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ORIGINAL RESEARCH

# Deep Learning Based Reconstruction of 3D-T1-SPACE Vessel Wall Imaging Provides Improved Image Quality with Reduced Scan Times: A Preliminary Study

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## ABSTRACT

**BACKGROUND AND PURPOSE:** Intra-cranial vessel wall imaging (IC-VWI) is technically challenging to implement, given the simultaneous requirements of high spatial resolution, excellent blood and CSF signal suppression and clinically acceptable gradient times. Herein, we present our preliminary findings on the evaluation of a deep learning optimized sequence using T1 weighted imaging.

**MATERIALS AND METHODS:** Clinical and optimized Deep learning-based image reconstruction (DLBIR) T1 SPACE sequences were evaluated, comparing non-contrast sequences in ten healthy controls and post-contrast sequences in five consecutive patients. Images were reviewed on a Likert-like scale by four fellowship-trained neuroradiologists. Scores (range 1-4) were separately assigned for eleven vessel segments in terms of vessel wall and lumen delineation. Additionally, images were evaluated in terms of overall background noise, image sharpness and homogenous CSF signal. Segment-wise scores were compared using paired samples t-tests.

**RESULTS:** The scan time for the clinical and DLBIR sequences were 7:26 minutes and 5:23 minutes respectively. DLBIR images showed consistently higher wall signal and lumen visualization scores, with the differences being statistically significant in the majority of vessel segments on both pre and post contrast images. DLBIR images had lower background noise, higher image sharpness and uniform CSF signal. Depiction of intracranial pathologies was better or similar on the DLBIR images.

**CONCLUSIONS:** Our preliminary findings suggest that DLBIR optimized IC-VWI sequences may be helpful in achieving shorter gradient times with improved vessel wall visualization and overall image quality. These improvements may help with wider adoption of IC-VWI in clinical practice and should be further validated on a larger cohort.

**ABBREVIATIONS:** DL deep learning; VWI = vessel wall imaging.

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## SUMMARY SECTION

**PREVIOUS LITERATURE:** Intracranial vessel wall imaging (IC-VWI) is technically challenging, given the simultaneous requirement for ultra-high-resolution imaging, as well as achieving excellent CSF and blood flow suppression in clinically reasonable scan times, while preserving the signal from the vessel wall. In recent years, there has been increasing interest in use of artificial intelligence (AI) based techniques to enhance image quality in IC-VWI

**KEY FINDINGS:** Deep learning-based image reconstruction (DLBIR) T1 SPACE sequences images showed consistently higher wall signal and lumen visualization scores, with the differences being statistically significant in the majority of vessel segments on both pre and post contrast images. DLBIR images had lower background noise, higher image sharpness and uniform CSF signal.

**KNOWLEDGE ADVANCEMENT:** Deep learning-based reconstruction of 3D-T1-SPACE vessel wall imaging is helpful in achieving shorter gradient times with improved vessel wall visualization and overall image quality

## INTRODUCTION

Intracranial vessel wall imaging (IC-VWI) has played an increasingly important role in routine neuroradiology practice in terms of detecting, characterizing, and differentiating various vasculopathies.[1-4] IC-VWI is technically challenging, given the simultaneous requirement for ultra-high-resolution imaging, as well as achieving excellent CSF and blood flow suppression in clinically reasonable scan times, while preserving the signal from the vessel wall.[2, 5, 6] Even though IC-VWI can be performed using either proton density or fast




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spin echo sequences using variable flip angle refocusing pulse, a recent survey of the American Society of Neuroradiology membership noted that the vast majority of responders predominantly used 3D sequences with T1-weighting (for example, SPACE [sampling perfection with application-optimized contrasts by different flip angle evolutions; Siemens Healthineers, Erlangen, Germany ], CUBE [GE Health Care, Milwaukee, WI, USA], or VISTA [volume isotropic turbo spin-echo acquisition; Philips Healthcare, Best, the Netherlands]).[2, 4]

Despite the enthusiasm and increasingly recognized role of IC-VWI in cerebrovascular pathologies, achieving clinically acceptable scan times while preserving image resolution remains a challenge. In terms of high spatial resolution in clinical practice, a voxel size of 0.5 mm isotropic is considered a reasonable starting point. However, most experienced centers use 3D acquisitions with isotropic voxels in the 0.4- to 0.7 mm range. At a voxel size of 0.5 mmisotropic, circle of Willis and second/ third order branches can be covered in about 7-10 minutes.[2, 6] The use of compressed sensing can help reduce scan times to about 7 minutes (or less, based on the acceleration factor) for whole brain acquisition, albeit with reduced contrast-to-noise ratio.[7] Similarly, even though the use of parallel imaging (such as controlled aliasing in parallel imaging results in higher acceleration [CAIPRINHA]) sequences can help reduce scan times, the image quality is considerably inferior due to the intrinsic loss of signal-to-noise for conventional reconstructions. [8] The long gradient times to obtain diagnostic quality imaging remain a challenge in widespread adoption of IC-VWI and can be especially problematic in clinically unstable patients such as those with acute stroke who may be unable to hold still through the acquisition.

In recent years, there has been increasing interest in use of artificial intelligence (AI) based techniques to enhance image quality in IC-VWI. Several of these have used unsupervised or self-supervised networks to reduce the image noise or improve signal to noise ratio, for T1-SPACE, proton density or MR angiography images.[9-11] However, these techniques largely rely on retrospective optimization of prospectively collected data and may not work well in motion-degraded data. More recently, several MRI vendors have introduced both 2D- and 3D- deep-learning based image acceleration techniques which can simultaneously improve image quality and reduce scan times.[12, 13] Even though these have shown promise in routine clinical practice, there is scarce literature regarding their utility and benefits in IC-VWI. This is relevant since these DL-based optimizations are often trained on a broader dataset covering different image contrasts and body regions and not specifically on IC-VWI data. The purpose of the current study was to perform a preliminary assessment of the image quality of the optimized DLBIR IC-VWI sequences compared the T1-SPACE VWI images used in clinical practice, both on pre- and post-contrast images. Herein, we present our preliminary experience with Deep learning-based image reconstruction (DLBIR) for IC-VWI using CAIPIRINHA-based T1 SPACE in healthy volunteers and patients.

## MATERIALS AND METHODS

### *Image acquisition:*

The study was approved by the institutional review board. We acquired non-contrast T1-SPACE IC-VWI images using the clinical and DL-optimized sequences in 10 healthy volunteers to compare image quality on non-contrast enhanced images. The inclusion criteria included absence of any current neurological complaints such as headaches, absence of any prior brain or spine surgery, no history of diabetes or hypertension and absence of any

contra-indication to MRI study (for example, non-compatible pacemakers or claustrophobia). We additionally acquired post-contrast T1-SPACE IC-VWI images using the clinical and DL-optimized sequences in five consecutive patients to compare image quality on contrast enhanced images. As these were patients who were getting a clinically indicated study, there were no specific inclusion criteria. Exclusion criteria were presence of motion (for both patients and volunteers) and inability to receive gadolinium-based contrast (for patients). However, none of the patients or volunteers were excluded due to the pre-specified exclusion criteria. Indications for IC-VWI in these patients included suspected vasculopathy (n=3), headache (n=1) and aneurysm (n=1). All images were acquired on a clinical 3T magnet (MAGNETOM Vida, Siemens Healthineers, Erlangen, Germany) using a 64-channel head/neck coil. The scanner software version was Syngo MR XA50.

The baseline sequence consisted of conventional CAIPIRINHA k-space sampling with parallel imaging reconstruction. The DLBIR sequence was also based on conventional CAIPIRINHA k-space sampling but used DL-based image reconstruction that generates images from k-space data using an architecture inspired by unrolled variational networks.[15] Using under-sampled k-space data and precalculated coil sensitivity maps as input, images are formed through 6 iterations comprising a data consistency update and a neural network based image regularization. The model was trained in a supervised manner using about 5000 training pairs derived from about 500 fully sampled 3D datasets of healthy volunteers acquired on 1.5 and 3T scanners (MAGNETOM scanners, Siemens Healthineers, Erlangen, Germany) in the head, abdomen, and pelvis. The obtained model parameters were then exported for prospective use in the scanner reconstruction. With the provided image enhancement, the reconstruction also allows for higher acceleration factors for conventional parallel image acquisitions. The same implementation was previously explored for abdominal T1-weighted imaging.[14]

The scanner parameters for both sequences are provided in **table 1**. These parameters were largely similar other than the use of higher acceleration and DL-based reconstruction in the DLBIR sequence. The scan time for the clinical and DLBIR sequences were 7:26 minutes and 5:23 minutes respectively.

**Table 1**: Technical parameters of the DLBIR and clinical IC-VWI sequences.

| | DLBIR T1 SPACE | Clinical T1 SPACE |
|---|---|---|
| **TR/TE (ms)** | 900/15 | 900/15 |
| **Flip Angle (◦)** | 120 | 120 |
| **Field-of-view ($mm^2$)** | 200x200 | 200x200 |
| **Matrix** | 384x326 | 384x326 |
| **Slice Thickness (mm)** | 0.55 mm | 0.55 |
| **Bandwidth (Hz/px)** | 407 | 407 |
| **Fat Suppression** | Yes | Yes |
| **Acquisition plane** | Sagittal | Sagittal |
| **Acceleration (PEx3DxShift)** | 3x2x1 | 2x2x1 |
| **Acquisition time (min:sec)** | 5:23 | 7:26 |

***Image evaluation:***

The image quality was independently evaluated by four neuroradiologists, each with at least six years of neuroradiology experience (range 6-15 years). All readers were board certified in radiology and held a certificate of added qualification in neuroradiology. All studies were reviewed on a clinical picture archiving and communications system (version 7.1.18, Visage imaging, San Diego, CA) with multi-planar capabilities. The DICOM headers for the images were hidden to avoid any potential identification of the use of DLBIR technique, with only the series number available to assess and grade image-quality. Images from same subject were evaluated

concurrently. Image windowing and use of multi-planar reconstruction was at the discretion of the individual readers.

Image quality was evaluated on a Likert-like scale using a four point rating and performed separately for the vessel wall (1= well defined; 2= mostly well-defined with some areas of suboptimal visualization; 3= mostly poorly defined with some well-defined areas; 4= non diagnostic) as well as vessel lumen (1=uniform flow suppression; 2= minor artifacts but diagnostic; 3= prominent intraluminal signal non-suppression; 4= non-diagnostic).[16] Additionally, the overall image quality was also reviewed in terms of lowest and highest background noise, image sharpness and homogeneity of CSF signal. A total of 11 vessel segments were evaluated for each sequence (bilateral ICA, MCA and ACAs, collectively referred to as anterior circulation and bilateral vertebral arteries, PCAs and basilar artery, collectively referred to as posterior circulation). For the MCA, ACA and PCA vessels, image quality was considered till the junction of second and third order branches. In patients undergoing IC-VWI with both sequences (n=5), the depiction of the underlying pathology was also subjectively evaluated in terms of visibility and reader confidence.

***Statistical evaluation:***

Mean reader scores were evaluated for each vascular segment. Individual segment scores for vessel wall and lumen were separately calculated for the non-contrast and contrast enhanced sequences and compared using paired samples t-test. A p-value of ≤0.05 was considered as significant. Descriptive statistics were used for background noise, image sharpness and homogeneity of CSF signal.

## RESULTS

The mean vessel wall and lumen visualization scores for the non-contrast images in healthy volunteers (n=10) are presented in **Tables 2 and 3** respectively. The DLBIR images showed overall statistically significant improvement in vessel wall (10/11) and lumen (11/11) depiction in nearly all evaluated segments (**Fig. 1**). For the basilar artery wall visualization, the DLBIR images were rated better in quality though the difference was not statistically significant.

**Table 2**: Mean vessel wall reader evaluation scores for the non-contrast and post contrast sequences for the IC-VWI images. P-values ≤0.05 are highlighted in bold.

| Vessel segment | DLBIR NC (n=10) | Clinical-NC (n=10) | p-value | DLBIR CE (n=5) | Clinical CE (n=5) | p-value |
|---|---|---|---|---|---|---|
| **Rt ICA** | 1.67 | 2.02 | **<0.01** | 1.5 | 1.75 | 0.13 |
| **Lt ICA** | 1.67 | 2.02 | **<0.01** | 1.45 | 1.75 | 0.06 |
| **Rt MCA** | 1.22 | 1.67 | **<0.01** | 1.2 | 1.75 | **<0.01** |
| **Lt MCA** | 1.3 | 1.65 | **<0.01** | 1.2 | 1.8 | **<0.01** |
| **Rt ACA** | 1.75 | 2.2 | **<0.01** | 1.55 | 2.2 | **<0.01** |
| **Lt ACA** | 1.8 | 2.22 | **<0.01** | 1.55 | 2.2 | **<0.01** |
| **Rt V4** | 1.55 | 1.8 | **<0.02** | 1.65 | 1.9 | 0.26 |
| **Lt V4** | 1.47 | 1.75 | **<0.01** | 1.45 | 1.9 | **<0.05** |
| **Basilar** | 2.07 | 2.22 | 0.28 | 1.7 | 2.15 | 0.58 |
| **Rt PCA** | 1.5 | 1.92 | **0.01** | 1.3 | 1.75 | **<0.03** |
| **Lt PCA** | 1.57 | 1.9 | **0.01** | 1.35 | 1.9 | **<0.01** |

**Table 3**: Mean vessel lumen reader evaluation scores for the non-contrast and post contrast sequences for the IC-VWI images. P-values ≤0.05 are highlighted in bold.

| Vessel segment | DLBIR NC (n=10) | Clinical NC (n=10) | p-value | DLBIR CE (n=5) | Clinical CE (n=5) | p-value |
|---|---|---|---|---|---|---|
| **Rt ICA** | 1.55 | 1.72 | **<0.01** | 1.55 | 1.75 | 0.10 |
| **Lt ICA** | 1.57 | 1.77 | **<0.01** | 1.55 | 1.7 | 0.19 |
| **Rt MCA** | 1.05 | 1.35 | **<0.01** | 1.15 | 1.5 | **<0.02** |
| **Lt MCA** | 1.2 | 1.42 | **<0.01** | 1.2 | 1.55 | **0.03** |
| **Rt ACA** | 1.1 | 1.35 | **<0.01** | 1.05 | 1.55 | **<0.01** |
| **Lt ACA** | 1.07 | 1.4 | **<0.01** | 1.2 | 1.55 | **0.03** |
| **Rt V4** | 1.52 | 1.7 | **0.05** | 1.7 | 2 | 0.16 |
| **Lt V4** | 1.45 | 1.65 | **<0.01** | 1.65 | 1.85 | 0.30 |
| **Basilar** | 1.7 | 1.92 | **<0.05** | 1.35 | 1.9 | **0.01** |
| **Rt PCA** | 1.32 | 1.55 | **<0.01** | 1.3 | 1.6 | **<0.03** |
| **Lt PCA** | 1.35 | 1.57 | **<0.01** | 1.25 | 1.6 | **<0.02** |

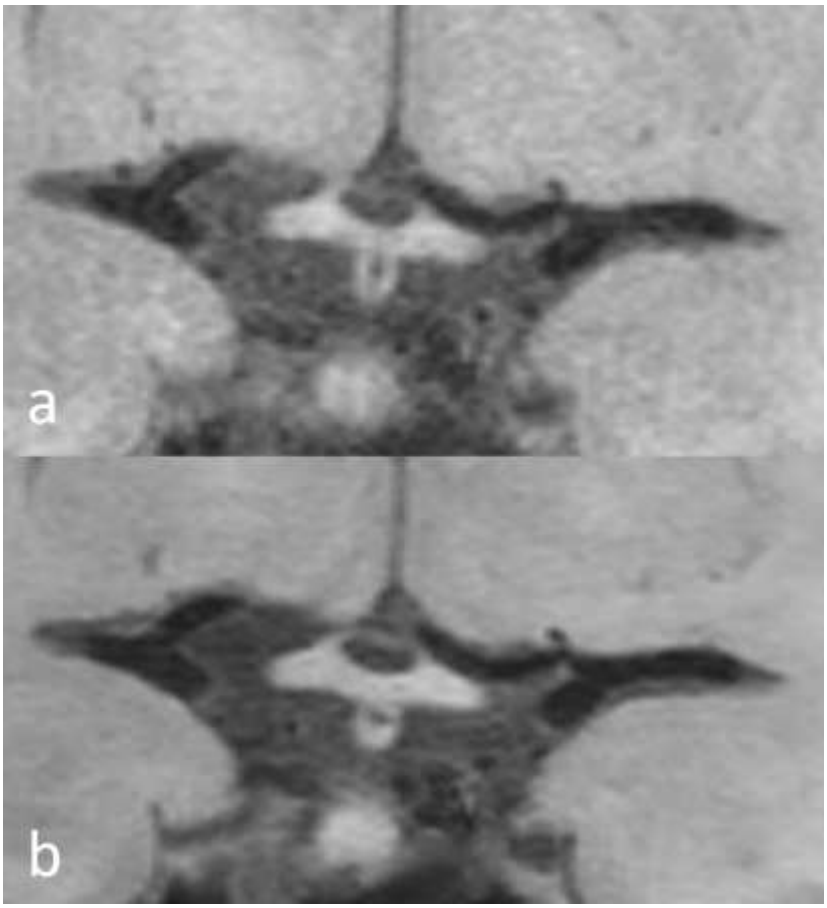


**FIG 1**. Coronal MPR images of the clinical (a) and DLBIR (b) sequence showing better visualization of the ICA terminus bilaterally, along with reduced background image noise (b).

Similar trends were also noted for the post-contrast sequences in patients (n=5), where DLBIR images were consistently rated better for wall and lumen visualization (table 2 and 3), with the image quality differences being statistically significant in majority of segments (vessel wall [7/11]; lumen [7/11]). DLBIR images were consistently rated as having lowest image noise (60/60 [15 subjects x 4 readers]) and more uniform CSF signal

(60/60) by all readers, and as having higher image sharpness (45/60) by most readers. The depiction of various intracranial findings was also consistently noted to be similar or better on the DLBIR images (**Fig. 2-5**). Flow artifacts in distal vessels were noted to be overall similar, but better seen on the DLBIR images given the reduced image noise and improved image sharpness.

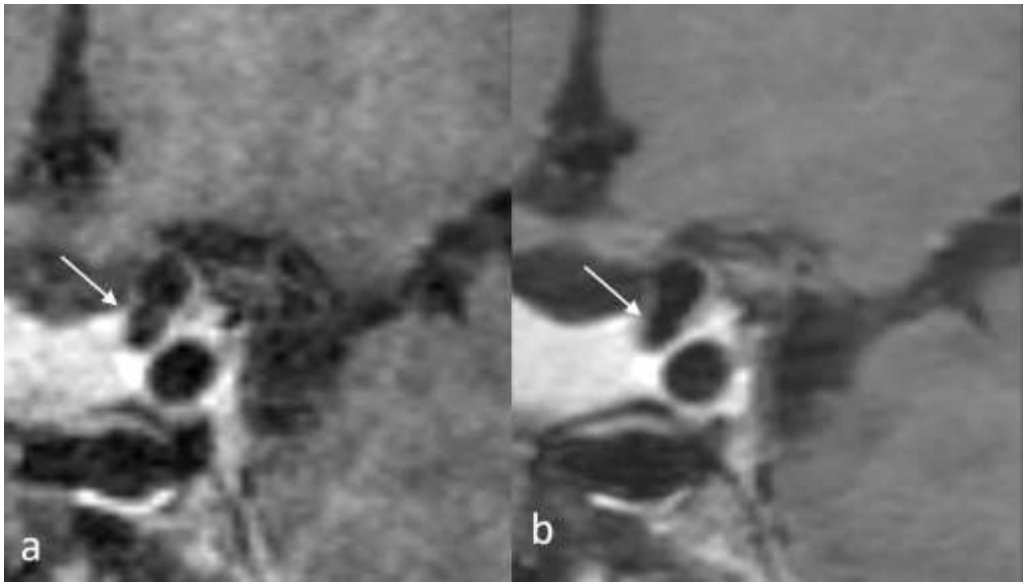


**FIG 2**. Coronal MPR post contrast images of the clinical (a) and DLBIR (b) sequence show a medially projecting left ICA aneurysm (arrows). Note that the aneurysm wall is better depicted in the DLBIR image (b).

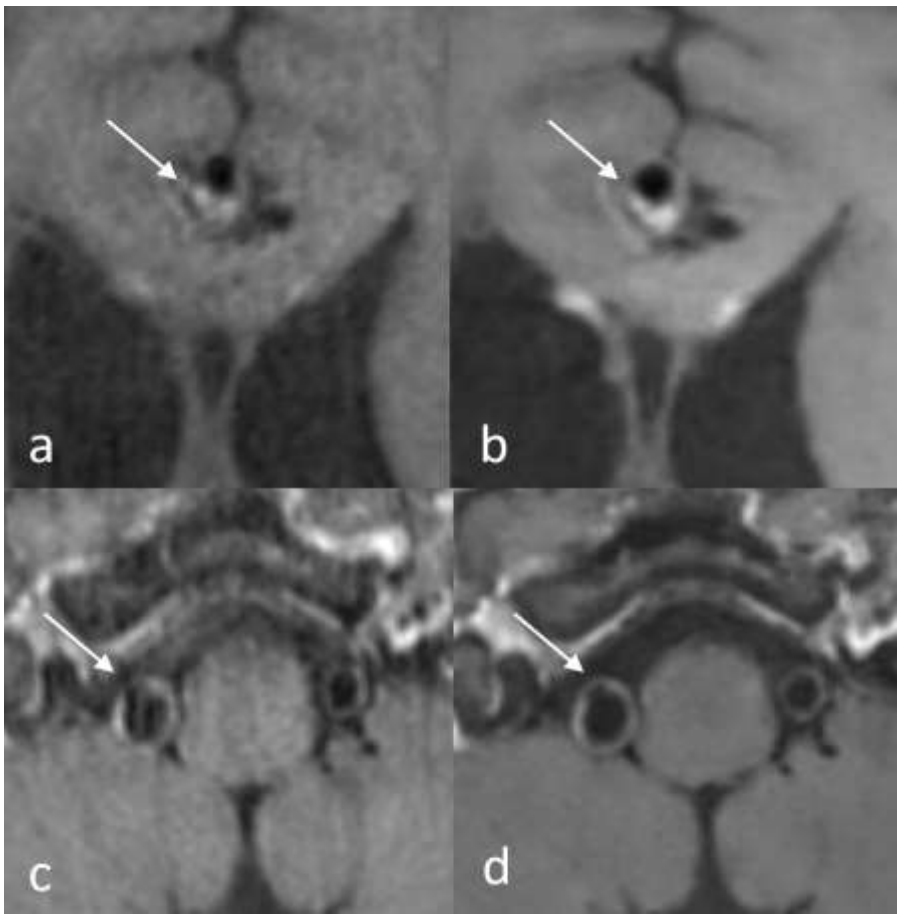


**FIG 3**. Post contrast reformatted images in two different patients. The top row shows atherosclerotic involvement in the right A2 ACA segment on the clinical (a) and DLBIR (b) images (arrows). The bottom panel, from another patient, shows early atherosclerotic changes in the right V4 segment (arrows). The hypointense wall signal corresponded to underlying calcification on the CT images (not shown) and is better appreciated on the DLBIR image (b).

## DISCUSSION

We evaluated DLBIR based and clinical IC-VWI T1-SPACE sequences for image quality across a subset of healthy volunteers and patients and noted that DLBIR images provided consistently improved vessel wall visualization, reduced intra-luminal artifacts, reduced image noise and provided uniform CSF signal when compared to the clinical VWI sequence, besides the approximately 30% reduction in scan times (446 secs for clinical sequence versus 323 secs for DLBIR sequence). The depiction of intracranial pathologies was also noted to be similar or better on the DLBIR images. Our preliminary findings are promising in terms of achieving clinically acceptable scan times for IC-VWI and need to be further validated on a larger cohort.

Given the technically challenging nature of IC-VWI, simultaneously overcoming multiple challenging requirements of improved wall signal, reduced intra-luminal flow artifacts and overall better image quality in clinically reasonable scan times is critical before widespread clinical adoption. In recent years, a few studies have shown that deep neural network-based image denoising methods may outperform conventional image denoising algorithms. This has further led to both self-supervised and unsupervised networks being proposed to reduce image noise and improve image quality.[9, 11, 17] Jung et. al., for example, recently proposed a MR-self Noise2Noise framework to improve image quality of MPRAGE images on brain scans.[11] The proposed network led to improvements in image quality over conventionally acquired images. Limited evaluation of T1-SPACE VWI images also showed improvement in image quality, although no evaluation of post contrast images was performed. Additionally, as the previously acquired images were retrospectively denoised, no improvements in scan times were investigated.

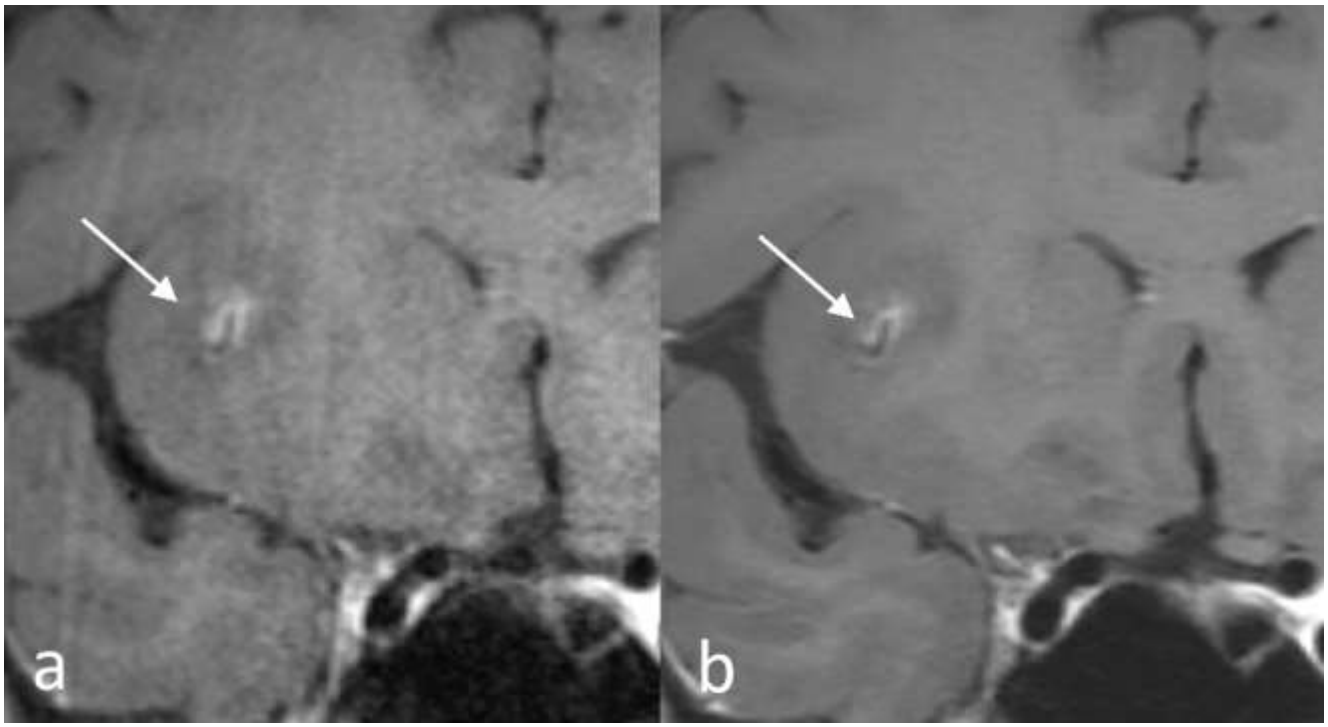


**FIG 4**. Coronal MPR post contrast images in a patient with biopsy proven cerebral amyloid angiopathy related inflammation. The vessel wall and surrounding leptomeningeal enhancement is appreciated on both clinical (a) and DLBIR (b) images. Note the improved background noise on the DLBIR images

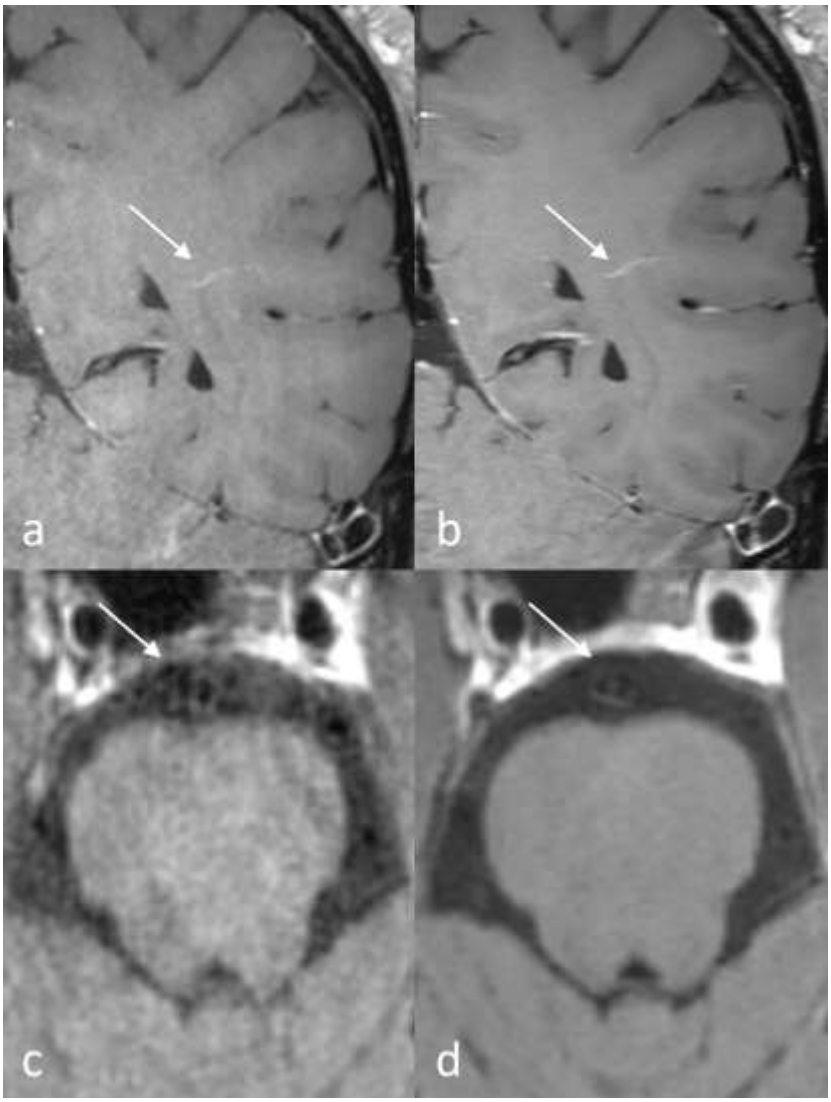


**FIG 5**. Top row images (a, b) from a patient show an incidental developmental venous anomaly in the left temporal region (arrow), equally well seen on the clinical (a) and DLBIR (b) images. Bottom row panel (c, d) from another patient with basilar artery fenestration. Image acceleration artifacts in the clinical image (c) almost obscure the underlying fenestration which is better seen on the DLBIR images (d).

Similarly, Zhou et. al., also developed a convolutional neural network (CNN) to retrospectively enhance acquired turbo spin echo images with point spread function blurring, demonstrating that images acquired with a longer echo-train length (ETL) could be retrospectively enhanced to produce similar image sharpness as images acquired using a shorter ETL.[17] Though the model offers improved image quality and potential scan time savings of about 25% when acquiring sequences with longer ETLs, the CNN must be retrained for different sequence parameters, especially when changing ETL, repetition time and driven equilibrium condition. Additionally, the impact of CNN-based processing on post-contrast sequences was not evaluated.

The current work shows that DLBIR images may not only help improve image quality, but also can provide considerable time savings, allowing for easier and widespread implementation in routine clinical practice. The reduced image noise, and consequently improved image quality can potentially improve reader confidence in

image interpretation. The savings in gradient times provide further room for adding additional tissue weightings such as T2-WI or time-of-flight MRA while maintaining overall scan times. Even though we only evaluated a limited number of patients with intra cranial lesions, these cases included a diverse array of pathologies, including atherosclerotic disease, cerebral amyloid angiopathy related inflammation, aneurysm, basilar fenestration, and developmental venous anomaly. In all cases, lesion depiction was similar or better on the DLBIR images. For example, the DLBIR images better depicted the aneurysm wall despite proximity to the cavernous sinus (fig 2). Similarly, visualization of atherosclerotic disease in the distal ACA was again better with the DLBIR sequence, as was the wall calcification in the V4 segment of vertebral artery (fig 3). Finally, the basilar artery fenestration in another patient (fig 5) was able to be visualized on the DLBIR images, despite near complete obscuration on the T1-SPACE images secondary to image noise. In the patient who eventually went on to have a brain biopsy and shown to have cerebral amyloid angiopathy related inflammation (fig 4), the DLBIR images had better image quality despite visualization of the pathology on both sequences.

Image quality rating on various parameters was consistently improved with the DLBIR images. This was largely statistically significant. Some of the 'non-significant' improvements may be secondary to the small sample size or type II error. More importantly, all image quality parameters trended towards improved ratings (table 2 and 3) despite scan time reduction by approximately 30%. Unlike compressed sensing and conventional parallel imaging-based VWI techniques where reduced scan times are accompanied by reduction in contrast-to-noise ratio and image quality, the overall image quality is improved along with reduced image noise despite similar reduction in gradient times. This is essentially achieved by a DL-based image reconstruction that is optimized for the same acquisition as employed for conventional parallel imaging. Instead of a linear reconstruction used in parallel imaging, the DLBIR sequence uses a k-space-to-image reconstruction based on deep learning. Prominent limitations of the DLBIR-based IC-VWI are the vendor specific nature and limited availability of the sequence currently. However, given the several technical challenges in IC-VWI, these preliminary results are encouraging. Future studies could further explore the usefulness of DLBIR-based IC-VWI in specific patient cohorts such as those with intra-cranial atherosclerosis, aneurysm or CNS vasculitis. Future work could also focus on combining DLBIR-based optimization with flow suppression techniques or compressed-sensing based IC-VWI to explore further optimizations in IC-VWI.

Despite the promising findings, our study has several limitations. We only evaluated a limited number of subjects, given the preliminary nature of the study. The generalizability of these findings would need to be further evaluated in larger cohorts with different patient groups/ disease prevalence. The evaluated DLBIR sequences are vendor specific, which limit generalizability. Other vendor specific algorithms were not evaluated. Concurrent use of intraluminal flow artifact suppression using delay alternating with nutation for tailored excitation (DANTE) pulse was not evaluated and may be further assessed in future work.[18] Our evaluation was limited to T1-weighted images and proton-density based IC-VWI sequences were not evaluated, primarily since most sites currently use T1-weighted sequences for clinical IC-VWI. Some authors have previously shown improved image quality with deep-learning based denoising on proton-density images as well.[9] This however was not the focus of our current work. Finally, objective calculation of signal-to-noise ratio on DLBIR images is mathematically complex, and only Likert-like rating from multiple readers was considered in the current work.

## CONCLUSION

Despite the multiple technical challenges in IC-VWI, there is continued enthusiasm and increasing clinical adoption, given its role in cerebrovascular pathologies. The adoption and further optimization of DLBIR methods may improve image quality while simultaneously reducing scan times to clinically acceptable gradient times. Our encouraging preliminary results should be further validated in a larger, multi-vendor setting.

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