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CT / Scientific Review

Advanced intelligent Clear-IQ Engine (AiCE) Deep Learning Reconstruction: a Narrative Scientific Review

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Artificial Intelligence (AI) has profoundly impacted medical imaging over the past decade, leading to the development of numerous algorithms and software tools for both research and clinical purposes. AI's applications in this field are widespread, ranging from automating image acquisition workflows to analyzing images by quantifying diagnostic imaging biomarkers[1].

One of the applications that AI has advanced in the last few years is image reconstruction in computed tomography (CT). Here, Deep Learning (DL) algorithms – a subset of AI methods – have been developed to overcome the major limitations of conventional reconstruction methods. These include the limited signal-to-noise ratio achievable through filtered backprojection (especially in low dose settings), the "plastic" appearance and long reconstruction times of clinically-applicable Model-Based Iterative Reconstruction (MBIR) methods, and the potential decrease of low-contrast resolution of Hybrid Iterative Reconstruction (HIR) due to changes in image texture at low-frequency noise[2].

In 2018, Canon developed the first commercially available Deep Learning Reconstruction (DLR) method: the Advanced intelligent Clear-IQ Engine (AiCE). This DL algorithm was trained with a target of high-quality clinical images, which were reconstructed with state-of-the-art MBIR. While capable of achieving top-tier image quality with sufficient iterations, MBIR is too time-consuming for routine clinical application, thus making its high-quality output a valuable ground truth for training DLR algorithms.

In the training phase, the input for AiCE was represented by low-quality image data that were simulated from the targets (i.e., the high-quality clinical scans). In this fashion, the DL algorithm was able to learn denoising capabilities on real patient data without the risk of generating new, false anatomical information or pathological structures. Once trained, the algorithm can reconstruct CT images with improved high- and low-contrast resolution, reduced noise, natural texture, and in a clinically acceptable processing time, significantly shorter than MBIR.

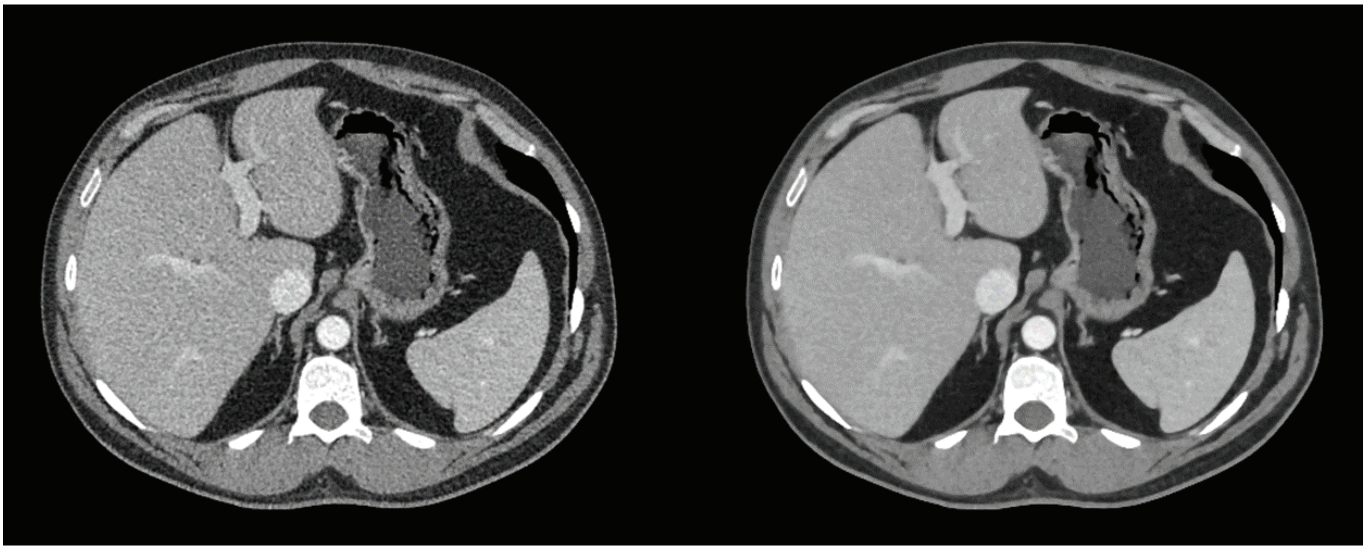
Numerous independent clinical scientific studies[3-20] have validated the potential and superior performance of AiCE over other reconstruction techniques. These publications consistently reported substantial and significant enhancements in subjective image quality across various clinical applications and patient groups, including chest[3-6], abdomen[3, 7-12], pelvis[9,11], head[13-16], lower extremities[17-18], and cardiac CT[19]. Notably, AiCE yielded image quality improvements of up to 48% compared to HIR in specific cohorts, such as obese (BMI > 25 kg/m2)[8, 12] and pediatric (age 3-9 years) patients[20]. Supporting these subjective findings, quantitative analyses also consistently demonstrated the benefits of AiCE. Reported improvements reached as high as 56% for image noise reduction[19], 56% for signal-to-noise ratio[10], 45% for contrast-to-noise ratio[14], and 19% for object detectability improvements[3].

For the majority of studies comparing AiCE with HIR (or other reconstruction techniques), researchers utilized the same acquired image data. This approach enabled a direct, paired comparison designed to reduce potential biases. However, certain investigations specifically explored the possibility of lowering radiation dose through AiCE. These studies employed varied acquisition protocols across patient groups[10, 16], acquired both low-dose and ultra-low-dose scans for individual patients[11], or adjusted the CT dose index (CTDI) based on measured noise levels[20]. The findings indicated a potential for significant radiation dose reduction using AiCE, estimated at tenfold in temporal bone imaging[16], between 36% and 77% in abdominal imaging[10, 11], and 52% in pediatric imaging[20].

These overall improvements in subjective and objective image quality metrics, together with the reduction of radiation dose, have the potential to translate into actual changes in imaging protocols, improved anatomical structure depiction, and, possibly, improved diagnostic interpretability. In this respect, evidence suggests that AiCE can be useful to reduce the Iodine load with no diagnostic inferiority compared to conventional volumes of contrast agent[10], to improve tissue differentiation in non-contrast cerebral CT[13], to enhance the clarity of anatomical landmarks in the inner ear[15], and to potentially increase sensitivity and specificity of lower extremity CT angiography[17]. Furthermore, thanks to its denoising capabilities, AiCE may also help avoid the loss in signal-to-noise ratio in thin-section CT images, which are typically only used as a problem-solving tool (and not routinely) due to their high noise content. This was evaluated in a recent study[9], where AiCE has been shown to improve subjective image quality in thin-section images, compared with both thin- and thick-section images reconstructed with HIR, without introducing any artifacts. These results may have an impact not only in diagnostic confidence, but also in streamlining the workflow of radiologists by reducing the number of reconstructions to be performed, and, consequently, the overall interpretation time.

While radiologists' image interpretation remains the gold standard, in the current era of precision medicine, is becoming more and more important to also rely on quantitative imaging biomarkers that may carry additional diagnostic information on disease types. From simple biomarkers (e.g., lesion size) to more complex textural features, the ability to depict quantifiable information with high accuracy, reproducibility, and precision is essential. Compared to iterative reconstruction, AiCE has demonstrated potential also in this direction, yielding higher reproducibility and diagnostic power of radiomic features in hepatic metastases characterization[7], reduced measurement error in airways of less than 0.5 mm diameter[5], and decreased error in lung nodule measurement of up to 83%[6]. These capabilities may result in improved confidence towards quantitative imaging biomarkers, and ultimately potentially allow for an improvement in patient management.

Based on the scientific findings reported, it is clear that AiCE can push the boundaries of image quality in CT, representing a software-based solution that overcomes the limitations of conventional reconstruction methods, and that has brought the image quality of CT to a next level of diagnostic interpretability.



Example of an abdominal CT scan reconstructed with Hybrid Iterative Reconstruction (left), and with AiCE Deep Learning Reconstruction.
CTDI-vol: 11.0 mGy. DLP: 605.7 mGy.

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