# DEEP LEARNING
## A NEW HOPE

# A single centre experience using DL to improve MRI image quality

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## BACKGROUND

Machine learning has wide range of applications in radiology and currently there is a heterogeneous mix of commercially available AI tools on the market.
Deep learning is a form of machine learning using multiple layers of artificial neural networks[1].
At HUTH we are using a form of deep learning to improve our image reconstruction known as AIR Recon DL (ARDL) by GE HealthCare.
It aims to reduce Gibbs ringing artifacts and enhance in-plane resolution through the utilization of Intelligent Ringing Suppression.
Additionally, it incorporates a noise reduction algorithm that enables a shorter scan time while maintaining the Signal-to-Noise Ratio (SNR), commonly referred to as MRI currency[2].
Implemented at Hull University Teaching Hospitals NHS Trust in December 2022, ARDL is currently used in neuroimaging of the spine, pituitary, and orbits.

## OBJECTIVE

To retrospectively assess the impact of implementing ARDL on MRI Spine image quality and scan time in a single centre

## METHODS

Image quality was assessed in terms of measuring the change in:

1. Ringing artefact and in plane spatial resolution: Phantom images with varying matrices.
2. SNR: Analysis of real patient imaging (retrospective comparison from before ARDL implemented).
3. Scan time: Based on a three-station MRI spine.
4. Qualitative image quality: Survey to assess the opinion of radiologists using the DL-based reconstruction in clinical practice

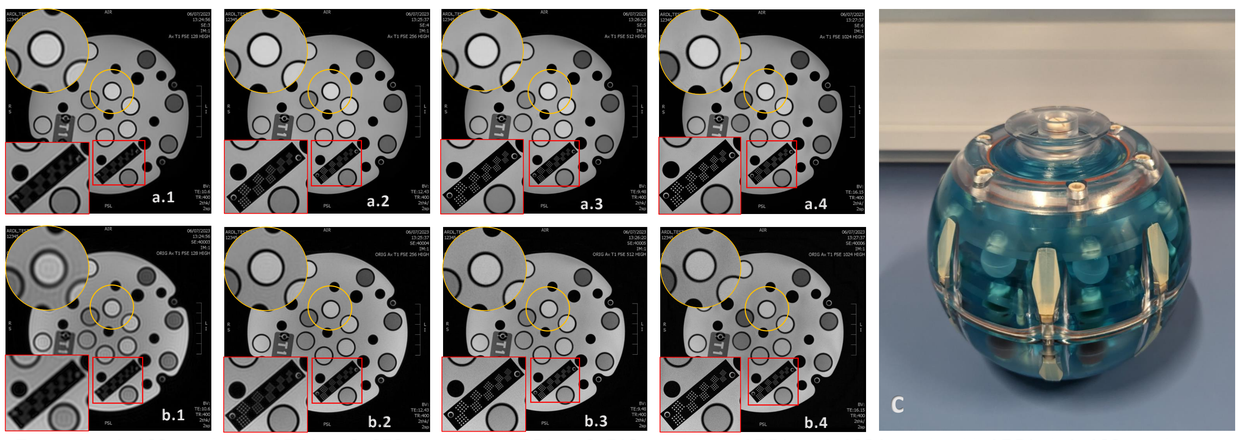
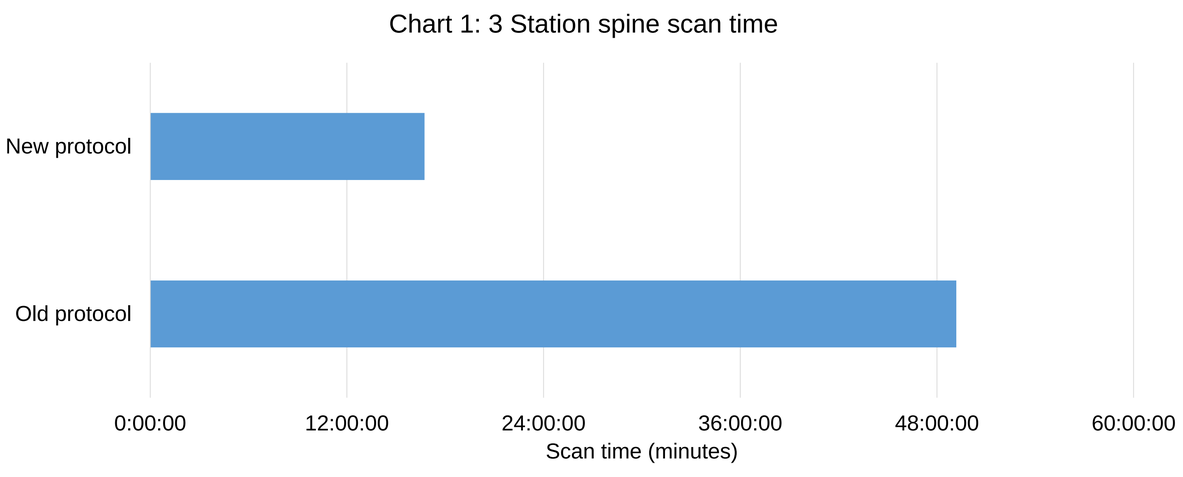



Figure 1: a.1; 128 matrix with ARDL, a.2; 256 matrix with ARDL, a.3; 512 matrix with ARDL, a.4; 1024 matrix with ARDL. b.1; 128 matrix raw image, b.2; 256 matrix raw image, b.3; 512 matrix raw image, b.4; 1024 matrix raw image. Zoomed circles; ringing artefact, Zoomed squares; In plane spatial resolution. ARDL was used with the high denoising setting. 200mm FOV. C; CaliberMRI essential phantom.



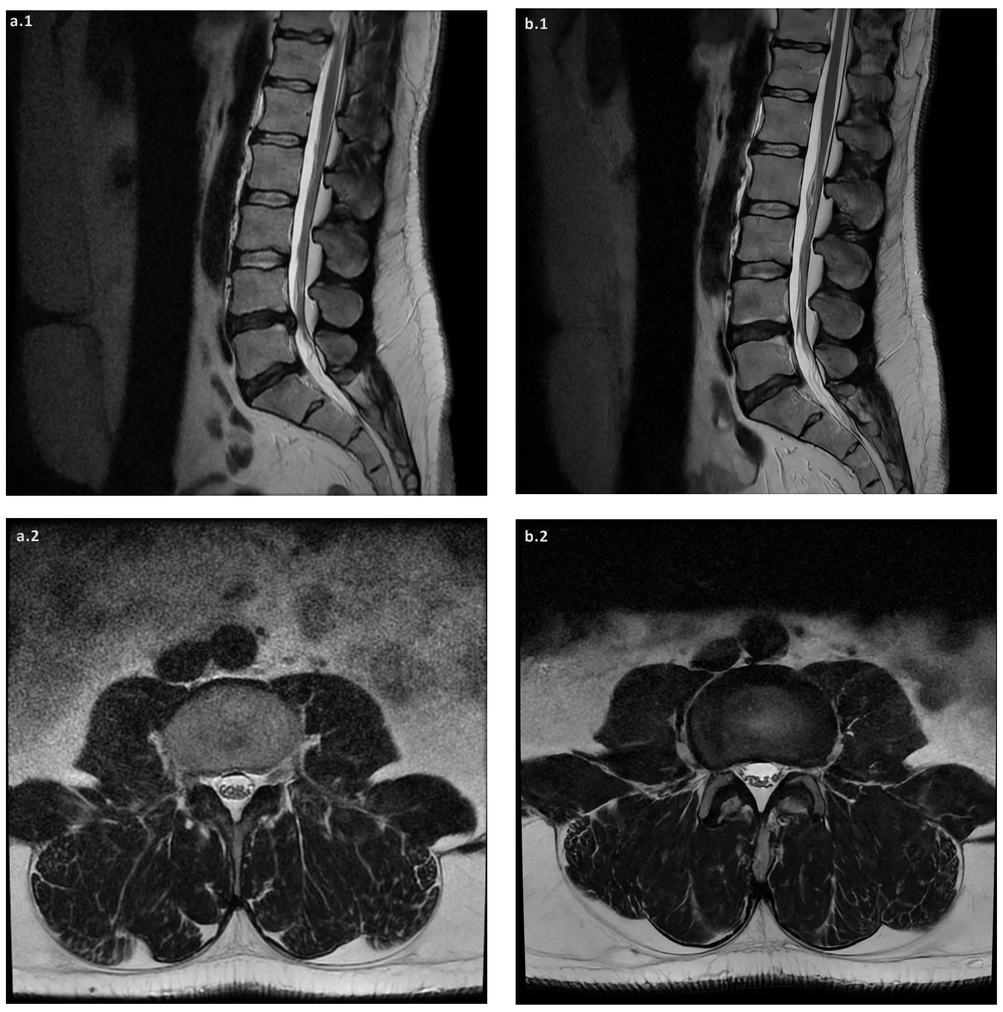
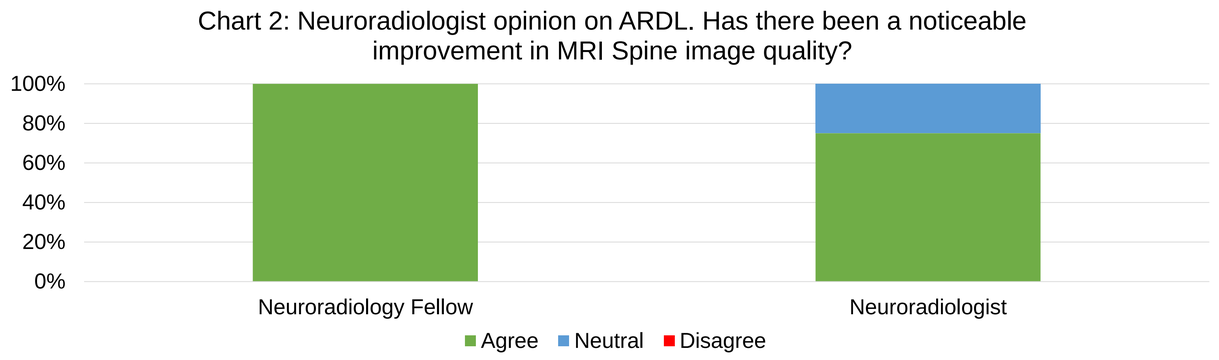




Figure 2: a.1, a.2; Sagittal and axial T2 MRI slices of the lumbar spine before ARDL implementation. Scan times: Sagittal T2 05:30. Axial T2 05:03.
B.1, b.2; Sagittal and axial T2 MRI slices of the lumbar spine of the same patient after ARDL implementation. Scan times: Sagittal T2 01:27. Axial T2 00:59

## RESULTS

1. Artefact reduction was seen greatest for the smaller matrix size and less apparent as the matrix size increases, The 0.40mm high-contrast spatial resolution grid was clearly resolved with a 512 matrix and ARDL but this level of detail is only visible in the original raw 1024 matrix.(Figure 1).
2. The average SNR improvement was 38% in the lumbar spine images (Figure 2).
3. A 66% reduction in scan time for a three-station MRI Spine was observed with the new protocol with equivalent or better image quality (Chart 1).
4. Two fellows and eight consultants responded to the survey with the majority (8/10) agreeing that there has been an improvement (Chart 2).




## CONCLUSIONS

**The implementation of ARDL in MRI spine imaging has led to a noteworthy improvement in image quality and reduced scan time. Consequently, our MRI department can potentially increase the volume of patients being scanned within the same timeframe in the future.**
**Current limitations include cost, motion sensitivity and the inability to use it with 3D sequences which are integral to many of our most common imaging protocols. Although these features are planned to be incorporated imminently within our trust.**
**Given the ever-increasing burden of demand placed on radiology, the use of deep learning tools may provide one way departments could improve efficiency and scan quality going forward.**

## REFERENCES

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2. Choy G, Khalilzadeh O, Michalski M, Do S, Samir AE, Pianykh OS, et al. Current Applications and Future Impact of Machine Learning in Radiology. Radiology. 2018;288(2):318–28. doi:10.1148/radiol.2018171820