

REVIEW ARTICLE

Breaking the Limits of Low-Field MRI: Deep Learning Approaches to Image Enhancement

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ABSTRACT

Low-field magnetic resonance imaging (LF-MRI) has emerged as a transformative technology, offering portable and cost-effective solutions for medical imaging in resource-limited settings. However, LF-MRI systems face inherent challenges, including low signal-to-noise ratio (SNR) and reduced spatial resolution, which can compromise diagnostic accuracy. To systematically address these fundamental limitations, which involve complex, nonlinear image transformations, deep learning (DL) presents a powerful solution due to its proven capability in learning such mappings from data. This review explores the pivotal role of DL techniques in overcoming these limitations, focusing on two critical applications: denoising and super-resolution. Recent advancements in DL architectures—such as U-Net, generative adversarial networks (GANs), and diffusion models (DMs)—have demonstrated remarkable success in enhancing LF-MRI image quality. For denoising, supervised models like U-Net and denoising auto-encoders (DAEs) effectively suppress noise while preserving anatomical details, while unsupervised approaches (e.g., Cycle-GANs) leverage unpaired datasets to bridge the gap between low-field (LF) and high-field (HF) MRI. In super-resolution, DL models like 3D U-Net and residual channel attention networks (RCANs) reconstruct high-resolution images from LF inputs, enabling finer detail visualization for clinical diagnostics. Key findings highlight the superiority of DL over conventional iterative methods in adaptability, robustness, and real-time performance. However, challenges persist, including data dependency, computational costs, and limited interpretability. Innovations such as diffusion-driven neural representations and dual-acquisition 3D super-resolution further push the boundaries of LF-MRI quality. This review underscores DL's potential to democratize MRI access, particularly in low-resource regions, while outlining future directions: improving generalization, reducing training data requirements, and integrating postprocessing pipelines. By directly tackling the key barriers of image quality, DL-enhanced LF-MRI is poised to make a significant impact in clinical scenarios where accessibility and speed are paramount, such as point-of-care diagnostics and emergency clinic, thereby helping bridge global healthcare disparities.

1 | Introduction

1.1 | History of Low-Field and Portable MRI: Utilities and Limitations

For several years, low-field magnetic resonance imaging (LF-MRI) system has been at the forefront of medical imaging, providing a noninvasive method to explore the intricate structures within the human body [1–3]. The root of LF-MRI could trace back to early MRI research concepts, gaining traction with advancements in magnet design [4–7]. These systems target environments traditionally lacking advanced medical imaging capabilities by reducing magnetic field strength to below 1T, minimizing infrastructure requirements and enabling easier installation and operation in decentralized medical settings [8, 9]. LF-MRI could fill the gap that conventional MRI systems face as insufficient clinical requirements and low flexibility [10, 11]. For instance, it could be equipped in low- and middle-income regions, where MRI implementations could not satisfy the need of in the local clinic [12, 13]. Many research works regarding the LF-MRI system and imaging quality enhancement had emerged.

Based on magnetic field strength, LF-MRI systems can be further categorized into low field (0.1–1 Tesla) and ultra-low field (<0.1 Tesla) MRI. Typical LF scanners include the 0.5T Synaptive Evry [14, 15] intraoperative scanner and the 0.55T Siemens Magnetom Free. Max [16, 17]. One well-known ultra-low field scanner is the 0.064T Hyperfine Swoop head scanner [18–20], which has been adopted by many groups globally. Additionally, several research initiatives have developed custom-designed systems, such as the 0.05T permanent dipole system at Chongqing University [21] and the 0.055T system at Hong Kong University [22, 23]. The clinical application of these LF portable MRI represents a significant advancement in making imaging more accessible. Not only do these compact systems facilitate rapid deployment in diverse clinical and field settings, but they also meet special critical needs (e.g., pediatric scan) in immediate care scenarios such as emergency medicine and disaster response, ensuring timely access to diagnostic information [6, 24, 25]. However, LF-MRI systems often experience significant noise, primarily due to the inherently lower signal-to-noise ratio (SNR) compared to high-field MRI (HF-MRI) systems [26]. This noise originates from various sources, including the electronic components of the MRI scanner (e.g., the preamplifier noise [27, 28]), thermal noise (e.g., Johnson-Nyquist Noise, majorly form the receiver coil [29–31]), and the magnetic environment itself (i.e., electromagnetic interference, EMI [32–35]). The lower magnetic field strength contributes to weaker signal emissions from tissues, making it difficult to distinguish between true signals and noise. Resolution is another limitation of LF-MRI, because weaker B_0 reduced SNR and forced larger voxels with longer scan periods. Thus, resolution recovery became the second key aspect focusing on the image quality enhancement. It is essential for evaluating intricate anatomical details and small pathological changes and reduce the processing time [36].

Many conventional iterative methods were developed to tackle these problems. Examples to improve resolution could be found in the applications of sparse sampling [37]

or interpolation [10, 38, 39]. Other techniques focusing SNR improvement could also be witnessed in denoising methods (e.g., signal-image domain filtering [40]) or tissue-wise segmentation toolbox (e.g., the FMRIB automated toolbox FSL-FAST [26]). However, these approaches often face significant limitations as excessive parameter tuning, which increased computational demands and led to variability in the results. Additionally, conventional iterative methods can be sensitive to noise and artifacts inherent. These methods are also “capped” in terms of performance, and their improvement is limited compared to DL. These disadvantages highlight the need for more robust and efficient approaches, such as those derived from deep learning, to advance LF-MRI technology and improve diagnostic outcomes.

1.2 | DL-Based Models and LF-MRI

The resurgence of low-field MR imaging in recent years has largely been driven by the advances in DL techniques. Learning-based models, particularly neural networks (e.g., U-net and fully convolutional networks [41–43]), are instrumental in enhancing image quality and diagnostics. Generally, various DL applications exploit prior anatomical knowledge from extensive datasets and overcome SNR limitations and facilitating efficient. Owing to the nonlinearity, learning-based methods increased the complexity and the stability of the computation and avoid the limitation as being a single-layer model. In addition to conventional supervised networks, typical unsupervised architectures such as generative adversarial networks (GANs) [44] and extensions (e.g., conditional GANs [45, 46] and Cycle-GANs [47–49]) have been developed, which reduced the need of paired images between LF and HF. Further unsupervised structures, for example, diffusion models (DMs) [50] and transformer learning [51], delivered enhanced image detail and fidelity. Depending on the application, learning-based structures can be tailored to meet specific training destinations and carefully captured training datasets where developments are needed. Figure 1 exhibits a visual comparison in the case of super-resolution. Detailed structures of these learning structures will be discussed in the following sections.

The foundation that guarantees the performance of DL-based models is the large scale and precisely designed training data, which benefit the network structures to learn patterns and reveal characteristics. Regarding the two main perspectives of LF enhancement, different learning-based models were developed and delivered many construction models. Datasets of denoising-based NNs are generated with pairs of noise-added (as inputs) and clean data (as labels or ground truth). Through this strictly supervised learning process, the networks learn to identify and suppress noise patterns while preserving essential anatomical details, and the final output will be more accurate with a higher SNR [52–57]. One typical noise comes from electromagnetic interference (EMI). EMI signals fluctuate due to nearby sources and the human body acting as an antenna [58]. Several training-set designs approach this issue by identifying and isolating interference patterns from the true imaging signals.

Considering the super-resolution training, the dataset was generally defined as the direct reconstruction from lower- to

higher-resolution images. Well-trained models can improve the detail and sharpness in MRI scans, making them more comparable to those acquired from HF systems. The capability of enhancing image quality is particularly important for applications requiring precise anatomical visualization. The studies [59–63], such as in neuroimaging and oncological assessments, revealed

that every additional detail can inform a more nuanced understanding of disease progression and response to treatment. However, learning-based models in low-field MRI face general challenges such as data dependency, high computational demands, lack of interpretability, and difficulties with generalization and artifact sensitivity, limiting their clinical application.

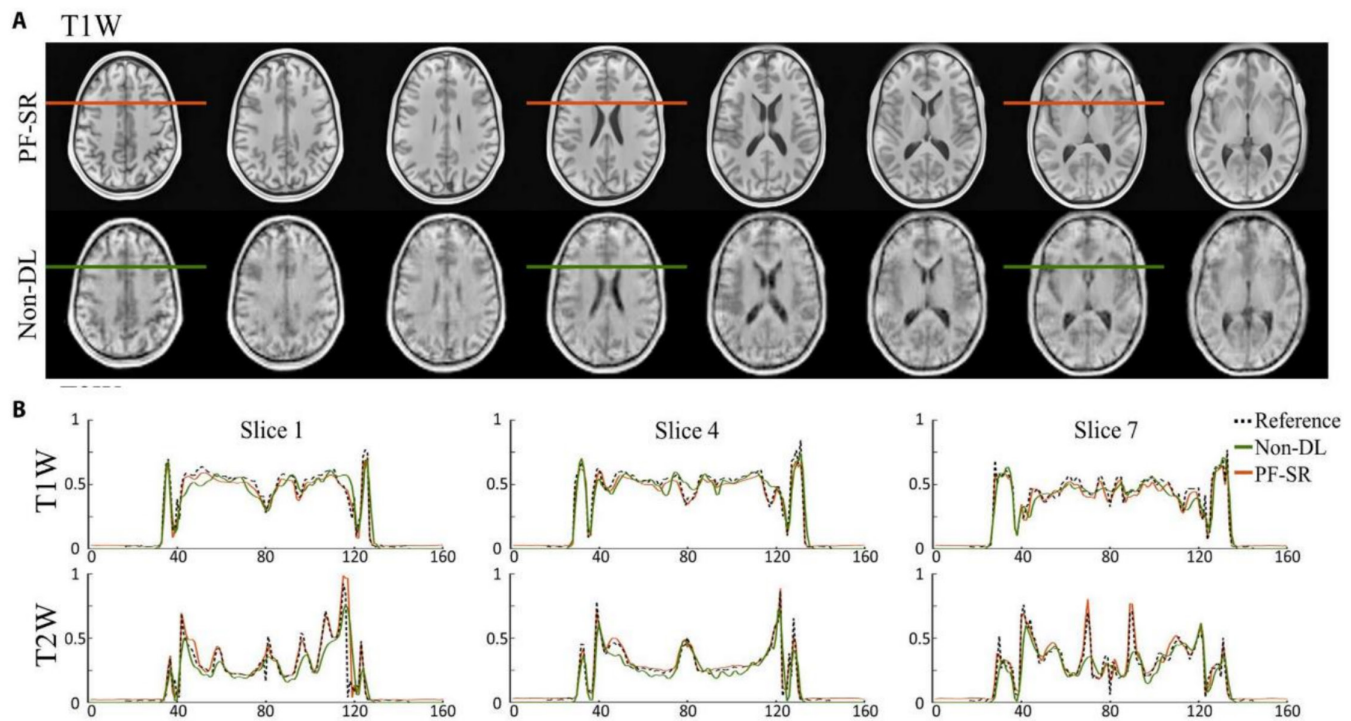


FIGURE 1 | Comparison between proposed DL method (partial Fourier super-resolution model) and traditional iterative method on 3D synthetic brain with noise [23]. LF data were simulated from HCP S1200 dataset (3T Siemens “Connectome Skyra” at WashU), including 3D T1W MPRAGE and T2W SPACE, both with 0.7 mm isotropic resolution. The visual illustration is performed on (A) T1W image and (B) intensity line profiles of both T1W and T2W data.

TABLE 1 | General comparison of deep learning-based and conventional algorithms in low-field MRI.

Feature	Deep learning-based methods	Conventional algorithms
Performance	Superior performance in image reconstruction, denoising, and classification through learned patterns	Performs well in basic tasks but limited in complex situations
Data requirements	Require large-labeled datasets but can generalize well with enough data	Operate effectively on smaller datasets, less dependent on vast amounts of data
Adaptability	Highly adaptable to different tasks with fine-tuning capabilities	Specifically designed for targeted problems, less flexible and extendable
Robustness	Greater robustness to noise and artifacts by learning inherent data features	More vulnerable to image noise and artifacts, may require additional corrections
Real-time capability	Enhanced real-time capabilities with optimized models or hardware	Efficient in real-time applications due to simpler processing
Automated feature learning	Automatically learns and extracts relevant features, reducing the need for manual input	Relies on predefined features; manual feature engineering required
Generalization to new data	Better generalization to unseen data with appropriate training and validation	May struggle with generalization to new or different dataset variations

Table 1 listed the general advantages of DL-based methods compared to conventional iterative solutions.

1.3 | Outline of This Review Paper

This review has the following structure. First, the advancements in denoising techniques utilized in LF-MRI will be discussed, focusing on how various DL methodologies enhance image quality by effectively reducing noise levels. Next, the super-resolution approaches will be introduced, enabling the acquisition of clearer and more detailed images that are essential for accurate diagnostics. This review paper will analyze several manuscripts to introduce the various network structures employed in this context, detailing their respective methodologies and implementations. Additionally, it will cover essential aspects of data preparation and postprocessing techniques that enhance image quality.

2 | Denoising Models via Supervised and Unsupervised Learnings

DL models, particularly convolutional neural networks (CNNs), have been highly effective in addressing this issue through advanced denoising techniques. Different research works have investigated multiple networks, which were trained on public datasets (e.g., Human Connectome Project) or typically designed biostructure or tissues (e.g., fetal body) to recognize and filter out noise while preserving essential image details.

2.1 | Supervised Denoising: U-Net Architecture and Extensions

A key CNN architecture applied in denoising is U-Net [41], known for its effective encoder-decoder structure. The encoder consists of convolutional layers followed by pooling layers, which compress the image while extracting important features. The decoder uses transposed convolutions to up-sample the feature maps and reconstruct the image. U-Net incorporates skip connections that link corresponding layers in the encoder and decoder sections, preserving spatial information and fine details. This design enhances the network's ability to filter out noise while maintaining crucial anatomical details. Thus, several HF-MRI denoising experiments [64–68] selected U-Net for improving image quality and diagnostic accuracy. Inspired by the successful implementation, LF-MRI reconstruction has also applied end-to-end training using U-Net.

A classical 3D isotropic U-Net architecture has been utilized with the mapping of two identical-size input and output cubes [69]. The U-net-based architecture in Figure 2a incorporates a bottleneck block [72, 73] that designed to connect the contracting and expanding paths. This bottleneck block is defined by the following three hyperparameters: the input filter, the number of shrinking layers, and the up-sampling scaling factor. For this implementation, a scaling factor of ($k=4$) was used, in which the network first down-samples the initial dimensions to become isotropic and then performs isotropic down- and up-sampling. Training was adjusted via the loss function pixel-wised mean squared error (MSE) [41]. The central methodological innovation is a probabilistic decimation

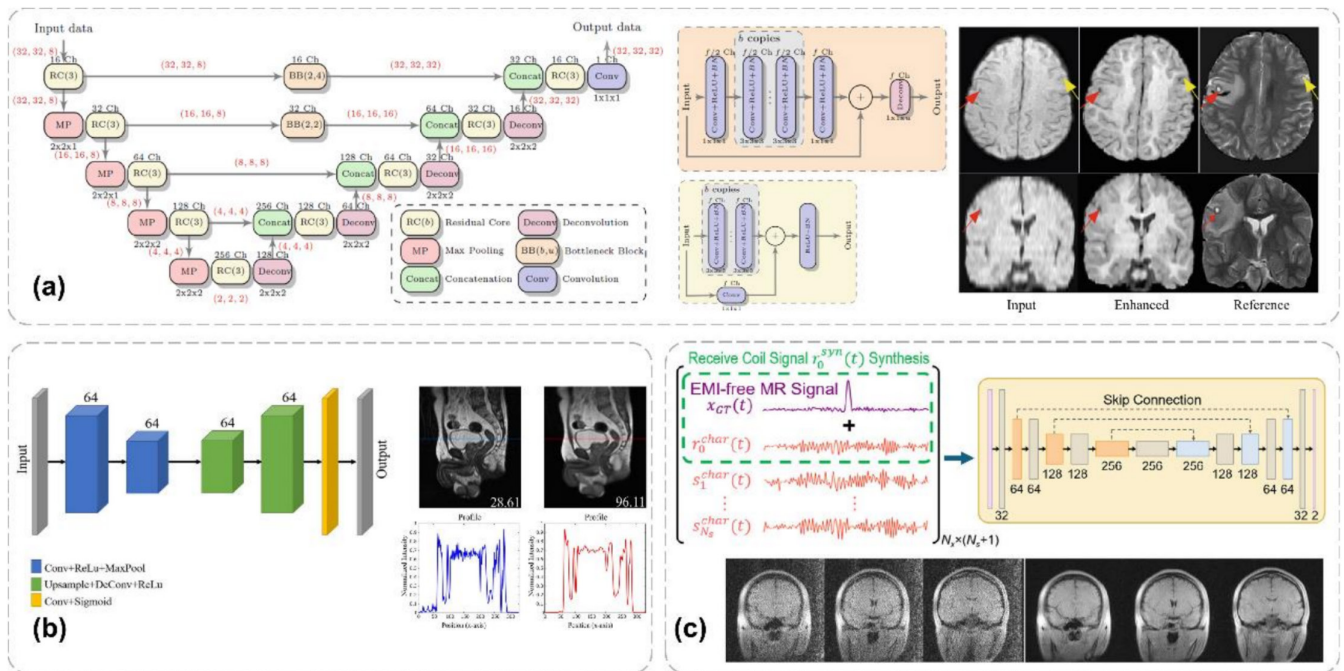


FIGURE 2 | (a) The diagram of anisotropic U-net with the illustration of bottleneck block and residual core [69], and results from image quality transfer (IQT) prediction on the LF epileptic patient data (0.36T MagSense 360 MRI System scanner, nonisotropic voxel size of 0.9 mm × 0.9 mm × 7.2 mm, including 6.0-mm slice thickness and 1.2 mm gaps). (b) Denoising auto encoder architecture [70], with image reconstruction from the 0.35T images (MR-Linac, MRIdian, ViewRay Inc., Oakwood Village, OH, USA). SNR measurement and profile lines are also exhibited. (c) A residual U-Net model is trained using 3D T1W image detected during the EMI signal characterization [71], on a home-built shielding-free 0.055T brain MRI scanner (gradient-recalled echo, TR/TE = 52/13 ms, flip angle = 40°, BW = 6.25 kHz, FOV = 250 mm × 250 mm × 320 mm, acquisition matrix = 128 × 128 × 32, and NEX = 2).

model designed to stabilize image quality transfer (IQT) training and improve low-field MRI reconstruction quality (e.g., on pediatric epilepsy data). However, the network was trained through T1-weighted images (Siemens Connectome scanner) from Human Connectome Project (HCP) dataset and make inference using the same ones, hence the diversity of the validation became the main disadvantage. A variation of conventional U-net was developed by Armando Garcia Hernandez et al. [70], known as the denoising auto-encoder (DAE). DAE was also established by the idea of U-net structure, without the layer concatenations and skip connection, shown in Figure 2b. The 2D pelvic dataset was acquired from Siemens 1.5T scanner and utilized to train the DAE model, with the Rician noise added. Loss function is customized to enforce the anatomical detection with a total variation (TV) penalty alongside MSE. The well-trained model illustrated a clinical transfer learning strategy that improved the real-world application from 0.35T MR-Linac (MRI-dian, ViewRay Inc., Oakwood Village, OH, USA). In addition, another DAE contribution by Ethan MacDonald et al. [74] exhibited the effective synthesis of high-quality (high-SNR, high-resolution) MRI from low-field, low-SNR inputs. The training was implemented using IXI database [75] containing 70 brain subjects acquired at 3T. This DAE architecture was implemented onto the seven-layer U-net structure, with the results that indicated DAE performed well with normally distributed noise. The other denoising study from David Schote et al. [76] also established a cascaded network to solve the B_0 inhomogeneity and distortion correction, which employed the U-net architecture

as the denoising section. Training data comprised retrospectively simulated LF knee MRI at $B_0 \sim 50$ mT.

EMI becomes another factor of the noise of LF-MRI system. Yujiao Zhao et al. [71] propose Deep-DSP, an architecture built from a residual U-net [73] that directly predicts EMI-free MR signals from raw data via an EMI characterization scheme from 3d-FSE acquisition. Deep-DSP enabled robust RF elimination for portable MRI. The processing pipeline is shown in Figure 2c. The model was trained using synthetic MRI data (created by adding simulated EMI-free signals to EMI-only MRI data) and EMI sensing coil data. The loss function used was L1 loss, optimized using the Adam optimizer. Evaluation data involved simulated phantoms and in vivo acquisitions. Simultaneous subjects were generated via the similar noise-adding method of training datasets. Experimental in vivo brain data were acquired from multiple EMI sensing coils on a home-built shielding-free 0.055T brain MRI scanner and a 1.5T whole-body scanner (with incomplete shielding).

Expanding upon the techniques of U-Net, diverse supervised learning architectures are explored for LF-MRI denoising. N. Koonjoo et al. [77] explore AUTOMAP, which featured two fully connected layers and multiple convolutional layers with rectifier nonlinearities, as Figure 3a shows. This work contributes the neural network directly to raw k -space data from extremely low-field MRI systems (6.5 and 47 mT). Its key innovation lies in operating in the sensor domain rather than the image domain, enabling superior noise suppression and

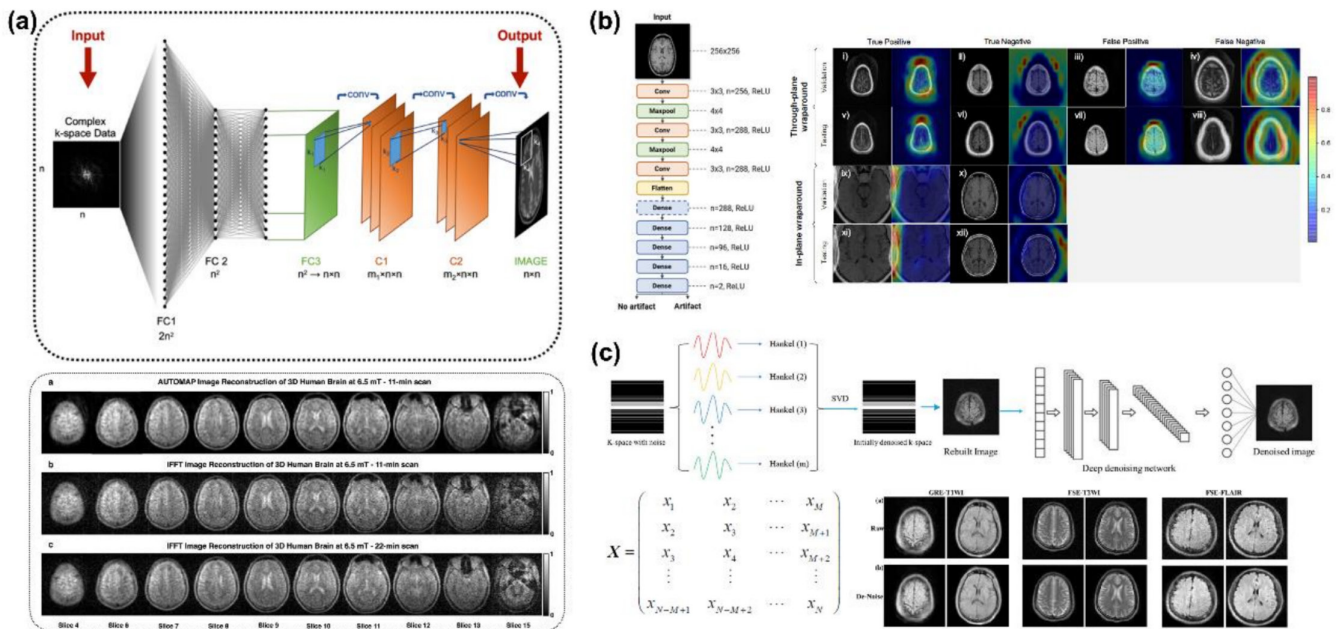


FIGURE 3 | (a) AUTOMAP neural network architecture and AUTOMAP [77] reconstruction at a customized 6.5mT scanner via a 3D human head dataset—an 11-min 3D acquisition (3D b-SSFP sequence with TR = 31 ms, matrix size = $64 \times 75 \times 15$, spatial resolution = $2.5 \text{ mm} \times 3.5 \text{ mm} \times 8 \text{ mm}$), compared with traditional IFFT (in both 11- and 22-min scan). (b) Architectures of the ArtifactID [78]: 2D convolutional neural networks, and the representative Grad-CAM heatmaps localized both types of wrap-around artifacts across TP, TN, FP, and FN samples from the validation and test sets, acquired from a 0.36T MagSense 360 (Mindray, China) open MRI scanner (parameters: TE = 15 ms, TR = 569–814 ms, slice thickness = 4–6 mm, matrix size varied from 192×192 to 512×512). (c) Denoising process for ULF MRI [21] via home-built 54mT scanner. The discrete time-domain signals can be initially structured into a Hankel matrix using the linear predictability principle. Results of Image enhancement include GRE-T1WI, FSE-T2WI, and FSE-FLAIR (Acquisition parameters for each sequence could be viewed in original manuscript).

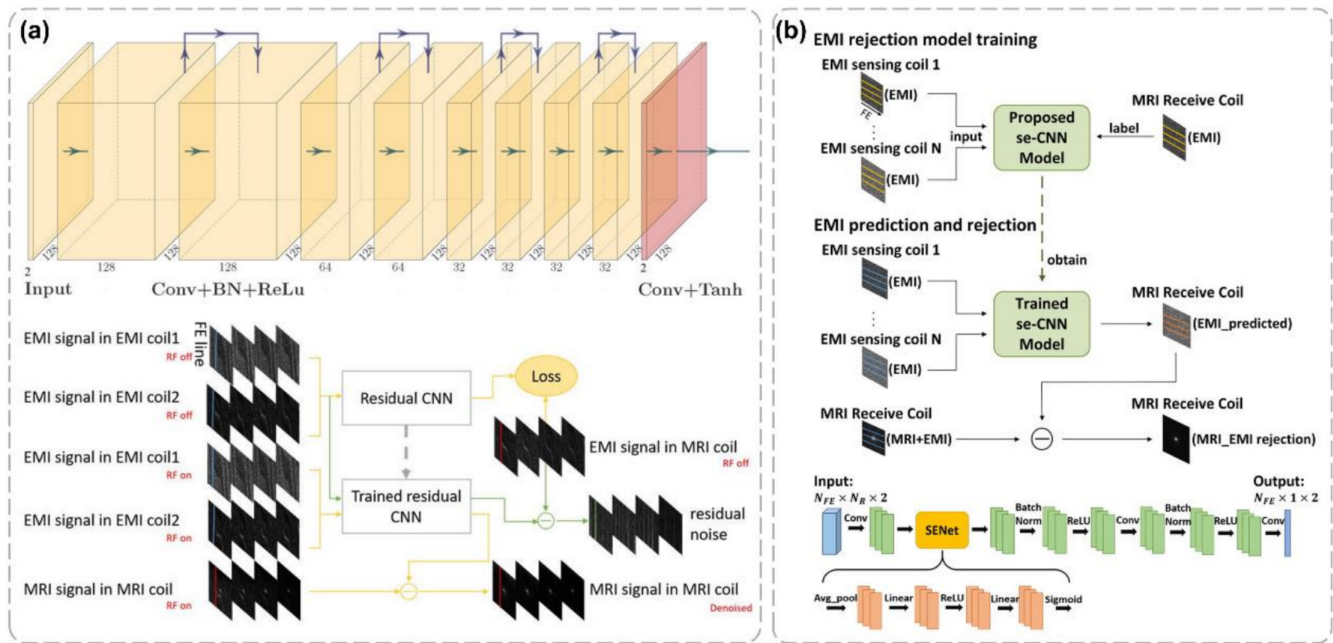


FIGURE 4 | (a) Dual-step algorithm for shielding-free LF-MRI, with a combination of four-block residual CNN and a triple-generator WGAN (TWGAN) [80]. (b) Architectures of the SENet attention mechanism incorporated within a three-layer CNN [81].

elimination of structured artifacts (e.g., spike noise) by learning a transformation between low-dimensional manifolds. Data were acquired using balanced SSFP sequences at a customized 6.5 mT scanner for both 2D phantoms and 3D in vivo brain imaging with adjustments in acquisition settings. The training datasets comprised 51,000 2D brain images from the HCP dataset and included synthetic data to improve robustness against artifacts. The training utilized RMSProp optimization with L1 loss penalties, focusing on k -space corrupted data to produce noise-free images, evaluated via metrics like RMSE and SSIM. Marina Manso Jimeno et al. developed the ArtifactID, a separate binary classification model [78], to identify wrap-around and Gibbs ringing artifacts in LF-MRI. Two datasets—one from the IXI database (Philips 1.5T, GE 1.5T, Philips 3T) and another from a LF-MRI scanner (0.36T MagSense 360 open MRI scanner)—were trained with the simulated artifacts. The key innovation of ArtifactID is the design of the modular, artifact-specific framework. This design integrates gradient-weighted class activation mapping (Grad-CAM) to provide explainable AI, visually localizing artifacts within the images. Grad-CAM visualizations [79] helped analyze model predictions and classify artifact occurrences, with the training process accounting for imbalances in artifact representation. The general structure of ArtifactID is viewed in Figure 3b. Another study conducted by Fanqin Meng et al. [21] established a two-step cascaded network that combines fast imaging from k -space with denoising, the pipeline is shown in Figure 3c. Its primary contribution is demonstrating a practical, sequential processing workflow that accelerated imaging with a supervised DL denoiser to improve the SNR and visual quality of ULF brain scans across multiple contrast weightings (T1, T2, and FLAIR). For fast imaging, the k -space data are undersampled and structured into a Hankel matrix, allowing low-rank matrix recovery via singular value decomposition (SVD) for initial noise reduction. For denoising, transfer

learning was implemented and trained on high-quality 1.5T MRI images, sourced from Chongqing University's hospital. Fine-tuning was processed using ULF MRI data acquired by the home-built 54mT scanner.

Beyond the U-net variants introduced earlier for EMI suppression, other CNN-based frameworks have also shown promising results in tackling EMI under different system configurations and noise environments. Yang Hu et al. [80] propose a dual-step denoising algorithm (DDA) for shielding-free LF-MRI, viewed in Figure 4a. The first step uses a four-block residual CNN to map EMI sensor signals to MRI coil noise. The second step employs a triple-generator WGAN (TWGAN) for refinement. Training data consist of k -space FE lines from a homemade shielding-free 0.11T scanner, with a dataset of 150 clean-noise pairs constructed by adding scaled residual noise to shielded-room acquisitions. Evaluation metrics include SSIM and NRSS (no-reference structural sharpness). TWGAN contributes to the secondary denoising refinement and enables superior performance and generalizability on low-field (0.11T) and ultra-low-field (0.055T) MRI data where hardware shielding is absent. Another EMI-rejection study investigated by Rongsheng Lu et al. [81] proposes a three-layer convolutional neural network (CNN) incorporating a SENet attention mechanism (se-CNN) shown in Figure 4b. The study developed a hardware-optimized method for active EMI rejection via a multi-indicator coil selection strategy. The SENet-CNN network achieved accelerated training for ~2 min. Data consist of EMI noise signals synchronously acquired from five optimized sensing coils and the main MRI receive coil on a 50 mT portable scanner. The model is trained on the k -space data pairs to map noise relationships with/without EMI. Evaluation employs SNR and interference suppression rate to quantify denoising performance and artifact reduction in phantom and in vivo human leg images.

2.2 | Self-Supervised Denoising: GAN-Based Networks, DMs, and Extension

Inspired by success in LF-MRI via conventional CNN backbones (e.g., U-net), GANs offer a complementary approach to enhancing image quality [44]. GANs could be visually considered as the parallel operation of two neural networks—the generator and the discriminator—that work in tandem to produce high-quality images from low-quality inputs. The generator creates images by learning from training data, while the discriminator evaluates the authenticity of these images, providing in-time feedback that improves the generator's output during the duration. Conditional GAN (cGAN) [45] introduced extra information, like class labels, to guide the generation process and produced more targeted outputs.

A GAN-based model for the LoHiResGAN model [19], which involved ResNet [73] components into 3D cGAN backbones, is designed for translating LF-MRI images to HF quality. The model evaluates its performance on data collected from 92 healthy individuals scanned at Monash Biomedical Imaging using both the Hyperfine Swoop (64mT) and Siemens Biograph mMR (3T) imaging systems. Empirical evaluations

demonstrated that integrating ResNet blocks significantly contributed to translating LF images effectively with clear anatomical detail recovery. The study also introduced the structural similarity index measure (SSIM) as an additional loss function, alongside mean absolute error (MAE) and binary cross-entropy (BCE) losses.

Instead of cGAN, which requires paired training, Cycle-GAN [47] became another extension that facilitates image-to-image translation using unpaired datasets. The network comprises two generators and two discriminators; one generator produces synthetic denoised images, while the second regenerates the original noisy image. The training was criticized with two loss functions: adversarial loss and cycle consistency loss. In a recent study [48], the entire Cycle-GAN architecture was implemented to improve the quality of LF (64mT, Hyperfine) MRI images by translating them to resemble HF (1.5T, GE Signa HDxt) resolutions. The main contribution and innovation of Cycle-GAN architecture lies in the unpaired image datasets that were matched by radiologists to ensure similarity in brain structures. The process involved a three-step workflow: deformable registration for unpaired images, the Cycle-GAN training, and multimodalities evaluation using

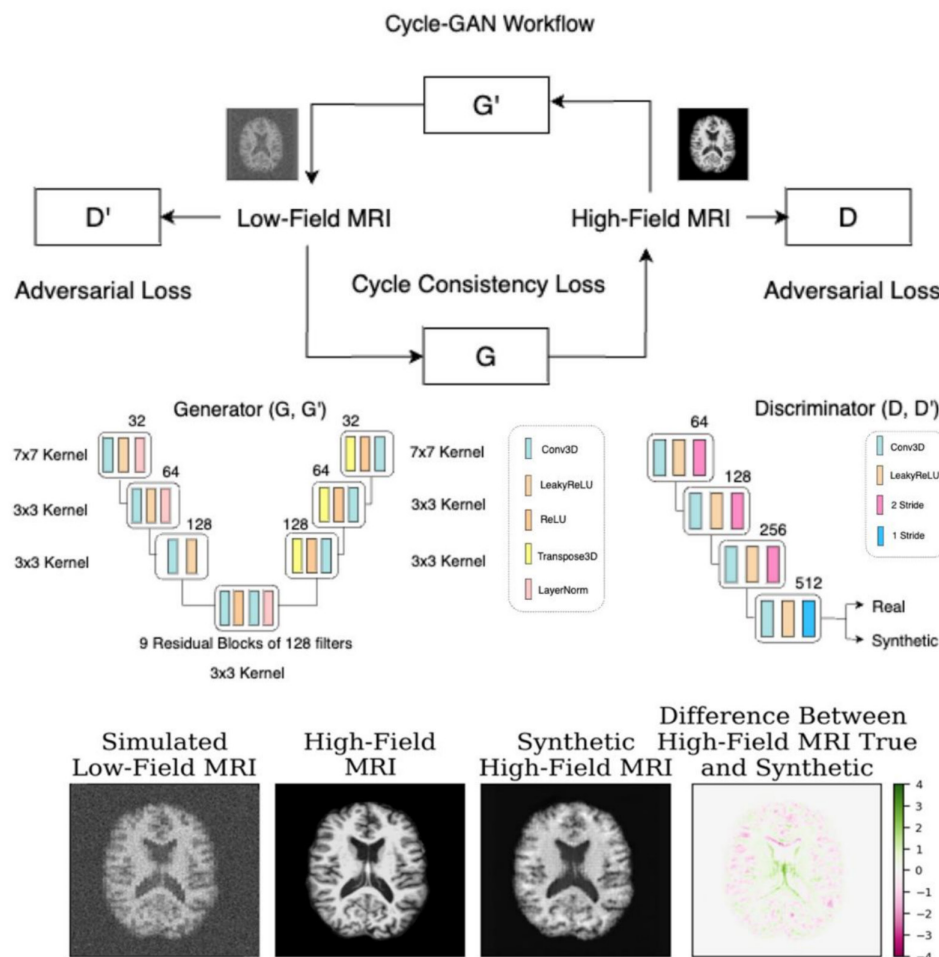
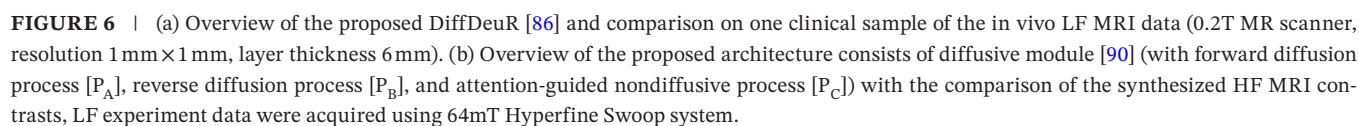


FIGURE 5 | Cycle-GAN workflow in LF-MRI denoising [49] with two generators and corresponding discriminators. G generates a HF-MRI from the LF-MRI and G' generates the LF-MRI back from the generated HF. Cycle-GAN predictions and different maps to the HF MRI is displayed. Test data are acquired from Open Access Series of Imaging Studies (OASIS-3) database (3T T1W, 1 mm × 1 mm × 1 mm). LF data are simulated to 1.5 mm × 1.5 mm × 1.5 mm with Rician noise, to emulate a low SNR of 70mT.

Differing from GANs that generate data in one step, DMs [83] are a class of generative models used to create data through



a process that systematically refines noise into structured, reconstructed outputs. This process is formalized in the denoising diffusion probabilistic model (DDPM) [84, 85], which incorporates a Markov chain to gradually add noise during training.

Building on these principles, the proposed DiffDeuR (diffusion-driven neural representation) [86] decomposes the enhancement challenge into two subproblems (e.g., data consistency and prior knowledge) and solved iteratively using a combined DM (specifically the score-based “VE-SDE” model [87]) and implicit neural representation (INR) [88, 89]. The pipeline is shown in Figure 6a. Validation experiments utilized T1-weighted LF data collected from a 0.2T MR scanner and compared it against a HF reference from a 3T uMR 790 MRI scanner. DiffDeuR demonstrates the key contribution to an unsupervised, zero-shot training scheme without requiring paired low-field/high-field training data. In addition, Sanuwani et al. investigated an architecture [90] that features an Adversarial Diffusive Module that employs a 2D GAN architecture, shown in Figure 6b. This study is the first that contributes a novel adversarial diffusion-based image translation framework to synthesize diagnostic-quality high-field (3T) MRI from ultra-low-field (64mT) scans. An attention-guided refinement module enhances high-level features. Crucially, the model is trained and validated on paired, real 64mT–3T brain MRI data (T1-w, T2-w, FLAIR) from healthy subjects. The architecture is based on a U-Net design integrated with ResNet components, facilitating robust feature extraction and image reconstruction [91]. Experiments used paired LF and HF images collected from Hyperfine Swoop (64mT) and Siemens Biograph mMR 3T imaging systems.

3 | DL-Based Methods in Super-Resolution

Building on the challenges of low spatial resolution in LF-MRI, this section examines how DL techniques for super-resolution are making a difference. The introduction emphasized the need for better image detail to support accurate diagnoses and create high-resolution images from lower-quality scans. Related investigations explored how various NN structures are established and how the training datasets, including paired and unpaired ones. Approaches using DL models are beneficial to mitigate the gap between LF and HF imaging quality, enhancing the usefulness of LF-MRI in various clinical situations.

3.1 | Supervised Super-Resolutions: CNN-Based and Residual Learning Architecture

The published studies provided examples of CNN-based implementation on resolution promotion. One of the typical model, U-net, helps in recovering fine details that are often lost during the down-sampling process. The typical symmetric encoder-decoder structure effectively learns to translate low-resolution images into high-resolution sections.

Juan Eugenio Iglesias et al. developed the LF-SynthSR [36] that enhances LF-MRI scans by correlating brain morphometry measurements between the synthetic low field and ground truth

high field images. A two-step 3D U-net structure was built that formed a chained network. The first one utilized the previous study SynthSR [92] for super-resolution and the second step was for segmentation. The LF-SynthSR method utilizes a synthetic data generator to expose the CNN to varied images. L1-norm loss and a semantic segmentation loss were used in the first and second U-net steps, respectively. Training data were collected from 20 participants from the OASIS database [93]. LF scans were acquired using the 64mT Hyperfine Swoop MRI system, and the corresponded reference HF data were acquired from 1.5T to 3T [92, 94]. The training dataset, featuring isotropic magnetization-prepared rapid gradient-echo scans, included segmentations of 39 regions of interest (ROIs). During testing, LF scans are co-registered and processed to generate synthetic outputs, which are then segmented with SynthSeg [94, 95]. Following the successful experiments, the poststep experiments, WMH-SynthSeg [96], extended the training dataset to those involving white matter hyperintensities (WMH). The WM-oriented training model automatically calculates ROI volumes on LF images with comparable accuracy to HF-MRI. WMH-SynthSeg enhances robustness by utilizing multitask learning to perform the following three tasks at once: image segmentation, joint synthesis and super-resolution. Unlike SynthSeg, which focuses solely on segmentation, WMH-SynthSeg’s multitask U-net predicts all three folds, although it retains only the segmentation outcome during testing.

Another 3D U-net model were investigated by Levente Baljer et al. [18], which achieved the neurodevelopment in infants from South Africa and Malawi, over the first 3 years of life. The well-trained network delivered the clear segmentation of deep brain structures using SynthSeg [95]. Fifty-six subjects ultimately contributing paired LF (Hyperfine 64mT) and HF (Siemens 3T). To explored model performance with varying input scan orientations, the network created three-channel-input, which consists of the following three orthogonal orientations: axial, sagittal, and coronal. Preprocessing techniques include dense-rigid registration and brain extraction via HD-BET. PSNR was selected as loss function to minimize the network parameters. Evaluation used metrics like Dice overlap and tissue volume correlations. Jo Schlemper et al. developed the U-net structure into an unrolling structure with compress sensing [53], that is, a 2D Nonuniform Variational Network (NVN). The NVN architecture consists of multiple learnable blocks, each including a CNN component inspired by U-net for image de-aliasing, a data consistency layer for handling non-uniform k -space data, and parameters to balance de-aliasing with data fidelity. Figure 7 directly illustrated the network architecture. The training dataset consisted of 160 ground truth T1 and T2 volumes from the HCP. For evaluation, FLAIR and T2W images from 10 patients were acquired from the Hyperfine POC MRI system (64mT). NVN was compared to other U-net-based methods via metrics as MSE, SSIM, and PSNR. NVN architecture contributes the image reconstruction from under-sampled data and the correction of hardware-induced system imperfections (e.g., encoding errors and eddy currents) in a single, fast (0.3 s/volume) step. Another study concerning fetal MRI was investigated by Kelly Payette et al. [97] involves T2* maps acquired at 0.55T (Siemens’ MAGNETOM Free.Max). Segmentation (including lungs, thymus, kidney pelvis, and liver) utilized an existing in-house U-Net using the MONAI

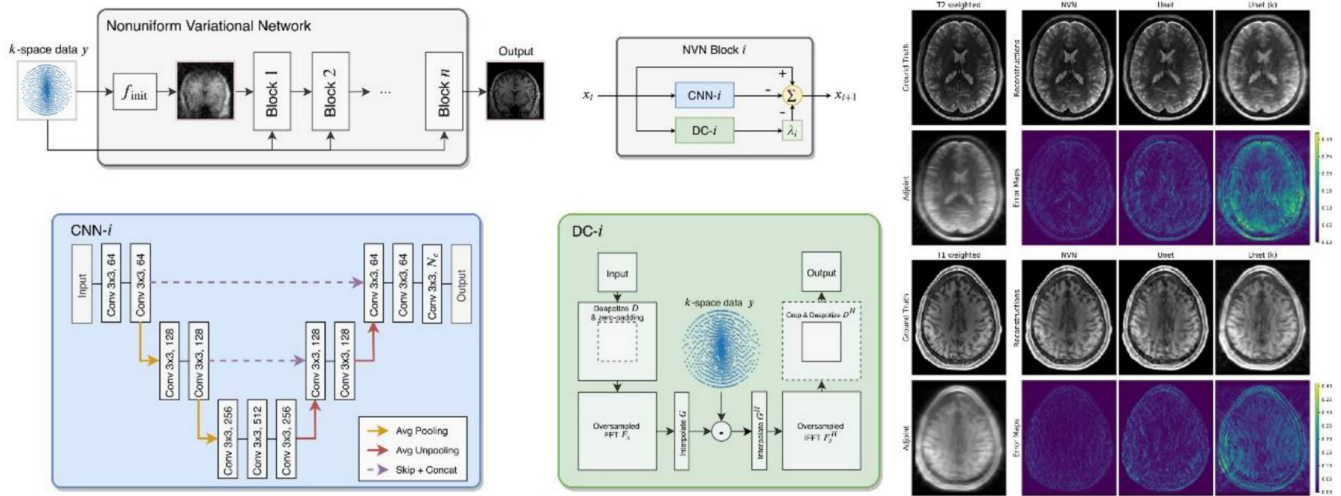


FIGURE 7 | The architecture of Nonuniform Variational Network [53]. Each block has three components: CNN, DC and λ . In detail, DC is a non-Cartesian DC layer and λ is the weighting term. The model has 5 blocks in total. Reconstructions for the T1-weighted (bottom half) and T2-weighted images (top half) from the simulated data acquisition with Hyperfine POC MRI system (64mT, FOV 180 mm $\times$ 180 mm $\times$ 180 mm, resolution 1.5 mm $\times$ 1.5 mm $\times$ 5 mm, and the acceleration factor of 3.5).

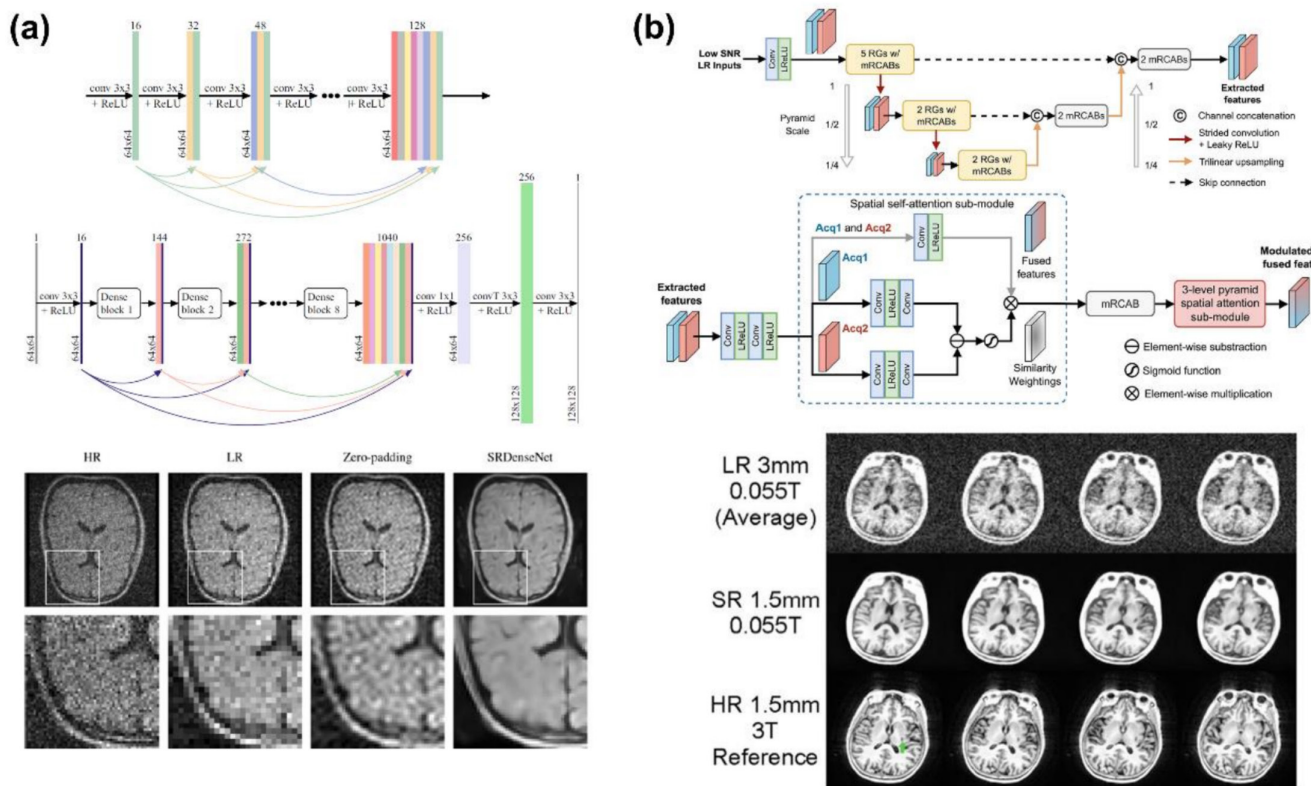


FIGURE 8 | (a) The architecture of SRDenseNet [101], with 8 dense blocks of eight convolutional layers each. Data acquisition was achieved from a home-made 50mT scanner (parameters: FOV 180 mm $\times$ 240 mm $\times$ 180 mm, 1.5 mm $\times$ 1.5 mm $\times$ 3 mm, TR/TE = 400 ms/20 ms, echo train length 5, acquisition bandwidth 20kHz). Results compared a conventional Zero-padding method. (b) Feature extractor module and attention fusion module based on residual channel attention blocks (RCABs) in Vick Lau et al. [106]. SR experiments on the low-resolution home-built 0.055T MRI brain acquired from a 58-year-old female with a small lacunar infarct in the left putamen due to chronic (> 11 months) ischemic stroke (3D T1W, 3-mm³ resolution, FOVs of 240 mm $\times$ 240 mm $\times$ 210 mm, acquired via 3D inversion FSE sequence, TR/TE/TI = 590/14/190 ms).

framework [98] with cross-entropy and Dice loss functions, refined by fetal anatomy specialists. However, limitations in this study revealed the lack of standard automated image processing tools, hindering wider clinical use.

In addition to directly training for resolution improvement, Reina Ayde et al. [55] trained a 3D residual U-net model and achieved the acceleration using complex images (both magnitude and phase information). LF datasets were acquired using

a custom-built transmit/receive coil at 0.1T MRI [99, 100]. The training dataset involved 10 fully sampled 3D spoiled gradient echo (GRE) scans of the human hand and wrist and underwent preprocessing and data augmentation. L2-norm (MSE) was employed as the loss function. The evaluation involved retrospective analysis using Gaussian sampling patterns to assess performance with a maximum of a fivefold acceleration rate. Validation data consisted of multiple undersampled k -space acquisitions to ensure effective reconstruction and performance evaluation against high-field MRI labels.

Despite of U-net-based models, other supervised models also contribute to the super-resolution in LF-MRI. DenseNet was also utilized to train the super-resolution by M. L. de Leeuw den Bouter et al. [101] with the structure consisting of blocks of densely connected convolutional layers [102]. The network is trained on 2D brain images sourced from the NYU fastMRI Initiative database [103, 104], which contains T1, T2, and FLAIR images acquired at 1.5T and 3T. The training used MSE as criteria, and the well-trained network was tested on LF in vivo human brains acquired from a 50mT scanner [105]. The network structure is demonstrated in Figure 8a. The network demonstrated a promoted pair-training mode with noise LR and noise-free HF data would recovery anatomical detail while shorten scan times. Vick Lau et al. [106] present a dual-acquisition 3D model, which includes three main components: feature extractor with multiscale residual channel attention blocks (RCABs) [107], attentional fusion module [108], and reconstruction model, trained with L1 loss. A general visualization is witnessed in Figure 8b. Two consecutively acquired 3D MRI datasets were utilized to achieve a $2\times$ up-sampling factor across all spatial dimensions. HF data were derived from the Wu-Minn HCP datasets [109] then down-sampled as training inputs. Evaluation brain data, involving 30 healthy volunteers and 8 patients, were acquired at a home-built 0.055T shield-free scanner [110] and GE 3T Sigma Premier (HF reference). The well-trained network delivered high generalizability from

young (e.g., 27 and 33 years male) healthy volunteers to elder patients with brain lesions (e.g., 58-years-old female with small lacunar infarct). Christopher Man [23] applied RCABs structure in the extension study, where the training was built on the down-sampled training data from k -space truncations. The proposed Partial super-resolution model (PF-SR) model accelerates the scan time by half in both healthy and pathological brain subjects. PF-SR and Deep-DSP [71] contributed the whole body imaging [22] for speed and quality, testing the 0.055T whole-body MRI scanner on the various body parts: brain, spine (cervical and lumbar), abdomen, lungs, musculoskeletal structures, and the heart (cardiac cine images). Neck angiography was also performed. The two learning-based models were effective in EMI elimination, acceleration, and super-resolution.

3.2 | Self-Supervised Super-Resolution: GAN Model Implementation

An extension study incorporating fundamental CNN structure (e.g., ResNet block) into GAN architecture is published by Sonia Laguna et al. [111]. The key innovation of the training exhibited on the combination of supervised pretraining on high-field data with unsupervised domain adaptation on unpaired scans. The model is established by a Cycle-GAN-based structure, consisting of three modules: domain adaptation (DA), a denoiser, and a super-resolution (SR) module, shown in Figure 9. The DA module combined CycleGAN and FastCUT [112] for unpaired translations, while the SR module utilizes a 3D ESRGAN [113] with 23 residual dense blocks. The training datasets include HF T1/T2 scans from 898 subjects from the HCP and LF Hyperfine scans of 11 subjects from MGH. The SR block was trained with L1 and adversarial losses, the denoiser used L1 loss, and the DA module balanced adversarial and cycle consistency losses. Evaluation was processed thorough the tissue segmentation by SynthSeg [94].

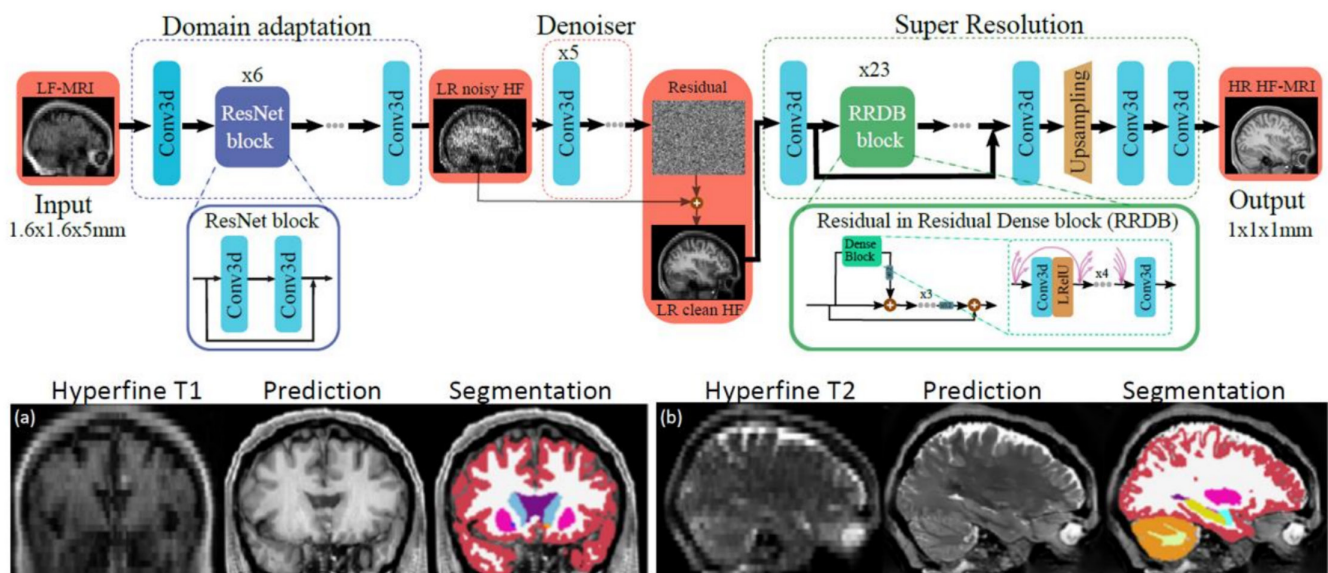


FIGURE 9 | Proposed 3D meta-architecture with building blocks [111]. Experiments were conducted from the Hyperfine 64mT system, resolution $1.5\text{ mm} \times 1.5\text{ mm} \times 5\text{ mm}$. Reconstruction results include sample outputs with FastCUT as DA.

4 | Discussion

This review paper has explored the advancements and challenges in DL-based LF-MRI, highlighting the potential these technologies have for enhancing image quality and diagnostic accuracy. We discussed the motivations for implementing learning-based methods, the importance of data preparation, model architecture, and postprocessing techniques. Furthermore, we addressed the generalization capabilities of trained networks across different datasets. Implementing learning-based methods in LF-MRI is essential because of the need for better imaging in environments with low SNRs [114] and limited spatial resolution. DL techniques offer powerful solutions to these challenges by using neural networks to enhance image quality through advanced filtering and denoising. These methods can learn complex patterns from data, making them particularly suitable for LF-MRI, where traditional methods often fall short in delivering the required accuracy. For clear and comprehensive overview, two comprehensive summary tables were made in Supplementary Tables 1 and 2 to visually synthesize the literature for each study mentioned in Sections 2 and 3.

For conventional end-to-end training, data preparation is a critical factor influencing the final performance of LF learning models [115]. High-quality, well-annotated training datasets are vital for the models to learn meaningful representations of LF-MRI images. Effective data handling, including normalization and noise reduction, enhances the training experience, leading to faster convergence and better performance. Additionally, the use of data augmentation can further improve model robustness by artificially expanding the dataset and capturing a wider range of scenarios. The architecture of the training model also significantly impacts training outcomes. Choosing the right architecture, such as U-Net or other convolutional neural networks, can enhance both accuracy and efficiency. Analyzing various studies reveals insights into effective architectures that provide the best trade-off between complexity and performance. This balance is crucial for optimizing the DL models for LF-MRI, ensuring that they deliver high-quality images without excessive computational demands.

Generalization is another important topic in LF-MRI. Advances in training DL models can lead to systems that perform effectively across multiple datasets. For example, whole-body MRI at 0.05 Tesla [22] demonstrates how a single trained network can yield consistent and reliable results, thus broadening the clinical applicability of LF-MRI. This adaptability suggests that DL models could become vital tools in everyday clinical practice, providing robust solutions to various imaging challenges.

Several promising directions are helpful to training efficiency. The application of unsupervised structures, such as GANs and DMs, offers potential for greater flexibility and efficiency. Techniques like conditional GANs and Cycle-GANs can improve training outcomes by bridging the gap between LF-HF MRI images without needing extensive paired datasets. Additionally, incorporating DMs may enhance the quality of LF-MR images, enabling better representation of anatomical structures. Transfer learning approaches could further streamline

the adaptation of models to new datasets, improving their applicability in diverse clinical situations.

Despite the many advancements, there are still limitations and challenges to address. One significant drawback in most DL-based studies is the reliance on large, high-quality annotated datasets, especially on the end-to-end training models. The performance of DL models depends heavily on the quality and diversity of training data. In many cases, obtaining sufficient annotated data can be challenging, particularly for rare conditions in Africa. There are also concerns about the interpretability of DL models; understanding how these models arrive at their decisions is crucial for justifying clinical practices based on their outputs. Explainable AI (XAI) is critical for training interpretable models and the nonnegotiable need for safety, trust, and clinical accountability in medical diagnosis. XAI techniques, for example, model-specific methods such as LRP [116], illustrate the exact sections of an MRI scan a DL model relied on for its decision. Another category, model-agnostic methods such as LIME [117], explains predictions by approximating the complex model locally with a simpler interpretable one. For conventional HF-MRI implementations, Grad-CAM classifies key regions for brain tumor or Alzheimer's diagnosis from CNNs [118–121]. CAM-based techniques adapted for graph networks pinpoint brain areas associated with conditions like autism [122, 123]. The core result is a saliency map overlaying the scan to show the model's focal regions for its prediction. Succeeded in HF-MRI applications, these XAI techniques could be further explored to enhance the interpretability and clinical trust in AI models developed for low-field MRI systems.

Moreover, several clinical applications of LF-MRI technology are particularly promising, especially in real-world scenarios involving metallic implants [124–128]. Imaging challenges posed by artifacts from metallic objects often limit traditional MRI techniques. However, advancements in DL-based segmentation and reconstruction have the potential to overcome these barriers, leading to clearer images and more accurate diagnoses. This capability may broaden the use of low-field MRI in institutions with limited access to high-field systems. For future studies, postprocessing algorithms [129–132] for the validation or inference data could be considered as a vital role in refining the images. After initial image reconstruction, techniques such as denoising and artifact correction can enhance image quality further. These refinements are essential for ensuring that images meet the standards required for reliable diagnostic use. Applying robust postprocessing techniques helps mitigate residual noise and improves the overall integrity of the images.

In conclusion, this review highlights the considerable progress made in integrating DL techniques into low-field MRI, solving the key issues as denoising and super-resolution. By emphasizing the importance of data preparation, model selection, and postprocessing, this review demonstrates how these advances can significantly improve imaging outcomes. As the field continues to evolve, ongoing research should address current limitations and explore new model architectures to enhance clinical applications. The potential for low-field MRI to provide valuable diagnostic insights in diverse medical contexts remains

significant, contributing to improved patient care and broader access to advanced imaging technologies.

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Data Availability Statement

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Table S1:** Summary of learning-based denoising methods in low-field MRI. **Table S2:** Summary of super-resolution in low-field MRI using deep learning-based methods.