Advanced intelligent Clear-IQ Engine(AiCE): Translating the Power of Deep Learning to MR Image Reconstruction

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Introduction

In magnetic resonance imaging (MRI), there are inherent tradeoffs between signal-to-noise ratio (SNR), scan time, and resolution due to limitations imposed by MR physics. These tradeoffs are depicted in Figure 1A. For example, higher SNR and resolution are desired for better image quality and higher diagnostic confidence but they often come at the cost of longer scan time. Going to higher field strengths is one of the approaches to reduce the inherent tradeoffs. This is illustrated in Figure 1B. However, imaging at higher field strengths has several challenges such as increased equipment and operating cost, increased safety risks due to higher heat deposition to the patient, and increased image artifacts due to higher field inhomogeneities. Canon Medical Systems introduces Advanced intelligent Clear-IQ Engine (AiCE)[1], which alleviates the fundamental tradeoffs between SNR, scan time, and resolution, as shown in Figure 1C. AiCE uses Deep Convolutional Neural Network (DCNN), a subtype of deep learning, which is trained to differentiate noise from the underlying MR signal. AiCE's relation with the different subfields of AI is shown in Figure 2. AiCE's architecture choices and training procedures are based on MR physics that allow the model to be interpretable and AiCE's performance to be explainable. Furthermore, AiCE is designed with the goal to be robust to the wide variety of MR images acquired in the clinical setting. With the introduction of AiCE, the power of deep learning is translated into clinical practice to provide exceptional image quality across a wide variety of clinical applications.

Advanced intelligent Clear-IQ Engine (AiCE): An Overview

Deep Learning Overview

Deep learning[2] has been successfully applied in many fields since 2012 after the introduction of AlexNet[3], the DCNN, which won the ImageNet image classification competition by a large margin compared to traditional methods. In this competition, participants were challenged to classify a data set of 150,000 photographs into a thousand object categories given 1.2 million images and 50,000 images for model development. Traditional methods often involve complex hand-tuned feature engineering, which is time consuming and sometimes suboptimal. The DCNN approach, on the other hand, requires no hand-engineered features but rather the algorithm automatically learns the features by seeing many examples.

DCNN, a subtype of deep learning, consists of an "artificial" neural network with many linear and nonlinear processing layers. The multi-layer structure of DCNN was inspired by the structure of the biological brain, where the input is processed, perceived, and represented at hierarchical levels. The deeper layers of the DCNN represent higher abstractions of the input. A natural question to ask is, "how does a DCNN learn and produce such hierarchical representations?" Each convolutional layer consists of many "artificial" neurons, which perform simple linear computations including multiplication, addition, and nonlinear thresholding. Neurons in one layer are connected to the next layer via a set of connections called weights and biases. The weights and biases are randomly initialized and then iteratively adjusted many times during training using backpropagation. By the end of the training process, the weights and biases are optimized to perform a specific task given the training data.

Applications of deep learning have been growing rapidly in healthcare and medicine ranging from disease classification and/or detection, image segmentation, prognosis prediction, and image reconstruction. With the introduction of AiCE, the power of deep learning is translated into the clinical setting to overcome the limitations that inhibit conventional image reconstruction and correction methods from producing high quality clinical images.

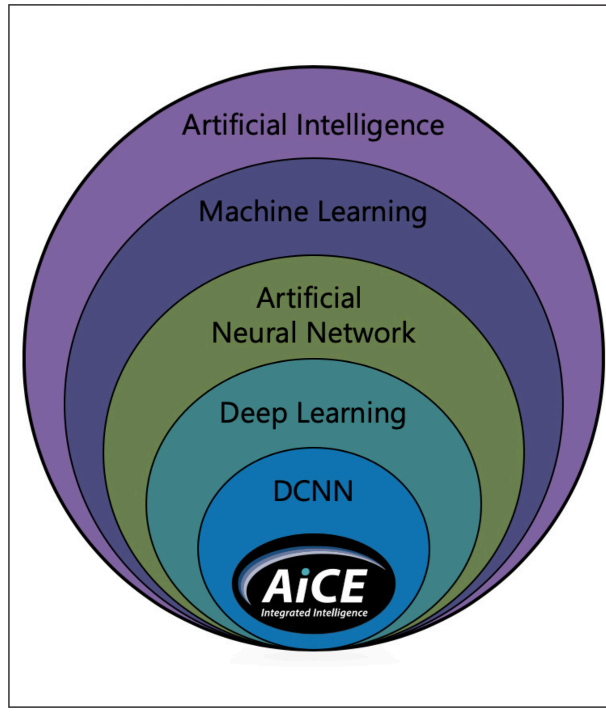

Figure 2. AiCE uses a subtype of Deep Learning called DCNN.

Advanced intelligent Clear-IQ Engine (AiCE): Unique Implementation and Training Procedure

As shown in Figure 3, the key feature of AiCE's network architecture lies in its transparency that results in an interpretable model with explainable performance. AiCE's network components such as the feature transformation layer and the soft-shrinkage activation layer are designed based on prior research in signal processing, compressed sensing[4], and image denoising[5]. In AiCE, the denoising steps are performed after the input images are transformed into a feature space using the discrete cosine transform. Another novel feature of AiCE is that it utilizes the "adaptive" soft-shrinkage activation layer, instead of the rectified linear unit activation layer which is commonly used in computer vision applications. Soft-shrinkage is a non-linear thresholding operation that is commonly used in image denoising and compressed sensing. In contrast to the classical soft-shrinkage layer, the threshold level of the adaptive soft-shrinkage layer used in AiCE is learned during the training process. That allows AiCE to be adaptive and more robust to a large range of input noise compared to the non-adaptive network. These architecture choices allow AiCE to be transparent and its performance to be interpretable, which are crucial to gain trust from the users.

AiCE's training is computationally intensive, however, the training is performed offline before the model is

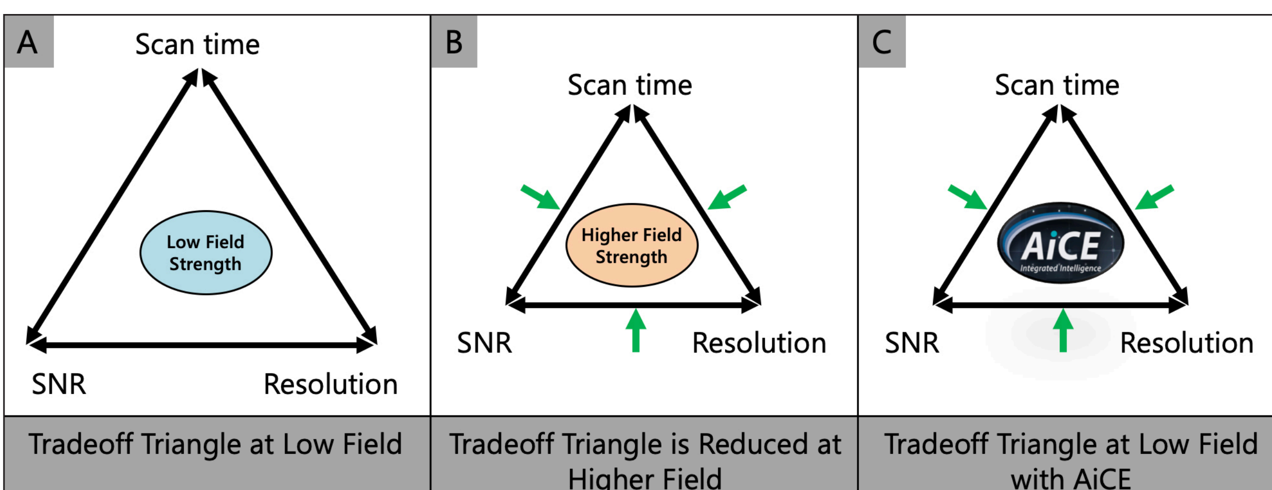

Figure 1. (A) Inherent tradeoffs between SNR, resolution, and scan time. (B) Higher field strength can reduce the triangular tradeoff but it is associated with several challenges such as increased equipment and operating cost, increased safety risks due to higher heat deposition to the patient, and increased image artifacts due to higher field inhomogeneities. (C) AiCE is able to alleviate the inherent and fundamental tradeoffs between SNR, scan time, resolution without the challenges associated with higher field strength. Note that the images are not necessarily drawn to scale.

deployed at the clinical scanner. During clinical use, the AiCE reconstruction is generally fast because there is only a single feed-forward computation. Such feed-forward computation is efficiently performed using a GPU and other modern computer hardware. Figure 4 depicts AiCE at deployment.

AiCE is designed to be robust to the many variations in MR clinical images caused by differences in scan protocol, imaging contrast, image SNR, body region, and field strength. In the AiCE architecture, a skip connection is applied to the zero-frequency component in the feature space that preserves the contrast of the input image. In other words, AiCE is robust to contrast variations coming from different field strengths and different clinical protocols. Noise removal is performed in the feature space, which protects the result from being affected by variations of spatial structure and contrast in the image. Geometric data augmentation further strengthens the robustness of AiCE to different body regions. Finally, noisy data augmentation is employed, in which images containing a range of clinically relevant noise levels are added into the training dataset. This training procedure enables the adaptive soft-shrinkage method to learn and adapt to the range of noise level and SNR observed in clinical setting.

Besides novel architecture and training procedure, preparing high quality training data is crucial for a

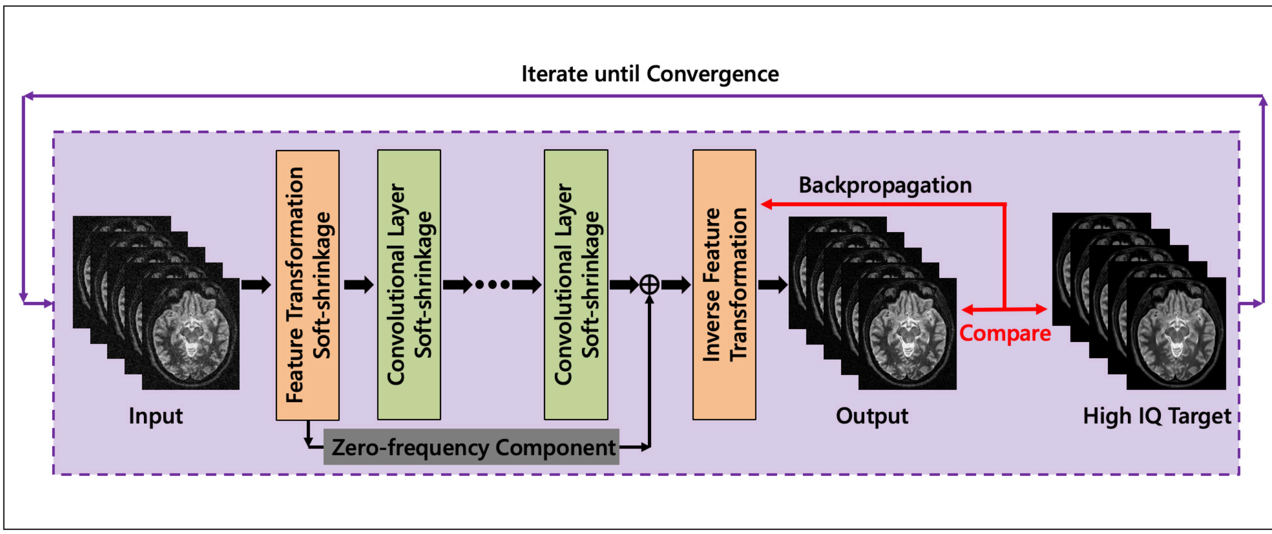

Figure 3. AiCE Network Architecture and training.

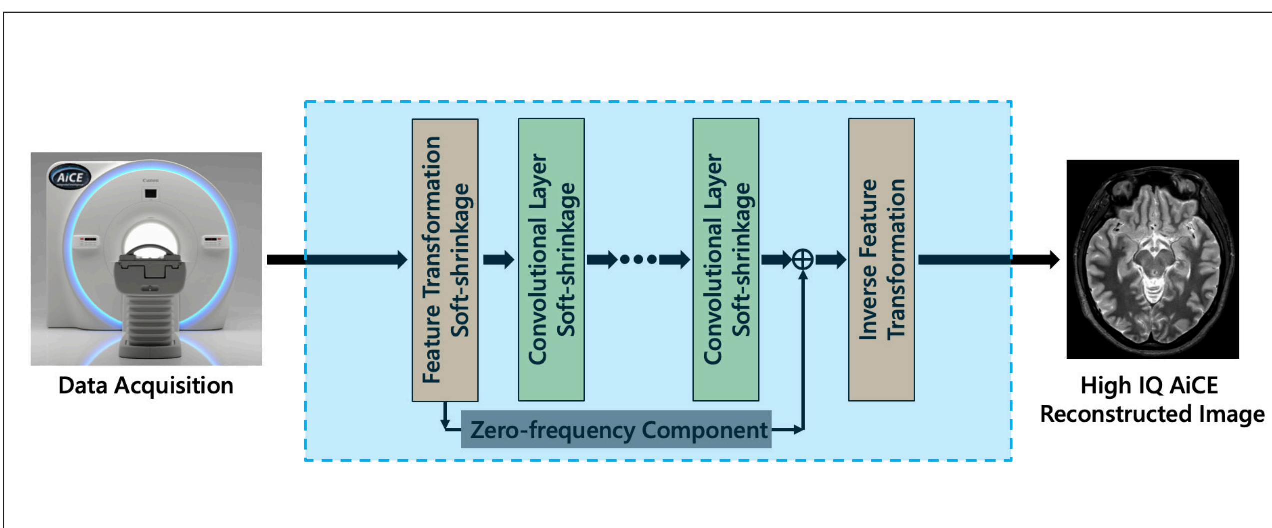

Figure 4. AiCE at deployment.

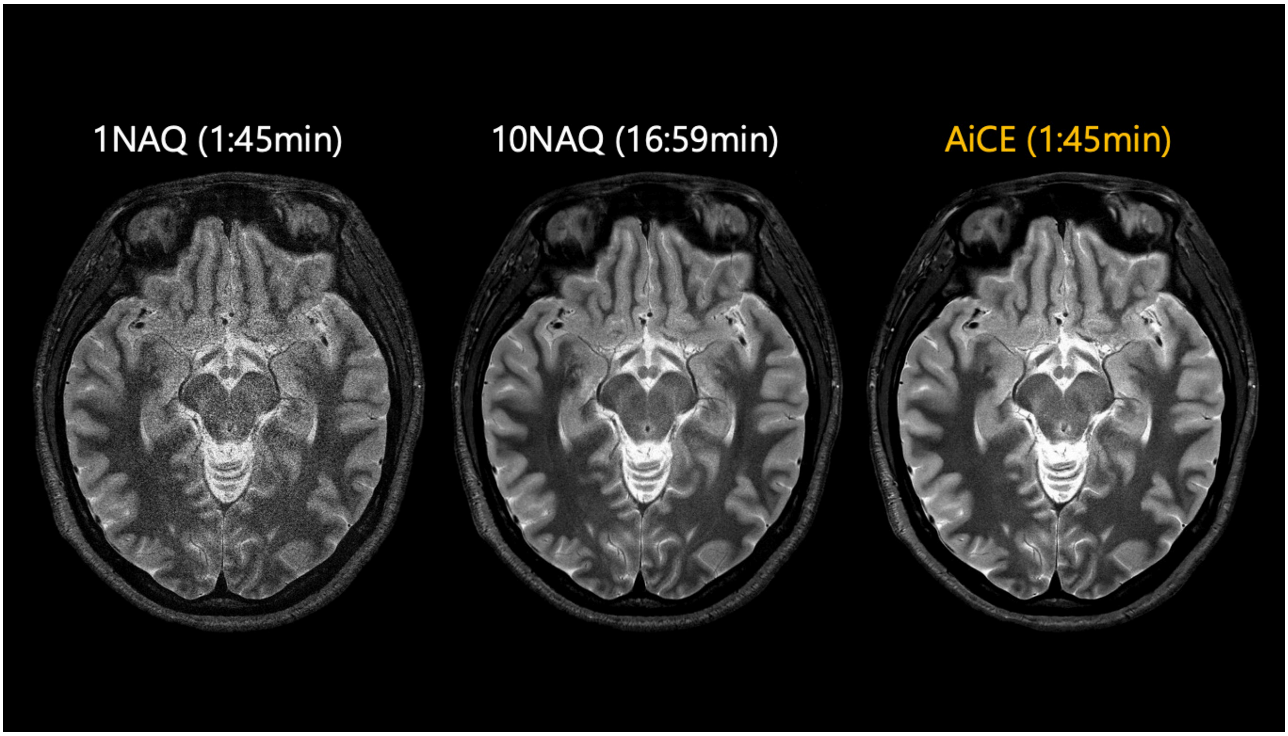

Figure 5. A representative example of the high quality brain image that was produced by AiCE in clinically acceptable scan time. (Disclaimer: 10 NAQs is not clinically practical).

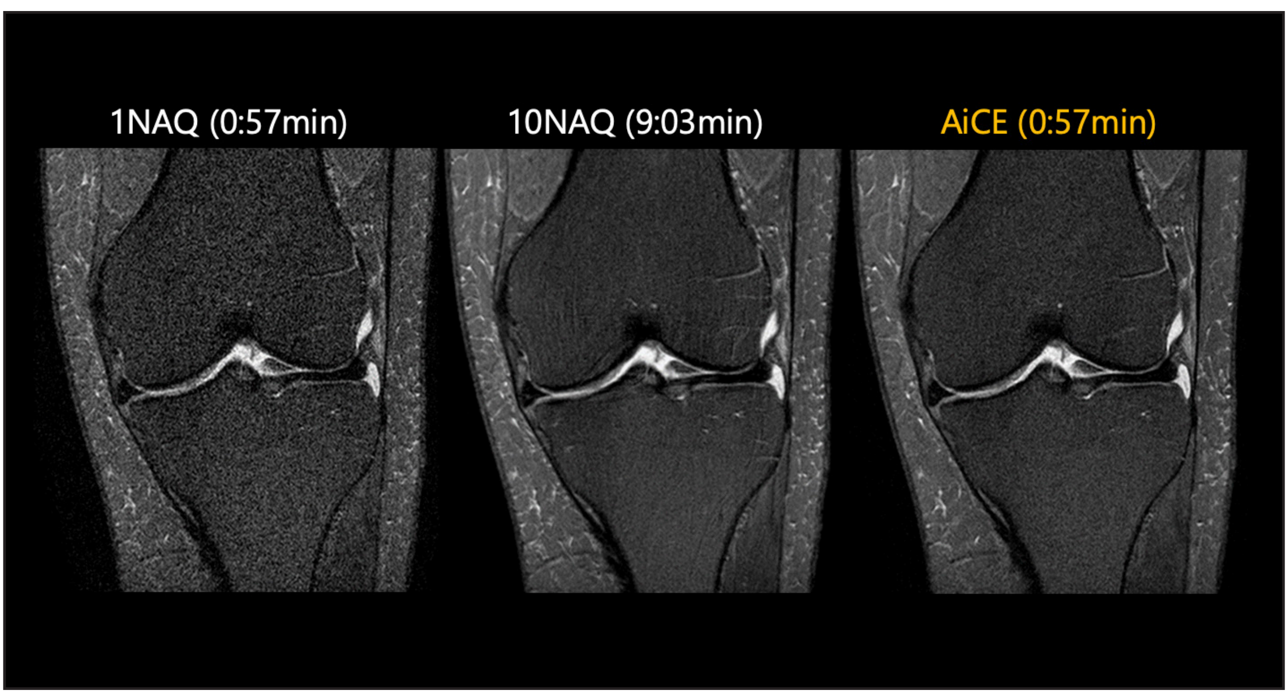

Figure 6. A representative example of the high quality knee image that was produced by AiCE in clinically acceptable scan time. (Disclaimer: 10 NAQs is not clinically practical).

successful deep learning project. AiCE is designed to transform a low quality noisy image into a high quality image with reduced noise. High quality target training images were prepared using motion registration and averaging of MRI images acquired with multiple averages (NAQ). The long scan time and intense pre-processing used for training data preparation are impractical in routine clinical workflow. AiCE is trained to produce exceptionally high quality images that are comparable to high NAQ images, without the burden of long scan durations and computation times. This performance was previously not practical with conventional methods.

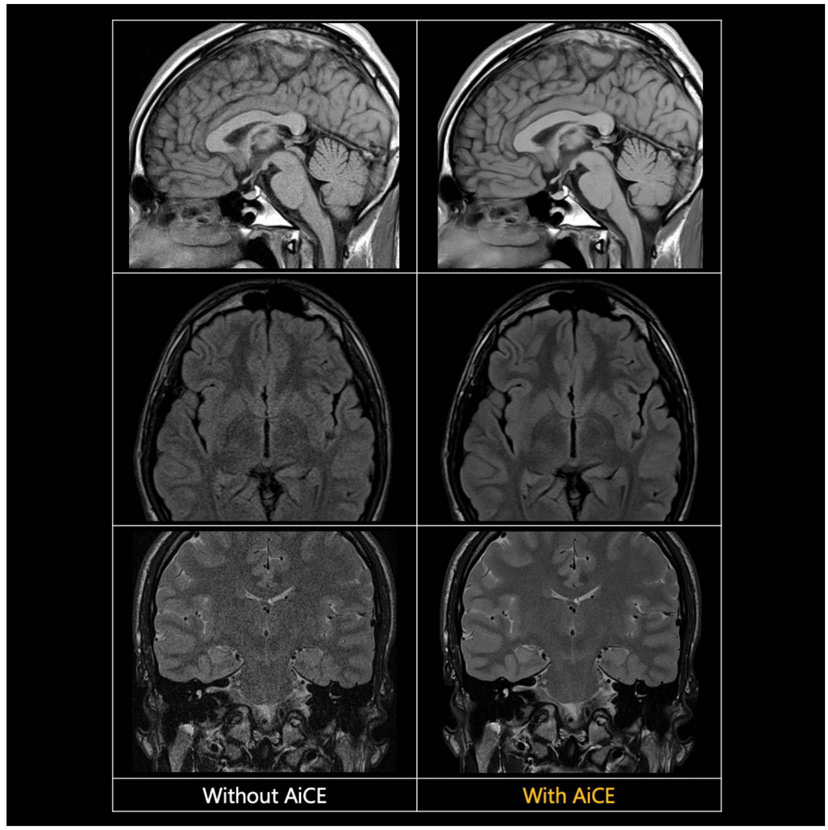

Figure 7. Examples of brain images without (left column) and with (right column) AiCE. High resolution and SNR images are obtained using AiCE in variety of contrasts and scan planes.

Advanced intelligent Clear-IQ Engine (AiCE): Robust Performance and Clinical Evaluation

High quality MR images generated using AiCE

Examples of high quality images generated using AiCE are shown in Figures 5 – 10.

Clinical Validation

Clinical evaluation was carried out to validate efficacy and safety of AiCE in the clinical setting. Clinical AiCE images were reviewed by six American board-certified radiologists. Each radiologist reviewed tens of thousands of AiCE reconstructed images and compared with images reconstructed using conventional methods (NL2, GA43, and GA53). Specifically, the reviewers were asked to compare and score images in terms of overall image quality, image sharpness, image contrast, image noise texture, SNR, and lesion/pathology conspicuity. The Wilcoxon signed-rank test statistics shows that AiCE statistically outperformed conventional reconstruction methods (NL2, GA43, and GA53) in all of the graded criteria

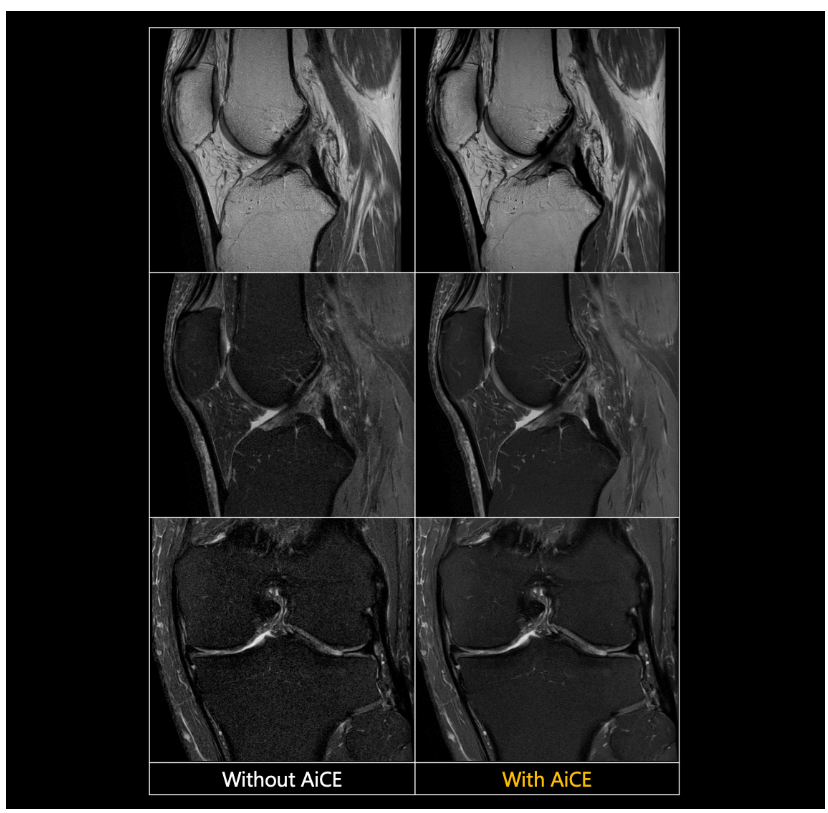

Figure 8. Examples of knee images without (left column) and with (right column) AiCE. High resolution and SNR images are obtained using AiCE in variety of contrasts and scan planes.

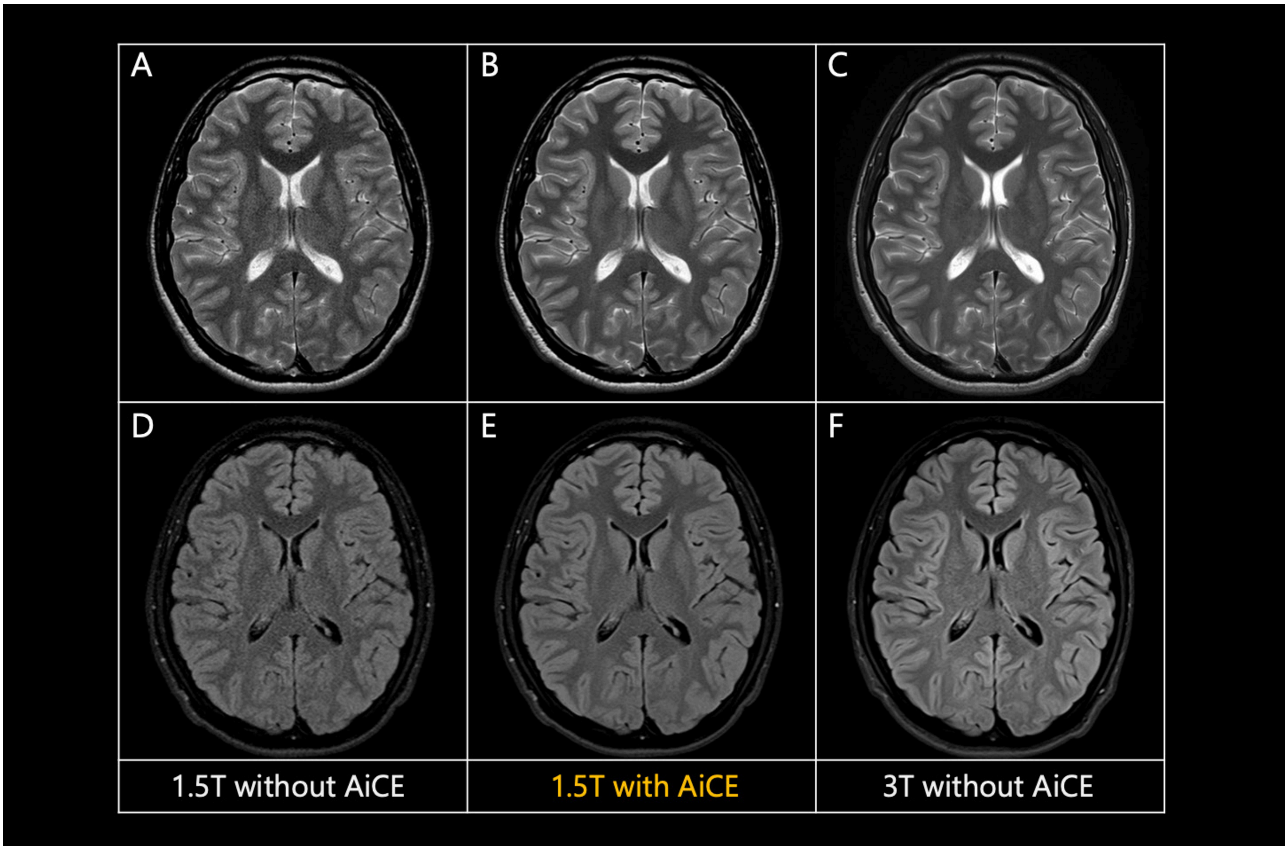

Figure 9. 1.5 T vs. 3 T brain images from the same subject. 1.5 T images before (A, D) and after (B, E) AiCE in comparison to 3 T images (C, F).

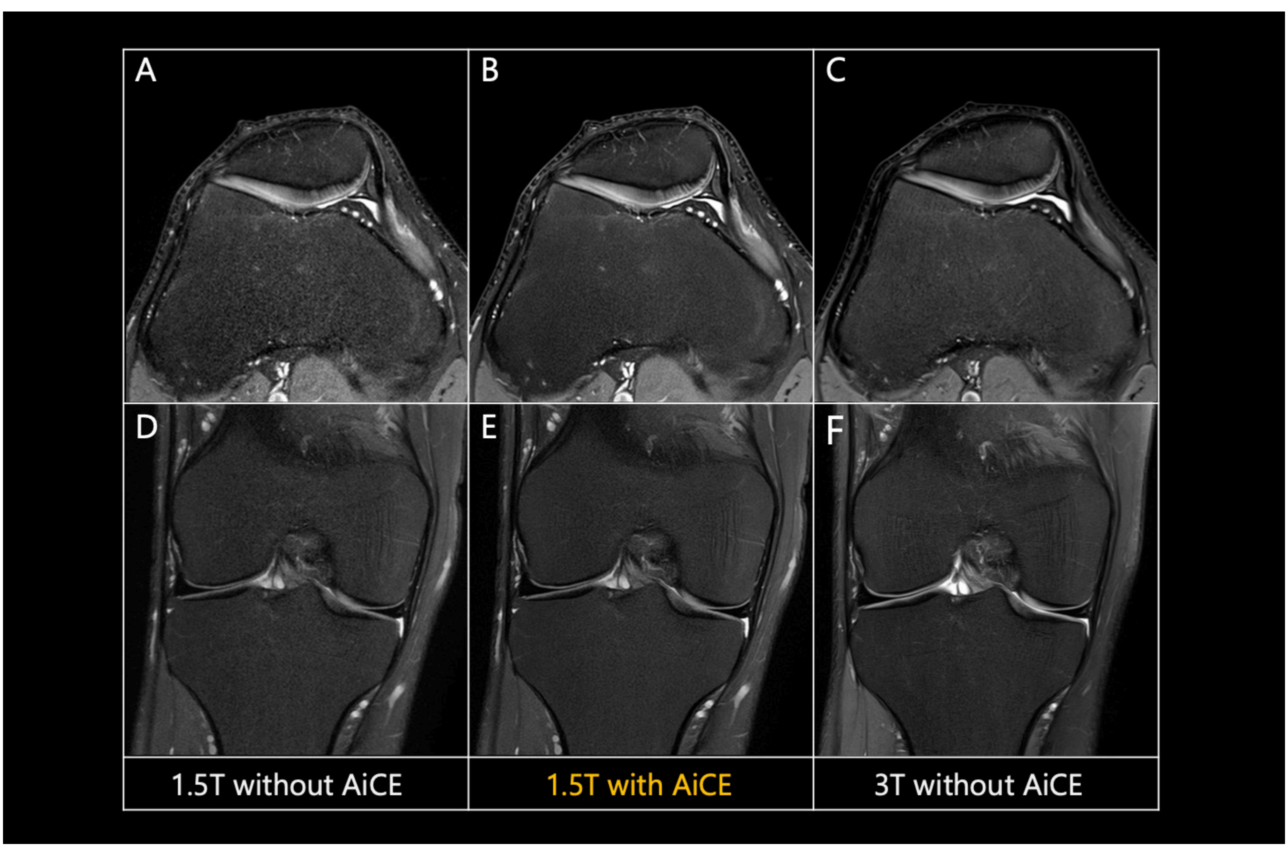

Figure 10. 1.5T vs. 3 T Knee images from the same subject. 1.5 T images before (A, D) and after (B, E) AiCE in comparison to 3 T images (C, F).

(P<0.05). As an example, the summary of overall image quality scores of brain and knee MRI are shown in Figure 11.

Summary

AiCE is a Deep Learning Reconstruction method that is designed based on the knowledge of signal processing and MR physics, which allows AiCE's model to be interpretable and AiCE's performance to be explainable. Furthermore, AiCE's architecture and training procedure are designed to provide robust performance to many variations of MR data in a clinical setting. With the introduction of AiCE, the power of deep learning is translated to the clinic producing exceptional image quality.

Acknowledgments

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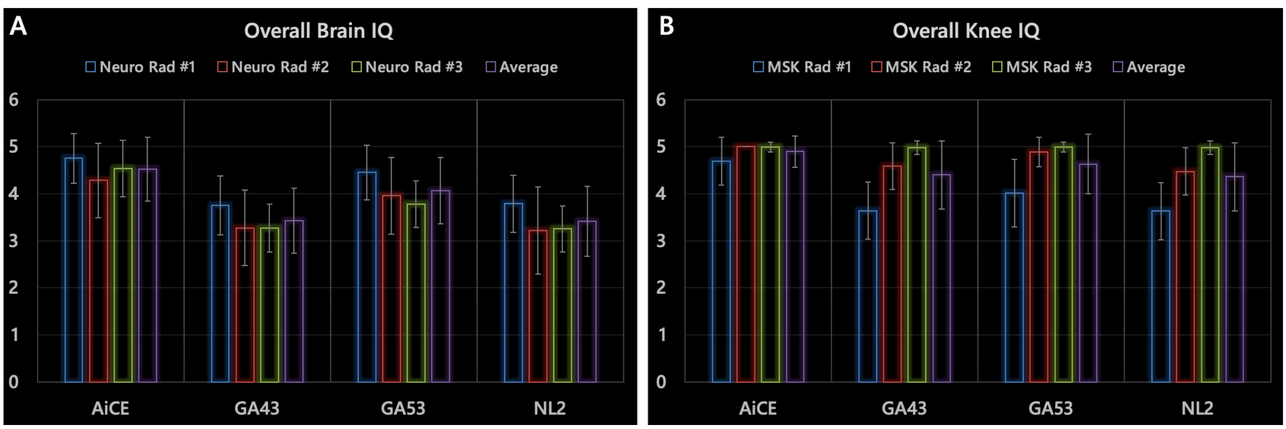

Figure 11. Overall image quality score of brain (left) and knee (right) MRI from six American board-certified radiologists. The Wilcoxon signed-rank test statistics shows that AiCE statistically outperformed NL2, GA43, and GA53 (P < 0.0001).

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