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Malagi, Archana Vadiraj; Li, Xinqi; Tao, Qian; Yang, Hsin Jung

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REVIEW

Advanced Cardiac MRI: Integrating AI and Machine Learning for Post Imaging Reconstruction

Archana Vadiraj Malagi[1] · Xinqi Li[1] · Qian Tao[2] · Hsin-Jung Yang[1]

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Abstract

Purpose of Review This review explores the advancements in deep learning (DL)-based cardiac magnetic resonance (CMR) reconstruction, focusing on its role in accelerating imaging, denoising, super-resolution, motion artifact correction, and quantitative mapping. It highlights the transition from parallel imaging and compressed sensing to artificial intelligence (AI)-driven approaches that enhance image quality and diagnostic accuracy.

Recent Findings Supervised and self-supervised DL models can significantly reduce scan times, enabling high-fidelity reconstructions from undersampled data. Generative adversarial network (GAN)-based super-resolution techniques enhance spatial resolution, while denoising networks improve signal-to-noise ratio. Motion correction strategies, including spatio-temporal learning, have enhanced free-breathing acquisitions. Physics-guided models incorporate MRI signal constraints for improved T1/T2 mapping and myocardial tissue characterization.

Summary DL-driven CMR reconstruction optimizes imaging speed, quality, and artifact suppression. Despite challenges in dataset standardization and clinical validation, AI is advancing real-time, high-fidelity CMR, facilitating broader clinical adoption.

Keywords Cardiac magnetic resonance imaging · Image reconstruction · Deep learning · Rapid imaging · Motion correction · Super-resolution

Opinion Statement

Recent advances in deep learning have significantly accelerated data acquisition, improved motion correction, and enhanced image contrast, directly addressing challenges like low signal-to-noise ratios and motion artifacts. These improvements reduce scan times, lowering patient burden while enabling more precise assessment of cardiac structure, function, and tissue characterization. Faster scans not only increase patient comfort and clinical throughput but also minimize motion-related artifacts, improving diagnostic reliability. Additionally, deep learning models can extract subtle features from large datasets, potentially revealing early disease markers that might be missed with conventional reconstruction methods.

However, the successful clinical translation of these technologies depends on several key factors. AI models must be rigorously validated using diverse, multi-center datasets to ensure generalizability across different vendors, patient populations, and disease conditions. This is particularly important as CMR systems vary widely in terms of hardware, field strength, and imaging protocols, requiring robust models that can adapt to these differences. Integration into clinical workflows must be seamless, without disrupting established protocols, and must comply with data privacy and regulatory standards. This requires close collaboration between engineers, radiologists, and regulatory experts to ensure that these tools are not only technically sound but also clinically viable and ethically responsible.

With continued innovation and careful implementation, AI has the potential not only to enhance the efficiency and accessibility of CMR but also to fundamentally transform cardiovascular diagnostics. This shift could pave the way

✉ Hsin-Jung Yang
Hsin-Jung.Yang@cshs.org

1 Biomedical Imaging Research Institute, Cedars-Sinai Medical Center, Los Angeles, CA 90048, USA

2 Department of Imaging Physics, Delft University of Technology (TU Delft), Mekelweg 5, Delft 2628 CD, Netherlands

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for more precise, patient-specific care, reducing the overall burden of cardiovascular disease and improving long-term patient outcomes.

Introduction

Cardiovascular Magnetic Resonance (CMR) imaging is a non-invasive, radiation-free modality widely utilized in clinical practice for diagnosing and assessing cardiovascular diseases. It provides comprehensive information on cardiac morphology, function, perfusion, myocardial microstructure, and hemodynamics, making it a critical tool for cardiovascular research and patient care [1, 2]. Despite these advantages, CMR faces challenges, including high costs, prolonged scan times, and high exam complexity. Moreover, image quality can be compromised by motion artifacts due to cardiac and respiratory movement, susceptibility effects from its proximity to the lungs, and difficulties in breath-holding, particularly in patients with severe cardiovascular conditions [3, 4].

To improve the efficiency and speed of CMR image acquisition, techniques such as parallel imaging (PI) and compressed sensing (CS) have been widely adopted. PI leverages the spatial sensitivity of multiple receiver coils to accelerate data acquisition by reducing redundant spatial encoding [5, 6]. CS, on the other hand, enables image reconstruction from under-sampled k-space data through nonlinear optimization, benefiting from the inherent sparsity of MRI signals via transformations such as wavelet decomposition [7]. While these methods have significantly advanced CMR imaging, they remain constrained by their dependence on hardware limitations, and reliance on complex parameter tuning and computational burden [8].

In recent years, deep learning (DL), a subset of artificial intelligence (AI), has emerged as a transformative approach in medical imaging, including CMR [9]. Before discussing the role of AI in CMR, it is essential to understand the fundamentals of image reconstruction. Reconstruction converts raw k-space data into clinically usable images, with key challenges including undersampling, motion artifacts, and noise. While traditional reconstruction techniques have improved acquisition efficiency, their reliance on handcrafted priors and iterative optimization limits their adaptability. In contrast, DL-based reconstruction has demonstrated superior image quality and speed by learning complex signal patterns directly from large datasets. DL has demonstrated potential across various aspects of CMR, including segmentation, classification, image enhancement, motion correction, and cardiac function analysis [10]. Technical advancements have demonstrated unprecedented imaging acceleration capacities with substantially shorter reconstruction times.

This chapter focuses on the role of AI in CMR image reconstruction, an essential step in the imaging workflow. We begin by discussing the fundamentals of CMR reconstruction, framing it as an inverse problem, and outlining general models of DL-based reconstruction. Next, we summarize the current implementation of DL-based image reconstruction models and review the state-of-the-art techniques that address key limitations in CMR. Finally, we will discuss the challenges and opportunities of DL-based image reconstruction in CMR. Through this discussion, we aim to highlight the evolving role of AI in optimizing CMR imaging and advancing its clinical and research applications.

General Models of Image Reconstruction in CMR

Image reconstruction is a fundamental step of magnetic resonance imaging that transforms raw frequency-domain measurements into clinically interpretable images. It is critical to achieve the desired imaging speed, spatial and temporal resolution, and disease sensitivity [11]. Unlike other organs in the human body, the heart is consistently moving through the cardiac and respiratory cycle. Key cardiac MRI sequences, such as cine, multi-parametric mapping, first-pass perfusion, and 4D flow images, require additional dimensionalities compared to the conventional static 2D images. This makes CMR reconstruction particularly challenging. In this section, we will briefly introduce the theory of MRI image reconstruction, the formulation of DL-based image reconstruction, and its application in cardiac MRI applications.

CMR Reconstruction Theory

MR image reconstruction can be formulated as an inverse problem that aims to retrieve the image $\mathrm{x} \in \mathbb{C}^{T \times X \times Y \times Z}$ which is consistent with the acquired k-space data $\mathrm{k} \in \mathbb{C}^{M}$. In CMR, x is a series consisting of T temporal frames and spatial dimensions X, Y, and Z, and M is the number of k-space locations acquired. The forward model of an undersampled image acquisition can be formulated as

$$\mathrm{k} = \mathrm{A}\mathcal{F}\mathrm{S}U\mathrm{x} + \in, \tag{1}$$

where A is the sampling operator, $\mathcal{F}$ is the spatial Fourier transform, S is the operator that applies the coil sensitivity profiles, $\boldsymbol{U}$ is the motion, and $\in$ is the measurement noise.

The inverse problem of reconstructing the images can be formulated as an optimization problem:

$$x^* = \mathrm{argmin}\frac{1}{2}\|A\mathcal{F}SUx - k\|_2^2 + \lambda R(x), \quad (2)$$

where $\mathcal{R} \in \mathbb{C}^{T\times X\times Y\times Z} \to \mathbb{R}$ is a regularization function and λ is a tunable parameter to impose priors and regularize the solution.

Over the past two decades, several strategies have been developed to accelerate CMR acquisitions and improve image quality. Parallel imaging techniques, such as SENSE and GRAPPA, leverage coil sensitivity profiles to reconstruct missing k-space data efficiently, enhancing spatial resolution and acquisition speed without requiring explicit regularization [5, 6]. CS exploits the sparsity of MR images in specific transform domains, such as wavelets, or applies dimensionality constraints to enable high-fidelity reconstructions from undersampled data through iterative optimization [7]. Additionally, low-rank tensor formulations utilize spatiotemporal correlations in dynamic MR data to constrain the solution space, leading to improved image quality in highly accelerated acquisitions [12, 13].

Although CS and low-rank approaches have demonstrated drastic advances in acceleration capabilities through the incorporation of learned priors, optimization-based iterative CMR reconstruction still faces challenges, including hyperparameter tuning and prolonged reconstruction time, particularly at high acceleration factors [14, 15]. To address these limitations, recent research has focused on DL-based reconstruction techniques, which offer promising solutions for fast and high-quality CMR imaging. The next section delves into these approaches, including k-space learning, supervised and unsupervised training paradigms, and novel network architectures tailored for CMR.

Deep Learning-based CMR Reconstruction

DL-based algorithms rapidly became a critical tool for CMR reconstruction. Recent review papers on DL-based CMR reconstruction [15, 16] provide a comprehensive overview and framework of existing methods and challenges. In this article, we focused on reviewing the recent advancements in DL-based reconstruction from an application-driven perspective. We separated the models based on whether they utilized the physics information from specific acquisition protocols and emphasized their role in improving reconstruction accuracy, motion compensation, and clinical reliability as shown in Fig. 1. Additionally, we highlighted recent developments in DL architectures, including unrolled networks, physics-based priors, and AI-driven tissue characterization techniques, which are paving the way for more robust and interpretable CMR reconstructions.

Deep Learning Approaches for CMR Reconstruction

DL neural network for CMR reconstruction can be categorized as into three approaches [17]: k-space-to-image learning, k-space-to-k-space learning, and image-to-image learning. In k-space-to-image learning, neural networks are trained to map raw k-space data directly to image-space representations, often leveraging convolutional neural networks (CNNs) or unrolled iterative schemes to enforce data fidelity and image quality constraints [15, 18–21]. This approach is particularly beneficial for undersampled acquisitions where missing k-space data can be inferred while performing an end-to-end transformation into the image domain. In contrast, k-space-to-k-space learning methods operate entirely in k-space, using DL to interpolate missing k-space data or apply nonlinear filtering to improve signal quality before image reconstruction. These methods, inspired by traditional parallel imaging techniques like GRAPPA, can help maintain consistency with acquired data while leveraging learned priors for more robust reconstruction [22]. Lastly, image-to-image learning methods work directly in image space, often refining initial reconstructions obtained via zero-filling or conventional methods by removing noise and artifacts. These techniques, including residual networks and generative adversarial network (GAN)-based models, focus on enhancing perceptual image quality and can be particularly useful for applications like super-resolution and denoising [23–27].

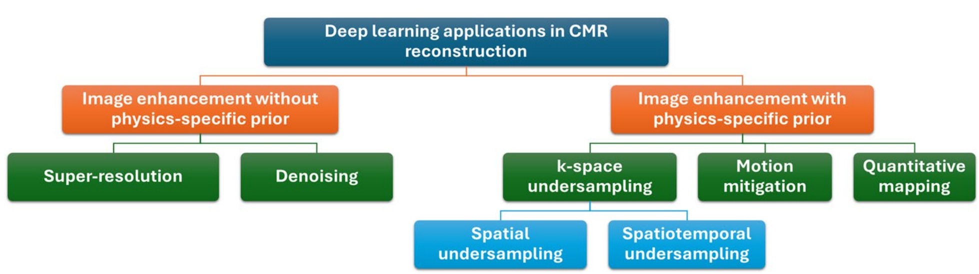

Fig. 1 Schematic representation of deep learning applications in CMR reconstruction, categorized into models incorporating image enhancement with physics-specific priors (e.g., k-space undersampling, motion mitigation and quantitative mapping) and without physics-specific priors (e.g., denoising, super-resolution)

Training Strategies in Deep Learning-Based CMR Reconstruction

The success of DL models for CMR reconstruction depends heavily on the training paradigm, which can be categorized as supervised learning, unsupervised/self-supervised learning, and physics-based regularization in unrolled models [15]. Supervised learning relies on paired fully sampled and undersampled data, training the model to minimize the difference between reconstructed and reference images. While effective, this approach requires large, high-quality datasets, which may not always be available.

Unsupervised and self-supervised learning techniques, such as SSDU (Self-Supervised Learning via Data Undersampling), avoid this limitation by training on only undersampled data, splitting it into two subsets to guide the learning process without requiring fully sampled reference images [28]. This strategy has demonstrated improved generalization to different imaging conditions, particularly in dynamic CMR [29]. Another promising direction is physics-based regularization in unrolled models, where deep networks integrate traditional iterative reconstruction constraints within a learned framework. These models unroll iterative optimization schemes into a deep network, incorporating data consistency layers and learned regularization functions to ensure high-quality reconstructions while reducing computational complexity. Such hybrid approaches enable more interpretable and physically consistent DL reconstructions, improving clinical adoption and robustness across different acquisition settings [30, 31].

Recent advancements in deep equilibrium models (DEQ) offer an alternative approach by formulating MRI reconstruction as an implicit neural network with effectively infinite layers, significantly reducing memory complexity while achieving state-of-the-art performance [32]. The Self-Supervised Deep Equilibrium Model (SelfDEQ) framework, introduced in [33], further extends DEQ by enabling self-supervised training directly from undersampled and noisy MRI measurements, leveraging Jacobian-Free Backpropagation (JFB) to optimize reconstruction accuracy without requiring fully sampled ground truth.

Neural Network Architectures for CMR Reconstruction

Multiple neural network architecture were proposed and applied in CMR reconstruction in recent years, consisting of derivation of multi-layer perception (MLP) [34], U-Net-based convolutional networks [19], recurrent neural networks [35], variational neural networks [36–39], generative adversarial networks [40, 41], unrolled networks [31] and diffusion networks [42, 43]. The network inputs range from single-coil 2D images/k-space, multi-coil 2D images/k-spaces, 3D k-space to 4D (3D + time) images/k-space. For example, Recon3DMLP [34] proposed a hybrid of CNN modules with small kernels for low-frequency reconstruction and adaptive MLP modules with large kernels to boost the high-frequency reconstruction. RCNN [35] exploits the dependencies of the temporal sequences on 2D + time dataset. CINENet [19] leverages the spatiotemporal redundancies based on the (3 + 1)D complex-valued convolutions. An overview of representative deep learning models and their applications in cardiac MRI reconstruction is presented in Table 1.

Applications of Deep Learning in CMR Reconstruction

In the following sections, we will summarize the development of DL-based CMR reconstruction models in recent years into categories based on the approaches and applications. We categorized the models into image enhancement with physics-specific priors (e.g., k-space undersampling, Motion mitigation and Quantitative mapping) and without physics-specific priors (e.g., denoising, super-resolution). Figure 1 shows schematic representation of deep learning applications in CMR reconstruction which will be discussed in this section.

Denoising Techniques

Denoising in CMR reconstruction is essential for improving image quality by reducing noise caused by the MRI system, sampling strategies, and physiological influences. Traditional denoising methods, including Gaussian smoothing, total variation minimization, and wavelet-based filtering, often compromise fine structural details by introducing blurring or loss of texture. To address these limitations, DL-based denoising techniques have emerged as powerful tools capable of preserving anatomical fidelity while effectively suppressing noise. CNNs [50], autoencoders [51], and GANs [44] have been widely applied in CMR denoising, leveraging large datasets to learn noise characteristics and reconstruct high-quality images. Unlike conventional filtering approaches, DL models can distinguish between noise and true signal variations, allowing for more accurate restoration of subtle myocardial structures. Additionally, self-supervised and physics-informed learning methods have been explored to enhance denoising without requiring extensive labeled training datasets.

Recent studies have demonstrated the effectiveness of DL-based denoising techniques in CMR imaging. In late gadolinium enhancement (LGE) imaging, where high noise

Table 1 Overview of deep learning architectures in cardiac MR reconstruction

Architecture type	Key features and applications	Example methods	Pros and cons
GANs	Adversarial generator–discriminator setup optimized with perceptual and pixel-wise loss functions. Applications include: • Denoising • Super-resolution • Spatial undersampling • Motion mitigation	DnSRGAN [44] DAGAN [41] SRPGAN [40]	Pros: • Sharp detail preservation • Visually realistic images Cons: • Risk of hallucination • Unstable training • High computational cost
U-Net-based CNNs	Encoder-decoder structure for feature localization and context integration. Applications include: • Super-resolution • Spatiotemporal reconstruction	CINENet [19] DURN [45]	Pros: • Efficient in learning spatial/temporal context • Widely adopted Cons: • Require customized architecture tuning • May struggle with fine detail at high acceleration rates
RNNs	Model's temporal dependencies in sequential data. Applications include: • Motion mitigation in cine images	CRNN [35]	Pros: • Captures motion trends • Good for time-resolved imaging • Preserve anatomical consistency over time Cons: • High training complexity • Heavily depend on accurate temporal alignment in the input data
Variational Networks	Unrolled optimization with learned regularization and data consistency. Applications include: • Spatiotemporal Undersampling	VSNet [36] CineVN [29] FlowVN [46]	Pros: • Incorporates MRI physics (data consistency term) with learned priors • Interpretable training with few parameters and efficient reconstruction Cons: • Moderate inference speed • Sensitive to noise
Unrolled Networks	Mimic iterative optimization for reconstruction. Applications include: • Spatiotemporal Undersampling • Motion mitigation	MEL [47] MCMR framework [31]	Pros: • High reconstruction accuracy • Train with larger volumes of data at once • Improves perceptual quality and robustness to acquisition variability Cons: • High training cost, Limited scalability for large 3D/4D data
Diffusion Models	Probabilistic sampling with conditional guidance. Applications include: • Super-resolution • 3D cine reconstruction	DBSR [48] DMCVR [43]	Pros: • High fidelity and robustness to noise Cons: • Slower than GAN/CNN models in clinical deployment settings • High compute load
Transformers	Utilizes self-attention mechanisms for long-range spatial dependencies Applications include: • Spatial undersampling, • Motion mitigation	SwinMR [49]	Pros: • Captures full spatial context • Adaptable to diverse tasks • Scalable to large dataset Cons: • Needs large datasets • Heavy compute requirements
Hybrid Models	Combines features from multiple architectures (e.g., CNN + MLP, GAN + U-Net, Diffusion model + GAN) Applications include: • Super-resolution • Denoising • Acceleration	DAGAN [41] Recon3DMLP [34] MEL [47] PerfGen [25]	Pros: • Flexibility to address complex tasks • Improved accuracy Cons: • Increased architectural complexity • Hard to train

GAN Generative Adversarial Networks, *DnSRGAN* Denoising Super-Resolution GAN, *CNN* Convolution Neural Network, *DMCVR* Diffusion Model for 3D Cardiac Volume Reconstruction, *DURN* Dual U-Net Residual Network, *DBSR* Diffusion model for blind cardiac MRI super-resolution, *SRPGAN* (Super Resolution Perceptual Generative Adversarial Network), *MLP* Multi-Layer Perceptron, *DAGAN* Deep De-Aliasing Generative Adversarial Networks, *RNN* Recurrent Neural Networks, *MARC* Motion Artifact Reduction using Convolutional networks, *CRNN* Convolutional Recurrent Neural Networks, *MEL* Memory-Efficient Learning levels often degrade myocardial scar visualization, Self-Supervised Physics-Guided Deep Learning (PG-DL) [52] for 3D LGE enables high-resolution reconstruction at 6× acceleration, achieving a peak signal-to-noise ratio (PSNR) of 37.5 dB and structural similarity index (SSIM) of 0.972 while outperforming CS in maintaining myocardial infarct contrast-to-noise ratio (CNR). DLRecon [50], a DL-based reconstruction algorithm, applies tunable noise reduction (NR) Levels of 25%, 50%, 75%, and 100%, improving signal-to-noise ratio (SNR) and sharpness. Evaluations demonstrated SNR improvements of up to 60% and a CNR increase of 20%, with PSNR reaching 39.2 dB at the highest NR setting.

Beyond LGE imaging, DeepT1, an AI-based denoising pipeline for myocardial T1 mapping, achieves a 15% reduction in coefficient of variation for T1 quantification, improving diagnostic reliability in native T1 analysis. Denoising Super-Resolution GAN (DnSRGAN) combines deep denoising networks with super-resolution enhancement, reconstructing high-quality cine MRI from undersampled low-SNR acquisitions (SNR < 15 dB), achieving PSNR of 39.1 dB and SSIM of 0.985, outperforming conventional bicubic interpolation and ESRGAN [44]. Finally, GAN-based CMR image enhancement refines cardiac structures by suppressing Gaussian noise with $\sigma = 10$–25%, achieving a 2.3 dB PSNR improvement over standard DL-based denoising methods while reducing structural distortion [53]. Collectively, these models enable noise-robust, high-fidelity denoising and image quality enhancement, ensuring superior diagnostic performance in late gadolinium enhancement, cine MRI, and myocardial tissue characterization.

Super-Resolution Techniques

Super-resolution (SR) in CMR imaging aims to enhance the spatial resolution of images beyond the native acquisition resolution, addressing limitations such as partial volume effects and the trade-off between spatial and temporal resolution [3]. Traditional interpolation-based methods, such as bicubic or spline interpolation, often fail to recover fine anatomical details, leading to blurring and loss of diagnostic information [54]. DL-based SR techniques have revolutionized this field by using CNNs, GANs, and transformer-based architectures to learn complex mappings between low-resolution and high-resolution images [44, 55]. These models extract high-frequency spatial features and restore lost structural details, resulting in sharper and more diagnostically useful images [55]. DL-based SR techniques learn spatial dependencies from large-scale datasets, enabling them to generalize across different acquisition protocols and scanner types [56]. Self-supervised and multi-frame SR approaches are also being explored to enhance through-plane resolution, allowing for improved 3D cardiac visualization without requiring additional scans [57, 58]. These advancements are particularly valuable in high-resolution imaging, which is crucial for accurate diagnosis and treatment planning. In this context, several studies have demonstrated significant improvements in image quality using DL-based SR techniques. 3D residual U-Net, trained on low-resolution (LR) and high-resolution (HR) whole-heart CMR datasets, utilizes residual Learning to refine high-frequency features, achieving 2× SR with a 3.1 dB increases in PSNR [26]. PFRN (Progressive Feedback Residual Attention Network) reconstructs finer myocardial structures using a progressive refinement strategy, resulting in a PSNR improvement of 2.8 dB and SSIM enhancement of 4.6% [59]. DURN (Dual U-Net Residual Network) Leverages residual blocks between adjacent U-Net layers to enhance SR, achieving PSNR values of 37.86 dB (2× upsampling), 33.96 dB (3× upsampling), and 31.65 dB (4× upsampling), outperforming traditional interpolation-based methods [45]. DBSR (Quadratic Conditional Diffusion Model) enhances blind SR by first estimating degradation priors and then refining them using diffusion-based denoising, Leading to 3.7 dB PSNR gains over GAN-based methods [48]. FBAN (Feedback Attention Network) applies multi-scale residual attention, progressively refining LR input features and yielding a 3.5 dB PSNR improvement over Enhanced Super-Resolution Generative Adversarial Network (ESRGAN) [60]. LSR-GAN (Laplacian Pyramid Super-Resolution GAN) reconstructs high-frequency cardiac structures with a 3.2 dB PSNR increase and a 5% SSIM improvement, while suppressing adversarial learning artifacts [61].

In myocardial perfusion imaging, PerfGen, a diffusion-based generative model, enhances contrast recovery while reducing normalized root mean square error (nRMSE) by 5.1% and increasing SSIM by 2.2% over traditional GAN-based SR models, ensuring improved ischemia detection [25].

A particularly promising application of SR DL models is in low-field MRI (0.55T and 0.35T), where the inherently reduced SNR and spatial resolution pose significant diagnostic challenges. In this setting, DL-based upsampling techniques help recover finer myocardial textures in both cine and LGE imaging, achieving near-equivalent diagnostic accuracy compared to standard 1.5T CMR. Specifically, DL-enhanced cine imaging at 0.55T demonstrates a 79% increase in myocardial SNR when transitioning from Cartesian to spiral-in-out balanced steady-state free precession (bSSFP) sequences [62]. Additionally, low-rank deep image prior reconstruction for free-breathing cine MRI at 0.55T and 1.5T ensures comparable diagnostic performance, proving that DL SR can bridge the resolution gap between low-field and high-field MRI [62]. Collectively, these models enhance spatial resolution, reduce scan times, and improve the clinical feasibility of CMR at lower field strengths, making MRI more accessible and cost-effective for broader healthcare applications.

Undersampling and Acceleration Techniques

MRI acquisition in CMR imaging is time-consuming, particularly when accounting for respiratory and cardiac motion, which can compromise imaging efficiency and introduce motion artifacts. To reduce acquisition time, traditional techniques such as PI and CS have been widely employed. However, PI relies on calibration data and is susceptible to reduced SNR and localized noise, which can degrade reconstruction accuracy [63]. In contrast, CS depends on the choice of sparsity transformation domain, appropriate regularization penalties, and iterative optimization algorithms, which makes the reconstruction quality dependent on hyperparameter tuning and requires prolonged reconstruction time [63].

In recent years, DL has emerged as a powerful tool for CMR reconstruction, with models such as residual networks and U-Net demonstrating significant improvements in reconstruction speed and quality. Advanced DL models can be categorized into data-driven end-to-end learning, which learns the mapping between undersampled and fully sampled data, and model-driven unrolled methods, which integrate DL with traditional iterative algorithms to solve the inverse reconstruction problem efficiently. These approaches offer promising solutions for fast and accurate CMR imaging, overcoming the limitations of conventional methods.

Spatial Undersampling

DL has significantly advanced spatially undersampled CMR reconstruction by leveraging data-driven priors to enhance image fidelity, reduce artifacts, and accelerate reconstruction times. DL-ESPIRiT, an extension of ESPIRiT-based PI, integrates DL with coil sensitivity maps, achieving high-quality cardiac cine MRI reconstructions at $R=12$, demonstrating superior performance over l1-ESPIRiT while preserving left ventricular segmentation accuracy [18]. DAGAN, a GAN-based reconstruction framework, effectively mitigates aliasing artifacts and improves perceptual quality at $R=2$ and $R=4$, although performance degrades at $R=8$ due to residual noise amplification [41, 64]. D5C5, a cascaded CNN architecture, enhances spatial fidelity at moderate acceleration factors but exhibits increased sensitivity to noise at higher acceleration rates [64, 65]. SwinMR, a transformer-based model utilizing self-attention mechanisms, surpasses DAGAN and D5C5 at $R=2$ and $R=4$, yet introduces synthetic structures at higher acceleration factors ($R=8$) [49, 64]. The 3D residual booster U-Net, designed for radial undersampled cardiac MRI, facilitates 200× faster reconstruction than traditional iterative techniques while maintaining a SSIM of 0.963 and a PSNR of 40.238 dB [66]. Similarly, k-SRNet, k-UNet, kt-SRNet, and kt-UNet integrate deep super-resolution techniques to enhance spatial detail recovery in highly accelerated cine MRI, outperforming conventional interpolation-based upsampling [23].

Hybrid physics-informed DL models further improve spatially undersampled MRI reconstruction by integrating MRI physics constraints, such as k-space consistency, coil sensitivity enforcement, and sparsity priors, directly into DL architectures, ensuring enhanced generalizability and reduced artifacts. SCR-DL, STR-DL, and SENSE-DL integrate iterative physics-guided reconstruction with coil sensitivity regularization, achieving SSIM values of 91.4% at $R=8$, outperforming conventional techniques such as GRAPPA (SSIM: 69.9%) and SENSE-DL (SSIM: 86.9%) [67]. DARCS, a memory-efficient deep CS framework for 3D whole-heart coronary MR angiography, enhances reconstruction by employing an artifact estimation network as an adaptive sparsifying transform, resulting in a 2 dB PSNR improvement over DAGAN and a 37% reduction in memory consumption [68]. Collectively, these models enable high-fidelity reconstructions at higher spatial acceleration factors, significantly improving the clinical feasibility of rapid, high-resolution cardiac MRI while maintaining diagnostic accuracy.

While spatial undersampling techniques primarily focus on accelerating individual frames, spatiotemporal undersampling techniques use redundancy across time to enable further acceleration while maintaining temporal coherence.

Spatiotemporal Undersampling

DL-based reconstruction models for spatiotemporal undersampling in CMR exploit spatial and temporal redundancies to improve image quality while significantly accelerating reconstruction. CINENet, a 4D DL-based reconstruction network, employs (3+1)D complex-valued spatiotemporal convolutions to process multi-coil data and reconstruct highly undersampled 3D Cartesian CINE MRI [19]. It enables single-breath-hold isotropic 3D CINE acquisition in Less than 10 s and achieves a 67% improvement in image contrast compared to iterative methods. MoDL-SToRM, a model-based DL framework, integrates SToRM manifold regularization with CNN-based denoising priors to reconstruct free-breathing and ungated cardiac MRI [69]. It reduces scan time by a factor of 5×, reconstructing high-fidelity images from 8.2s of acquisition time per slice compared to the standard 42s SToRM acquisition. FlowVN [46], a deep variational network for 4D flow MRI, reconstructs undersampled data with Learnable spatiotemporal filter kernels, reducing reconstruction time to 21 s while maintaining high accuracy in flow quantification. TD-DIP, a time-dependent deep image prior method, reconstructs cardiac dynamic sequences without external training, leveraging a temporal manifold constraint to generate smooth cardiac motion representations [21]. It outperforms CS-based approaches while maintaining high spatial resolution. MEL (Memory-Efficient Learning) [47], a framework designed for high-dimensional MRI, enables efficient DL-based unrolled reconstruction for spatio-temporal CMR while reducing GPU memory consumption, thereby allowing for larger-scale 3D and 2D + time reconstructions without performance degradation. GLEAM (Greedy Learning for Accelerated MRI) [70] further addresses the computational challenges in dynamic imaging by employing a module-wise training strategy, achieving a 1.8 dB PSNR improvement in 3D reconstructions while reducing training memory footprint. 3D U-Net for real-time phase contrast CMR [71] is tailored for rapid velocity quantification in congenital heart disease, Leveraging deep artifact suppression with U-Net-based regularization to reduce reconstruction time from 59s (CS) to 3.9s, achieving faster and more accurate flow assessment . mDCN (Multi-level Densely Connected Network) [72], optimized for 5D cardiac MR multitasking, reduces feature-space computation time from 20 min to 0.39 s, a 3000× speed improvement, making high-dimensional CMR reconstruction feasible for clinical application. Collectively, these models enable real-time CMR imaging, improved motion fidelity, and enhanced dynamic contrast estimation, significantly advancing DL-driven spatiotemporal undersampling in cardiac MRI.

Motion Mitigation Techniques

Motion artifact reduction in CMR imaging is critical for ensuring high-quality diagnostic images, as cardiac and respiratory motion can introduce blurring, ghosting, and misalignment of anatomical structures [73, 74]. Traditional approaches to motion correction, such as breath-holding, electrocardiogram (ECG) gating, and navigator-based tracking, often extend scan times, increase patient discomfort, or result in incomplete data acquisition [3]. Retrospective motion correction techniques, including image registration and non-rigid motion estimation, have been developed to mitigate these issues but may struggle with complex motion patterns and signal inconsistencies [75].

DL-based motion artifact reduction has emerged as a transformative solution by leveraging CNNs, recurrent neural networks (RNNs), and transformer-based architectures to learn motion patterns and predict artifact-free reconstructions [74, 76, 77]. These models can be trained on large datasets of motion-corrupted and clean images to automatically identify and correct motion-induced distortions. For instance, Lyu et al. (2020) [74] proposed a recurrent neural network to extract spatial and temporal features from motion-blurred cine cardiac images, significantly improving image quality. Additionally, physics-informed DL methods integrate motion compensation directly into the image reconstruction pipeline, reducing artifacts while preserving fine cardiac structures.

Motion artifacts significantly impact the quality of CMR, leading to blurring and ghosting that compromise diagnostic accuracy. To mitigate these artifacts, GAN-Automap integrates adversarial learning within an AUTOMAP-based reconstruction pipeline, refining motion-corrupted k-space data into high-fidelity images [20]. This model was trained using 25,000 images from the UK Biobank dataset, achieving substantial artifact suppression and PSNR improvement of 4.2 dB over traditional Fourier-based reconstruction. Similarly, View2Dmotion [76] proposes a deep-learning-based motion simulation and correction tool, designed to generate synthetically corrupted datasets for training, which enhances model robustness in handling real-world motion inconsistencies, reducing motion-induced streaking artifacts by 68%. MARC (Motion Artifact Reduction using Convolutional networks) employs a multi-channel CNN to suppress motion artifacts in dynamic contrast-enhanced MRI (DCE-MRI), demonstrating a 30% improvement in SNR and an SSIM increase of 5.1% [77]. For cine CMR, bi-directional ConvLSTM and multi-scale convolution networks integrate long-range temporal dependencies, significantly reducing motion-induced frame misalignment by 43% and ghosting by 57%, while maintaining high temporal resolution [74].

Advanced motion-compensated reconstruction techniques, such as Motion-Compensated MR Reconstruction (MCMR), refine the interplay between motion estimation and reconstruction through iterative unrolled Learning frameworks. The MCMR approach Leverages groupwise motion estimation, achieving artifact-free motion estimation and high-quality cine reconstruction at acceleration factors up to 20×, with a PSNR increase of 3.8 dB compared to conventional CS methods [31]. In contrast, MALLRT (Motion Aligned Locally Low Rank Tensor) applies CS and tensor-based low-rank models to correct motion misalignment across dynamic cardiac frames, resulting in substantial improvements in signal-to-error ratio (SER) by 32% and SSIM by 4.3% [78]. Finally, MALLRT-based End-to-End Motion Correction integrates motion correction and SR to reconstruct high-resolution 3D cardiac volumes, achieving a 60% reduction in inter-slice misalignment and a Dice similarity coefficient of 0.974 for the left ventricle (LV) [45] . Collectively, these models exemplify the growing potential of DL in enhancing cardiac MRI reconstruction, reducing scan time, and improving the accuracy of functional and structural assessments.

Quantitative Mapping Techniques

Quantitative CMR has been significantly enhanced by DL-based methods that allow for simultaneous multi-parametric mapping, reducing acquisition times and improving motion robustness. Deep Image Prior Magnetic Resonance Fingerprinting (DIP-MRF) [79] combines low-rank subspace modeling with DL to reconstruct T1, T2, and proton density (PD) maps without requiring in vivo training data. This self-supervised framework integrates CNNs with a mathematical model of cardiac MRF, mitigating motion artifacts and accelerating image reconstruction. DIP-MRF was validated at 1.5T in 18 healthy subjects and 10 cardiomyopathy patients, demonstrating a nRMSE reduction of 30% compared to dictionary-matching approaches and strong correlation with reference phantom values (R^2 >0.999). The method successfully shortened breath-hold duration from 15 to 5 heartbeats while maintaining high fidelity in myocardial T1 and T2 values, with a bias of −9 ms for T1 and +2 ms for T2, improving diagnostic feasibility for patients with irregular heart rates.

Expanding beyond MRF, Deep T1-T2 Multi [80] integrates convolutional and recurrent neural networks to estimate T1 and T2 maps directly from undersampled CMR data, bypassing dictionary-based pattern matching. In a study involving 58 healthy subjects at 1.5T, this approach reconstructed T1-T2 maps in under 400 ms per slice, a 700× acceleration compared to conventional dictionary-based methods. The DL model achieved a T1 deviation of only 3.6 ms and T2 deviation of −0.2 ms relative to dictionary-based results, demonstrating high robustness across varying cardiac rhythms.

Challenges and Future Directions

Data Scarcity

One of the fundamental challenges in DL-based CMR reconstruction is the limited availability of high-quality datasets. As noted earlier, the CMR data collection is difficult and expensive, as a result, research groups lacking large-scale data collection infrastructure face substantial barriers to reproducing results and making comparisons to existing methods in the literature. Recent years, the NYU Langone Healthy has released the fastMRI dataset containing multi-channel knee and brain MRI raw data and has largely facilitated the development of clinical applications in the brain. The success of scaling laws in other fields also demonstrates that the amount of computation and data used can have substantial impacts on a model's performance [81]. However, these images are inadequate for (3+1)D (time domain) application in cardiac imaging. Recently, more and more public and standard cardiac datasets have been built to accelerate the development of cardiac community, including the CMRxRecon dataset [82–84]. Future work should prioritize on developing robust data sharing frameworks and establishing large-scale, diverse datasets as standardized benchmarks for the field [85].

Instabilities and Hallucinations

DL-based CMR reconstruction faces challenges with instabilities and hallucination-like artifacts, particularly when models encounter data outside their training distribution or under high acceleration factors (e.g., >5 folds) [64, 86]. Hallucinations appear as false structures such as nonphysical myocardial enhancement or erroneous diffusion tensor parameters arising from inaccurate priors or k-space inconsistencies [64, 86]. These artifacts can be misidentified as pathologies (e.g., false scar tissue) or obscure subtle anatomical changes, risking misdiagnosis or unnecessary interventions [87]. While unrolled networks and physics-informed architectures mitigate risks by integrating data consistency layers and MR physics, limitations persist in pathologies underrepresented in training data and computational stability at ultra-high accelerations [64, 86]. Current solutions prioritize hybrid DL-CS frameworks and adversarial training to balance artifact suppression with diagnostic fidelity [68, 87].

Computational Cost and Efficiency

Computational cost and efficiency significantly impact DL-based CMR reconstruction, influencing both clinical feasibility and image quality. The high dimensionality of CMR data (spatial plus temporal) increases computational demands, with 3D whole-heart reconstructions often requiring > 16 GB GPU memory [64, 83]. While DL methods like unrolled networks (e.g., VarNet) improve reconstruction quality, they can increase computational load by 30–50% compared to purely data-driven approaches [88]. However, once trained, DL models offer substantial speed improvements; for instance, the MoCo-MoDL [88] framework achieves reconstruction times of ~30 s for 3D images, approximately 240 times faster than traditional methods. This shift in computational burden from reconstruction to training allows for near real-time clinical applications. GPU acceleration plays a crucial role in DL-based CMR reconstruction, leveraging high-performance parallel computing through multi-threaded execution and multi-core architectures [89]. Libraries such as cuDNN optimize GPU efficiency by enabling fast matrix computations, convolutional operations, and memory management, significantly reducing reconstruction time while maintaining high image fidelity [89].

Clinical Translation and Validation

Despite technical progress, DL-based reconstruction still faces challenges in clinical translation. Current DL models often struggle with generalization across different scanning protocols, hardware configurations, and patient populations. The sensitivity to variations in acquisition parameters, such as acceleration factors and sampling patterns, poses challenges for widespread deployment. Moreover, the handling of motion artifacts, particularly in patients with irregular heart rhythms or breathing patterns, remains an open problem. The previous comparison [90] have already mentioned the discrepancy between statistics of image quality metrics and quality scores from human experts. Non-contrast CMR, driven by AI-based models using cine-CMR and T1 mapping, offers a promising future by reducing costs, scan times, and eliminating contrast-related risks [91]. However, challenges include the need for large, diverse datasets, algorithm transparency, and multicenter validation, while future advancements can leverage AI-driven tissue characterization and rapid imaging techniques for broader clinical application in ischemic and non-ischemic cardiomyopathies.

MRI vendors have advanced AI-based image reconstruction, with recent DL-based CMR techniques showing robust vendor-specific validation. For example, with GE HealthCare's AIR™ Recon DL achieving sharper myocardial borders in free-breathing late gadolinium enhancement (LGE) studies through k-space-optimized networks [50], while Siemens Healthineers' Deep Resolve enhances SNR and image sharpness in cardiac DTI, improving myocardial border definition and diffusion tensor visualization while ensuring more reliable quantitative parameters like fractional anisotropy (FA) and mean diffusivity (MD) [92]. Philips' SmartSpeed, integrated into pediatric CMR protocols, enabled improved image quality in fetal cardiac cine MRI by enhancing the apparent signal-to-noise ratio (aSNR) by 61% and the apparent contrast-to-noise ratio (aCNR) by 85%, while also improving diagnostic confidence in evaluating cardiovascular structures [93]. Canon Medical's Advanced intelligent Clear-IQ Engine (AiCE) which enhances image quality [94], while AI–assisted compressed sensing (ACS) developed by United Imaging Intelligence (UII) and United Imaging Healthcare (UIH), integrate CS, PI, and half-Fourier (HF) acceleration technique into a unified AI-driven reconstruction framework [95]. However, comprehensive peer-reviewed CMR validation studies are necessary for the wider spread of these systems.

Physics and Physiology Guided CMR Reconstruction and Novel CMR Contrasts

CMR reconstruction explicitly models MRI signal generation principles and tissue physiology to improve image reconstruction [96, 97]. It can integrate fundamental signal encoding models, such as the Bloch equations, into the reconstruction process, allowing direct estimation of quantitative tissue properties, such as T1 and T2 relaxation times, diffusion coefficients, and flow velocities. The incorporation of the models enables improved parameter estimation and reduces motion artifacts [98], making them particularly effective in dynamic CMR applications, including myocardial perfusion imaging, quantitative mapping, and flow-sensitive acquisitions [99]. Furthermore, DL enables the development of novel imaging contrasts, allowing for extracellular volume (ECV) and myocardial fibrosis assessment without contrast agents. Virtual Native Enhancement (VNE) and Cine-Generated Enhancement (CGE) leverage generative DL models to synthesize LGE-equivalent images from native T1 maps and cine imaging, eliminating the need for gadolinium contrast. VNE, trained on 4,271 datasets from 912 patients, achieved a scar quantification accuracy of 84%, with a Pearson correlation of 0.89 and ICC of 0.94 against conventional LGE, showing superior image quality while reducing scan time and cost [100]. Similarly, CGE, validated in 430 acute myocardial infarction patients across three centers, demonstrated a sensitivity of 91.27% and specificity of 95.83% in detecting infarcted regions, offering a practical non-contrast alternative for myocardial viability assessment [101]. Collectively, these DL-based approaches not only improve efficiency but also broaden the accessibility of multi-parametric CMR by offering faster, motion-robust, and contrast-free quantitative imaging solutions with advanced contrast that were not currently available in routine clinical practice [13, 102]. These advancements in DL-based CMR reconstruction are transforming clinical practice by enabling faster, more comfortable, and more informative cardiac imaging examinations. As research continues, we can expect further improvements in image quality, acquisition speed, and the development of novel CMR contrast tailored to the complexities of cardiac motion and physiology.

Conclusions

Deep learning (DL) has revolutionized cardiac magnetic resonance (CMR) reconstruction by enhancing imaging speed, spatial resolution, artifact suppression, and quantitative mapping. AI-driven techniques, including self-supervised learning, transformer-based models, and physics-guided networks, have significantly improved fast imaging, denoising, super-resolution, motion correction, and facilitate novel CMR contrasts. Despite these advancements, challenges remain, including data scarcity in dynamic CMR acquisitions, model instabilities, hallucination artifacts at high acceleration factors, and computational constraints that limit real-time deployment. Additionally, the need for large-scale multi-center validation and regulatory approval remains a barrier to widespread clinical adoption. Future research should focus on developing standardized datasets, improving model interpretability, optimizing DL architectures for efficiency, and integrating multi-modal imaging and hybrid AI-physics models to enhance robustness. As AI-driven CMR continues to evolve, real-time, automated, and personalized imaging solutions are becoming increasingly feasible, paving the way for broader clinical implementation and improved patient outcomes.

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  This review provides a comprehensive overview of recent advancements in deep learning-based reconstruction methods for cardiac MRI, highlighting their potential to enhance image quality and accelerate acquisition times. It also discusses key challenges and future directions in clinical deployment.

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  This review presents a detailed discussion on the role of machine learning in MRI reconstruction, emphasizing how AI-driven approaches can optimize image acquisition, reduce scan times, and improve diagnostic accuracy. It provides valuable insights into neural network architectures and learning strategies for MRI applications.

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Declarations

Informed Consent This study did not involve human participants or patient data; therefore, informed consent was not applicable.

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