coordinators for all radiology residencies across the country with the request to distribute to residents and attendings at the site.

Outcome

A total of 69 radiologists responded to the dose survey and 78 radiologists responded to the diagnostic survey. Respondents were predominantly from academic centers and included residents, fellows and attending physicians. Almost half of respondents described their radiology skill-set as general versus subspecialty.

When asked if the randomized images were diagnostic 28% of reviews of standard reconstruction images (STD) and 91% of PixelShine images (PS) were rated diagnostic. If an image was rated non-diagnostic with the standard reconstruction 89% of reviews considered the images diagnostic when reconstructed with PixelShine. Only 9% of reviews of PixelShine images classified them as non-diagnostic compared to 72% of STD. If a STD image was considered diagnostic only 5% of the time was the PS image considered non-diagnostic.

When respondents were asked to grade an exam as one acquired with a low-dose or routine technique, 92% of the time the low dose images were correctly categorized as acquired with low dose technique versus 25% responses about PixelShine versions of the same images. In fact, 75% of respondents felt that the images they classified as acquired with low-dose technique were acquired with routine technique when PixelShine was applied to the same data.

Discussion

Many reconstruction techniques have been proposed for computed tomography. The machine learning tool described takes an existing image and improves the reconstruction based on manipulations learned from a training set of data. In this case, the tool was applied to images reconstructed from low dose acquisitions and survey respondents found the post-processed images to be comparable to what they would expect from a routine dose examination. In many cases, the PixelShine tool processed images that respondents considered non-diagnostic, and brought it to a quality they thought was diagnostic. Respondents also felt PixelShine processed images diagnostic at a much higher rate 91% versus 28% for standard reconstructions.

From these preliminary results, this ANN tool appears to be a valuable post processing tool for images with higher noise or artifact possibly creating diagnostic images from data initially non-diagnostic. This could provide a tool for improving data before interpretation or allow for decreases in radiation dose during exam acquisition while providing similar quality final images.

Conclusion

This machine learning tool for image processing provides improved image quality over standard reconstruction techniques, as assessed by many reviewers from across the country. This is a innovative use of AI technology in a way that has the potential to greatly reduce medically related radiation exposure to our patient population and add value to radiology.

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Keywords

machine learning, neural network, image reconstruction, computed tomography,