

Comparative Analysis of Image Quality and Scan Time of Artificial Intelligence-Assisted Compressed Sensing and Conventional Non-ACS MRI Sequences in Brain Imaging

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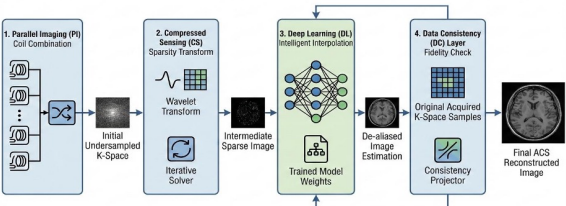
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Introduction

Magnetic Resonance Imaging (MRI) remains the clinical gold standard for soft-tissue characterization; however, its utility is frequently constrained by protracted acquisition times, which increase susceptibility to motion artifacts and limit patient throughput. Fast MRI is important for improving patient throughput and mitigating motion artifacts, which is particularly beneficial for pediatric and seizure patients. Shorter examination times reduce the need for pediatric sedation, enhance safety, and enable timely diagnosis in uncooperative patients(1). Standard MRI sequences are limited by the Nyquist-Shannon theorem, which requires fully sampled k-space data to avoid aliasing(2). This creates a constant compromise between scan time, SNR, and

spatial resolution (3)(4). ACS, or Deep Learning-based Compressed Sensing (DL-CS), improves upon older methods by combining the acceleration techniques of PI and CS with deep learning algorithms (5)(6). In a standard acquisition, the scanner fills the raw data matrix (k-space) line by line; however, ACS sequences intentionally acquire only a fraction of these lines through incoherent under sampling, typically maintaining a dense sampling of the k-space center for image contrast while randomly skipping peripheral lines to reduce time(7)(8).

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The reconstruction process begins by utilizing the sensitivity profiles of multi-channel receiver coils, such as SENSE or GRAPPA, for initial spatial localization(9). The CS component then exploits the mathematical property of sparsity, assuming that medical images can be compressed in a transform domain, like a wavelet, without information loss (10). Building upon this foundation, deep learning networkstrained on massive datasets of high-resolution imagesact as intelligent interpolators that augment or replace the traditional iterative CS solvers. These networks recognize complex anatomical patterns and remove aliasing noise with significantly higher speed and fidelity than traditional CS alone. Finally, to prevent structural hallucinations, a data consistency layer ensures that the AI-reconstructed image remains mathematically faithful to the originally acquired raw k-space samples(11)(12).

Despite the widespread use of ACS sequences in high-field MRI, a critical gap remains regarding its rigorous diagnostic validation in neuroimaging. Furthermore, quantitative metrics like Peak Signal-to-Noise Ratio (PSNR) do not always correlate with the qualitative diagnostic confidence required in clinical practice(13)(14). This study aims to bridge the existing research gap through a comprehensive multiparametric comparative analysis of Artificial Intelligence-assisted Compressed Sensing (ACS) versus standard Non-ACS sequences using high-field 3 Tesla (3T) by comparing their qualitative and quantitative image quality and scan time in brain imaging.

Methods and Materials

This observational study was conducted at Maharishi Markandeshwar deemed University Mullana, India, supervised by Radiology department.

Study Population

The study was carried out over a period of August 2025 to January 2026. During this period, 60 patients who underwent magnetic resonance imaging (MRI) of the brain in the Department of Radiology were enrolled in the study. The participants had an average age of 40±21 years. Written informed consent was obtained from all participants prior to their inclusion in the study, and ethical principles of the Helsinki declaration revised in 2013were followed.

Inclusion Criteria

Patients, both inpatients and outpatients, who were clinically indicated for brain MRI following clinical consultation, review of past medical history, and physical examination were included in the study.

Exclusion Criteria

Patients with unknown clinical history, those with contraindications to MRI (such as implanted ferromagnetic devices or severe claustrophobia), and patients whose images demonstrated excessive motion artifacts compromising image quality were excluded. Additionally, medico-legal cases and patients who did not provide informed consent to participate in the study were also excluded.

Imaging Protocols

Table 1: Brain MRI parameters

Parameters	ACS(T2-FSE-TRA-ACS-FAST)	Non-ACS(T2-FSE-TRA-Non-ACS-FAST)
TE	107.52s	115.2s
TR	5414s	
Voxel size	0.67*0.60*5.00mm	
Gap	1.7mm	1.5mm
Acceleration level	3	-
Total acceleration factor	2.22	-
Slice thickness	5mm	
FOV	200*230mm	
Matrix size	301*384mm	

MRI brain imaging was performed using a 3-Tesla superconducting magnetic resonance imaging system (United Magnetic Resonance Omega) with a dedicated brain coil. All included patients were scanned using both ACS (T2-FSE-Trans-ACS-FAST) and Non-ACS (T2-FSE-Trans-Non-ACS-FAST) sequences in the transverse plane. Imaging protocols for the ACS sequence were optimized for clinical imaging, and the same parameters were subsequently copied and applied to the Non-ACS sequence to ensure consistency in image acquisition for comparison.

Data analysis

Multiparametric quantitative and qualitative data analysis of scan time, quantitative image quality parameters such as signal to noise ratio (SNR) and

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contrast to noise ratio (CNR), as well as qualitative image quality parameters such as white matter-grey matter differentiation, sharpness, signal homogeneity, artifact, lesion visibility and overall image quality were done using IBM SPSS statistics-V28 software. Pair sample t-test and Wilcoxon signed rank tests were used, and P-value of 0.05 was considered as significant level.

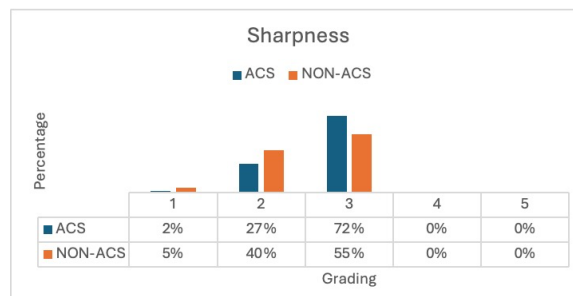
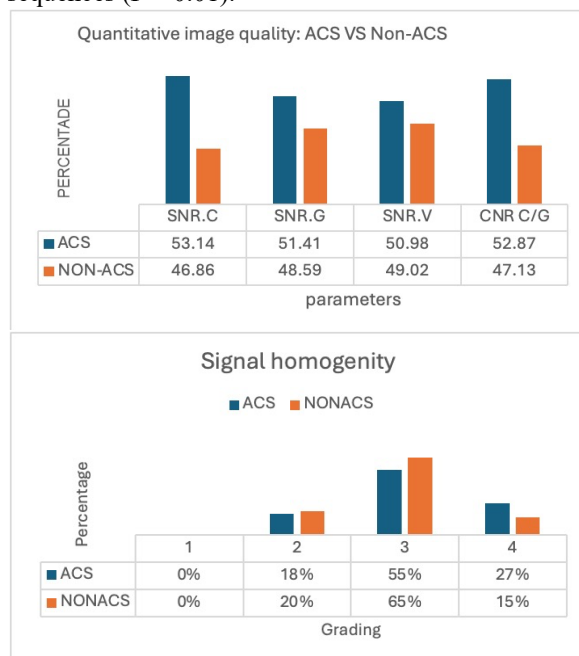
Results

Scan time

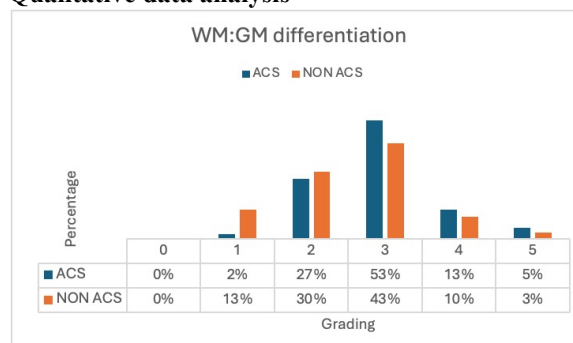
At acceleration level of 3 and total acceleration factor of 2.22, ACS sequence scan time was 49seconds, while Non-ACS sequence scan time was 103seconds, presenting 52.43% reduction in scan time of ACS over Non-ACS sequence.

Quantitative image quality analysis

The quantitative image quality analysis showed that the mean SNR of the caudate was slightly higher in the ACS group (26 ± 10.20) compared to the Non-ACS group (22.93 ± 12.46), demonstrating statistical significance ($p = 0.01$). The SNR of the genu was 21.81 ± 6.88 in the ACS group and 20.61 ± 7.42 in the Non-ACS group, with no statistically significant difference ($p > 0.05$). Similarly, the SNR of the ventricle showed no statistically significant difference between the ACS group (38.67 ± 25.89) and the Non-ACS group 37.19 ± 23.5 , $P > 0.05$. The CNR (caudate/genu) was 8.01 ± 4.05 in ACS group and 7.14 ± 4.02 in the Non-ACS group, showing a statistically significant difference between the two sequences ($P = 0.01$).



Qualitative data analysis



White matter-grey matter differentiation

White matter-grey matter (WM:GM) differentiation was qualitatively assessed using a 0–5 point grading scale, where excellent = 5, very good = 4, good = 3, poor = 2, very poor = 1, and cannot be differentiated = 0. In the ACS sequence, 53%(n=32) of images were graded as good (score 3), 27% (n=16) as poor (score 2), 13% (n=8) as very good (score 4), 5% (n=3) as excellent (score 5), and 2 (n=1) % as very poor (score 1), while no images were graded as 0. In the Non-ACS sequence, 43%(n=26) of images were graded as good (score 3), 30%(n=18) as poor (score 2), 13%(n=8) as very poor (score 1), 10%(n=6) as very good (score 4), and 3% (n=2) as excellent (score 5), with no cases graded as 0. The mode score for both ACS and Non-ACS sequences was 3, indicating that most images demonstrated good WM:GM differentiation, and statistical analysis showed no statistically significant difference between the two sequences (>0.05).

Sharpness

Image sharpness was evaluated using a 1–5 point grading scale, where excellent = 5, very good = 4, good = 3, poor = 2, and very poor = 1. In the ACS sequence, 72 (n=31) % of images were graded as good (score 3), 27% (n=28) as poor (score 2), and 2%(n=1) as very poor (score 1), while no images were graded as very good (score 4) or excellent (score 5). In the Non-ACS sequence, 55% (n=33) of images were graded as good (score 3), 40% (n=24) as poor (score 2), and 5% (n=3) as very poor (score 1), with no images graded as very good (score 4) or excellent (score 5). The mode score for both ACS and Non-ACS sequences was 3, indicating that most

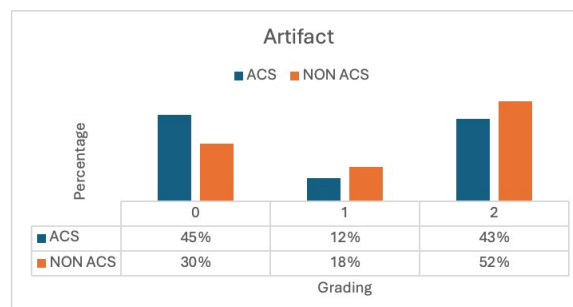
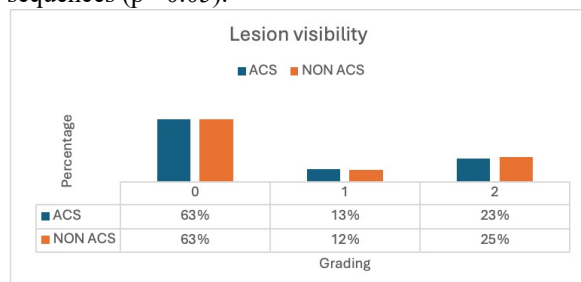
images demonstrated good image sharpness, and statistical analysis showed no statistically significant difference between the two sequences ($p > 0.05$).

Signal homogeneity

Signal homogeneity was evaluated using a 1–4 point grading scale, where homogeneous = 4, mildly heterogeneous = 3, moderately heterogeneous = 2, and severely heterogeneous = 1. In the ACS sequence, 55 (n=33) % of images were graded as mildly heterogeneous (score 3), 27% (n=16) as homogeneous (score 4), and 18%(n=11) as moderately heterogeneous (score 2), while no images were graded as severely heterogeneous (score 1). In the Non-ACS sequence, 65%(n= 39) of images were graded as mildly heterogeneous (score 3), 20%(n= 12) as moderately heterogeneous (score 2), and 15%(n= 9) as homogeneous (score 4), with no images graded as severely heterogeneous (score 1). The mode score for both ACS and Non-ACS sequences was 3, indicating predominantly mildly heterogeneous signal distribution in both sequences, and no statistically significant difference was observed between the two groups ($p > 0.05$).

Artifact

Artifact severity was assessed using a 0–2 point grading scale, where absent = 0, present and interfering with image interpretation = 1, and present but not interfering with image interpretation = 2. In the ACS sequence, 45% (n= 27) of images showed no artifacts (score 0), 43% (n= 26) showed artifacts that did not interfere with image interpretation (score 2), and 12%(n= 7) showed artifacts that interfered with image interpretation (score 1). In the Non-ACS sequence, 52% (n= 31) of images were graded as score 2, 30%(n= 18) as score 0, and 18%(n= 11) as score 1. The mode score was 0 for the ACS sequence and 2 for the Non-ACS sequence, and no statistically significant difference was observed between the two sequences ($p > 0.05$).

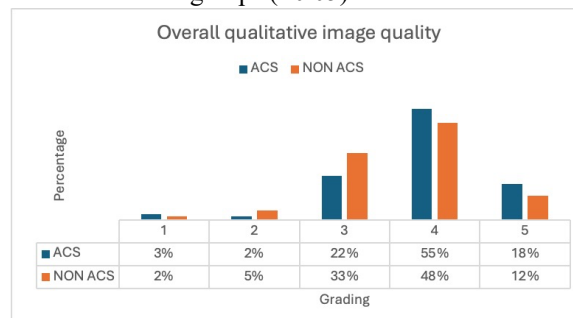


Lesion visibility

In the ACS sequence, 63%(n= 38) of images showed no lesion (score 0), 23% (n= 14) of images had well-visible lesions (score 2), and 13% (n= 8) of images showed lesions that were present but not clearly visible (score 1). Similarly, in the Non-ACS sequence, 63% (n=38)of images showed no lesion (score 0), 25% (n= 15) of images had well-visible lesions (score 2), and 12%(n= 7) of images showed lesions that were present but not clearly visible (score 1). The mode score for both sequences was 0, reflecting that most images did not contain lesions. Among the images with lesions, the majority were well visualized, and no statistically significant difference in lesion visibility was observed between ACS and Non-ACS sequences ($p > 0.05$).

Overall qualitative image quality

Overall image quality was assessed using a 1–5 point Likert scale, where excellent = 5, very good = 4, good = 3, poor = 2, and very poor = 1. In the ACS sequence, 55%(n= 33) of images were graded as very good (score 4), 22% (n= 13) as good (score 3), 18% (n=11)as excellent (score 5), 3% (n= 2) as very poor (score 1), and 2% (n= 1) as poor (score 2). In the Non-ACS sequence, 48% (n=29) of images were graded as very good (score 4), 33% (n= 20) as good (score 3), 12% (n= 7) as excellent (score 5), 5% (n= 3) as poor (score 2), and 2% (n= 1) as very poor (score 1). The mode score for both ACS and Non-ACS sequences was 4, indicating generally very good overall image quality in both sequences, and no statistically significant difference was observed between the two groups (>0.05).



Discussion

This study aimed to comparatively evaluate the quantitative and qualitative image quality parameters, alongside scan time efficiency, of AI-assisted compressed sensing (ACS) versus conventional Non-ACS sequences in brain MRI. Across 60 patients (mean age 40 ± 21 years), a primary advantage of ACS is the optimization of clinical workflow through rapid acquisition. We observed a substantial 52.43% reduction in scan time with ACS sequences compared to Non-ACS. This acceleration significantly outpaces the time savings reported in some recent literature for neuroimaging. For instance, Gu et al.(15) reported a 29.2% scan time reduction in brain MRIs for elderly patients, while studies on musculoskeletal and spine imaging have reported reductions ranging from 18.9% to 40% depending on the anatomical region (16)(17).

However, our high acceleration factor is heavily corroborated by recent deep-learning validations in other anatomical regions. For example, Dratsch et al. (18) demonstrated a comparable 54% faster image acquisition (178 s versus 384 s) for 3D knee MRI sequences using a deep learning-based algorithm. Similarly, in shoulder MRI, a deep learning-based algorithm allowed for extreme acceleration, showing that 4-fold acceleration for Non-ACS sequences and 13-fold acceleration for 3D sequences could be achieved without a significant loss of quality compared to reference sequences(19). The superior acceleration achieved in our study highlights the robust capability of deep learning reconstructive networks to maintain k-space integrity even at higher undersampling factors.

Quantitatively, ACS yielded statistically significant improvements in localized signal-to-noise ratio (SNR) and contrast-to-noise ratio (CNR). Specifically, SNR at the caudate nucleus was significantly higher in ACS sequences ($p = 0.01$), and CNR between the caudate nucleus and the genu of the corpus callosum demonstrated a distinct advantage ($p = 0.01$). No statistically significant differences in SNR were observed at the genu of the corpus callosum or the lateral ventricle. These findings add an important layer to the existing literature. While Zheng et al.(20) found no significant difference in CNR and slightly higher SNR in conventional compressed sensing for rectal imaging, and Sui et al. (17) reported no significant differences in SNR/CNR for lumbar spine imaging, our data suggests that ACS may provide targeted quantitative benefits in specific neuroanatomical regions, enhancing intrinsic tissue contrast where standard sequences often struggle. This potential for objective improvement is supported by wider musculoskeletal findings, where AI-based reconstruction of shoulder MRI achieved better objective image quality than

conventional compressed sensing utilizing the same acceleration factor.

ACS sequences provided better gray and white matter differentiation, with fewer cases rated as very poor (2% vs. 13% in Non-ACS). Image sharpness and signal homogeneity were also markedly improved. Importantly, ACS demonstrated a superior ability to suppress artifacts; 45% of ACS images were completely artifact-free compared to only 30% of Non-ACS images, and artifacts interfering with interpretation were notably less frequent. This aligns closely with Gu et al.(15), who concluded that ACS provides superior image quality and strong diagnostic reliability ($\kappa = 0.70-0.86$). Furthermore, our qualitative results mirror the broader consensus seen across musculoskeletal, pelvic, and spinal imaging(16), (20).

Conclusion

In conclusion, AI-assisted compressed sensing (ACS) represents a significant advancement in brain MRI, allowing faster scan times without sacrificing diagnostic quality. Compared to conventional Non-ACS sequences, ACS maintains and, in several key areas, enhances overall image quality while drastically reducing acquisition times. Our study demonstrates that ACS sequences can be efficiently used in brain imaging, especially for pediatric patients, patients with uncontrollable movements, and other emergency cases where fast imaging and the reduction of motion artifacts are required.

Limitations and Future Recommendations

This study included only two non-contrast MRI sequences acquired in the transverse plane, and both the acceleration level and acceleration factor were fixed to provide diagnostic image quality. Future studies should include a wider range of standard MRI sequences acquired in different imaging planes, with variable acceleration factors and acceleration levels. Additionally, both contrast-enhanced and non-contrast MRI examinations should be evaluated to validate the findings across the full spectrum of brain MRI imaging.

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Conflict of interest

All authors have no conflict of interest

Data privacy

All patient data were collected for clinical use and kept per institutional data management. No personal identification data were collected for research purpose.

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