Improved Bone and Cartilage Segmentation in Knee MRI Using a Super-Resolution Convolutional Neural Network

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INTRODUCTION: Magnetic resonance imaging (MRI) is useful for assessing knee joint health and has been used to examine bone and cartilage in the context of the onset and progression of osteoarthritis [1,2]. Segmentation of cartilage and bone from MRI has been widely used in prior studies to quantify morphology, detect degeneration, and evaluate treatment outcomes [3,4,5]. However, high-resolution (HR) MRI has long acquisition times, leading to higher costs, patient discomfort, and a larger susceptibility to motion artifacts [5]. Alternatively, low-resolution (LR) MRI is much faster and more affordable, but may not fully capture the 3D geometry of cartilage and bone. Super-Resolution (SR) models such as the Super-Resolution Convolutional Neural Network (SRCNN) propose to bridge this gap through learned up sampling, predicting HR detail from LR inputs [6]. Though SRCNN has been applied to knee MRI in other contexts, there is a lack of data that evaluates how SRCNN impacts downstream cartilage and bone segmentation performance from knee MRIs [7-9]. The goal of this study was to assess the impact of SRCNN on automated bone and cartilage segmentation in knee MRI. We hypothesized that using SRCNN to enhance LR MRI would improve auto-segmentation accuracy compared to a LR baseline.

METHODS: A total of 60 knee double echo steady state (DESS) MRI scans (28 with 512x512 pixels; 32 cropped to 256x256 pixels, centered on the tibiofemoral joint) collected across multiple previously acquired IRB approved study datasets including 10 asymptomatic males and 22 asymptomatic females (age: 22–48 years; BMI: 18.9–30.1kg/m^2) were used. All DESS MRI scans were obtained using the same 3.0 T scanner (TrioTim; Siemens Healthcare) using the same imaging parameters (field of view = 16cm × 16cm; image resolution = 0.3 × 0.3 × 1.0mm; flip angle = 25°; repetition time = 17ms; echo time = 6ms). All scans were down sampled (by a factor of 2) and then up sampled using bicubic interpolation (which averages the values of nearby pixels to estimate new pixel values) to simulate LR MRI. Each LR MRI was paired with HR MRI for training. The SRCNN was optimized using mean squared error loss (with convergence defined as stability of the validation loss) and hyperparameters (batch size and learning rate) were selected via grid search. The SRCNN model was first trained on the cropped scans to learn the mapping from LR to HR images. Once convergence was reached, the model was fine-tuned using an additional 24 uncropped scans to optimize for standard MRI input dimensions. The best-performing model, as determined by the dice loss function (a measure of segmentation overlap), was then applied to four unseen validation scans to create super-resolution predictions (**Figure 1**). For task specific evaluation, an automated segmentation pipeline that was previously developed [10] was applied to HR (ground truth), LR, and SRCNN-enhanced images. Binary masks of the tibia, femur, femoral cartilage, and tibial cartilage were generated, and segmentation performance was evaluated with dice coefficients, comparing LR to HR and SRCNN to HR segmentations.

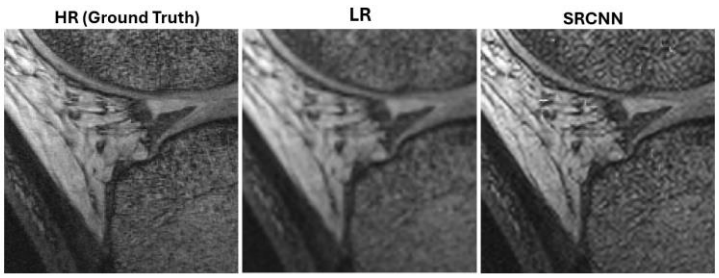

Figure 1: *Comparison of high-resolution ground truth, low-resolution input, and SRCN-predicted images for a selected region of interest in knee MRI.*

RESULTS: Qualitatively, SRCNN predictions produced more defined and consistent cartilage boundaries within the validation dataset (**Figure 2**), with the greatest improvements in regions where LR generated blurred or irregular edges. SRCNN super-resolution improved automated segmentation accuracy across the validation dataset compared to LR segmentations, with gains observed for the femur, tibia, and their respective cartilage (**Table 1**).

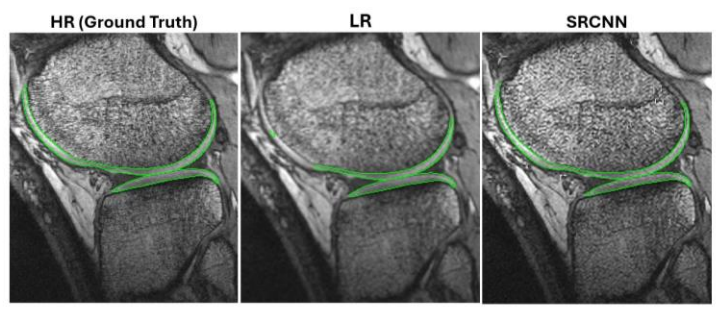

Figure 2: *Automated cartilage segmentation performance for HR ground truth, LR input, and SRCNN predictions. Green outlines represent automated segmentation masks for femoral and tibial cartilage.*

DISCUSSION: This study demonstrated that SRCNN improves bone and cartilage segmentation accuracy compared to bicubic interpolation of LR MRI scans. The improvements were most evident in segmentation performance, highlighting the importance of task-specific evaluation. Visually, SRCNN reconstruction provided a clear and more precise identification of bone and cartilage structures. Our findings build on previous work showing that SRCNN can enhance knee MRI data [7–9] and extend it by demonstrating that these benefits translate directly to downstream bone and cartilage segmentation tasks. These improvements are particularly relevant for osteoarthritis research, where accurate cartilage and bone segmentation supports evaluation of tissue response after exercise [11], assessment of cartilage loading during weight-bearing MRI [12], and longitudinal monitoring of degenerative changes [5]. The strong improvements in the femur and femoral cartilage suggested that SRCNN may be especially effective in regions where boundary clarity is most critical for segmentation. Future work will investigate how image resolution and reconstruction methods influence biomechanical measurements, such as cartilage strain. A limitation of this study is that LR scans were simulated through down sampling rather than acquired directly; future work should evaluate SRCNN performance on directly collected LR MRI. In conclusion, the SRCNN has the potential to shorten scan times, reduce costs, minimize motion artifacts, reduce patient burden, and streamline image analyses.

	Femur Cartilage	Femur	Tibia Cartilage	Tibia
SRCNN	0.931 ± 0.016	0.965 ± 0.006	0.958 ± 0.016	0.984 ± 0.010
LR	0.884 ± 0.043	0.520 ± 0.290	0.954 ± 0.015	0.961 ± 0.009

Table 1: *Mean Dice coefficients (± standard deviation) for automated segmentation of femur, tibia, and associated cartilage in knee MRI. Values compare LR and SRCNN-predicted images against HR ground truth segmentation masks.*

SIGNIFICANCE/CLINICAL RELEVANCE: The use of SRCNN potentially enables the use of faster, lower-resolution MRI scans without losing segmentation accuracy. This approach has the potential to shorten scan times, reduce costs, minimize motion artifacts, reduce patient burden, and streamline image analyses.

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