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Review

# Diagnostic Accuracy of Radiomics Versus Visual or Threshold-Based Assessment for Myocardial Scar/Fibrosis Detection on Cardiac MRI: A Systematic Review

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## Abstract

**Background:** Myocardial scar and fibrosis predict adverse cardiac outcomes. Late gadolinium enhancement (LGE) cardiac magnetic resonance (CMR) is the reference standard for detection. However, it requires gadolinium-based contrast agents (GBCAs), which may be unsuitable for some patients. Cine balanced steady-state free precession (bSSFP) sequences are universally acquired in routine CMR. They may enable contrast-free scar detection via radiomics analysis. **Aim:** To systematically review the diagnostic accuracy of cine CMR radiomics for myocardial scar or fibrosis detection. The reference standard is visual or threshold-based LGE. **Methods:** This review followed PRISMA guidelines and was registered in PROSPERO (CRD420251121699). We searched MEDLINE, Embase, and Cochrane Library up to 8 August 2025. Eligible studies compared cine CMR radiomics with LGE-based assessment in patients with suspected or known scar/fibrosis. Quality was assessed using QUADAS-2 and Radiomics Quality Score (RQS). **Results:** Five retrospective studies (n = 1,484) were included. Two focused on myocardial infarction, two on hypertrophic cardiomyopathy, and one on ischaemic versus dilated cardiomyopathy. Diagnostic performance was good to excellent (AUC 0.74–0.96). Methodological heterogeneity was substantial in reference standards, segmentation, preprocessing, feature selection, and modelling. Only one study used external validation. QUADAS-2 showed high bias risk in patient selection and index test domains. RQS scores were low (30–42%), indicating limited reproducibility and validation. **Conclusions:** Cine CMR radiomics shows promise as a non-contrast alternative for detecting myocardial scar and fibrosis. However, methodological standardisation, multicentre validation, and prospective studies are needed before clinical adoption.

**Keywords:** radiomics; myocardial scar; cardiac MRI; cine MRI; late gadolinium enhancement

## 1. Introduction

Accurate detection of myocardial scar and fibrosis is clinically essential, as both replacement and interstitial fibrosis are key drivers of adverse cardiac remodelling and occur across a spectrum of conditions, including ischaemic injury, myocarditis, and cardiomyopathies. These pathologies exhibit distinct morphologic patterns and underlying mechanisms that influence prognosis and management [1–3]. Imaging-detected myocardial scar or fibrosis consistently predicts poorer outcomes in both ischaemic and non-ischaemic cardiomyopathies, with greater scar burden and specific distribution patterns associated with higher risks of mortality, heart failure events, and

ventricular arrhythmias [4–6]. Therefore, imaging methods capable of reliably detecting and quantifying myocardial scar are of major clinical importance.

Cardiac Magnetic Resonance (CMR) is widely regarded as the reference standard for non-invasive assessment of myocardial structure, function, and scar, owing to its high spatial and temporal resolution and the lack of ionising radiation [7–9]. Late Gadolinium Enhancement (LGE) is the clinical gold standard for detecting and quantifying focal myocardial scar or fibrosis, providing high-contrast visualisation of fibrotic tissue through differential gadolinium distribution. It offers excellent spatial resolution and reproducibility, with robust evidence supporting its application across a wide range of cardiac pathologies [9,10]. However, LGE performance may vary across diseases: in ischaemic heart disease, it clearly delineates transmural scar in the presence of contrast administration, while in hypertrophic cardiomyopathy diffuse interstitial fibrosis may be underestimated due to absent or subtle enhancement [11,12].

Despite its strengths, LGE requires intravenous Gadolinium-Based Contrast Agents (GBCAs), which, although generally well tolerated, are contraindicated in severe renal impairment because of the risk of nephrogenic systemic fibrosis and may also be unsuitable in patients with hypersensitivity [13]. LGE also prolongs scan time, depicts scar at a single time point, and requires additional imaging beyond routine cine sequences. Concerns over the environmental impact of unmetabolised gadolinium excretion have further prompted interest in non-contrast alternatives [14,30]. Studies report anthropogenic gadolinium concentrations in surface waters up to 0.1–1 µg/L in urban areas, reflecting widespread contamination from medical use. Cine balanced Steady-State Free Precession (bSSFP) imaging, the backbone of routine CMR protocols, is universally acquired and provides high-resolution, high-contrast visualisation of ventricular anatomy and wall motion without the need for contrast agents, offering a potential platform for scar and fibrosis assessment [9,10]. Recent studies have explored non-contrast methods like T1 $\rho$  mapping for fibrosis detection [28,29].

Radiomics converts medical images into quantitative features. These include shape, intensity, and texture metrics. It characterizes tissue heterogeneity beyond visual perception [15,16]. In CMR, radiomics captures sub-visual changes. It improves diagnosis, prognosis, and classification with proper feature selection, machine learning, and validation [15–17,31]. Although established in oncology, its use in cardiac MRI for scar detection via cine imaging remains in its early stages [15,16]. Multiple studies have demonstrated that cine CMR radiomics can differentiate between scarred and non-scarred myocardium when benchmarked against visual or threshold-based LGE assessment [20–24]. However, marked methodological heterogeneity, including variations in segmentation protocols, feature extraction methods, modelling strategies, and validation approaches, limits direct comparison and generalisability. Given the universal acquisition of cine sequences in routine CMR, integrating radiomics to non-invasively and efficiently identify scar or fibrosis offers the potential to substantially expand the diagnostic utility of CMR without increasing scan time or requiring contrast administration.

This systematic review aims to critically appraise and synthesise the available evidence on the diagnostic accuracy of cine CMR radiomics for myocardial scar and fibrosis detection. We also appraise methodological quality using both the QUADAS-2 framework and the Radiomics Quality Score, in order to highlight areas for improvement and promote reproducibility in future research.

## 2. Materials and Methods

### Protocol and registration

This systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement [20]. The protocol was prospectively registered in PROSPERO (registration number: CRD420251121699).

### Eligibility criteria

A PICO framework was used to define eligibility criteria. Eligible studies included:

1. **Population:** Patients undergoing cardiac magnetic resonance (CMR) for suspected or known myocardial scar or fibrosis.

2. **Intervention / index test:** Radiomics analysis applied to cine balanced steady-state free precession (bSSFP).
3. **Comparator / Reference standard:** Visual or quantitative threshold-based assessment of scar or fibrosis on CMR.
4. **Outcome:** Diagnostic accuracy studies directly comparing radiomics-derived metrics to the reference standard.

Only studies assessing myocardial scar or fibrosis detection or quantification using radiomics (cine or LGE CMR) compared against a visual or threshold-based reference standard for scar/fibrosis were included. Studies focusing on acute myocardial infarction, microvascular obstruction, or other pathologies without scar/fibrosis quantification as the reference standard were excluded.

#### **Information sources and search strategy**

A comprehensive literature search was conducted in MEDLINE, Embase, and the Cochrane Library from database inception to 8 August 2025, without language restrictions. The complete search strategy, including detailed search terms, is provided in Supplementary Material S1. To ensure completeness, reference lists of all included studies and relevant reviews were manually screened, and grey literature sources were searched for additional eligible studies.

#### **Study selection**

All search results were imported into the reference management software EndNote, and duplicates were removed. Two reviewers (CM and RD) independently screened titles and abstracts, followed by a full-text assessment of potentially eligible studies against the pre-determined inclusion criteria. Disagreements were resolved by consensus or adjudication by a third reviewer (HT).

#### **Quality assessment**

Methodological quality and risk of bias for each study were assessed using the QUADAS-2 tool, which evaluates four domains: patient selection, index test, reference standard, and flow/timing, with applicability concerns assessed in parallel. In addition, radiomics-specific methodological quality was appraised using the Radiomics Quality Score (RQS), a 16-item framework assessing aspects such as image protocol reporting, feature robustness testing, model validation, biological/clinical validation, and data/code sharing. Scoring details are provided in Supplementary Material S2.

#### **Data extraction**

Two reviewers (CM and RD) independently extracted data using a pre-piloted form capturing study characteristics (year, country, patient population), MRI acquisition parameters, segmentation and feature extraction methods, modelling approaches, performance metrics, comparator performance, and validation strategies. Discrepancies were resolved by consensus or adjudication by a third reviewer (HCT). Data extraction and management were performed using Covidence, the Cochrane Collaboration's screening and data extraction platform.

#### **Data synthesis**

Due to substantial heterogeneity in populations, reference standards, radiomics workflows, validation strategies, and reporting of performance metrics, a quantitative meta-analysis was not feasible. Instead, a narrative synthesis with structured tabulation was performed, grouping studies by reference standard and population where possible to facilitate qualitative comparison and identify methodological trends. Only a subset of studies reported operating-point metrics such as sensitivity, specificity, or accuracy. Most results were limited to Area Under the receiver operating characteristic Curve (AUCs), which, while comparable across studies, constrain assessment of clinically applicable thresholds

### **3. Results**

#### **Study selection and characteristics**

The systematic search identified five studies meeting the predefined inclusion criteria, yielding a total of 1,484 participants. All were retrospective observational studies, conducted between 2018 and 2025, with sample sizes ranging from 42 to 718 participants. Two studies focused exclusively on patients with prior myocardial infarction, two on hypertrophic cardiomyopathy, and one on the

differentiation between ischaemic and dilated cardiomyopathy. In all cases, cine CMR radiomics was compared against LGE-based assessment of scar or fibrosis, with the reference standard defined either visually or via quantitative thresholding. While three studies included only internal cross-validation or train/test splits, one incorporated a fully independent external test cohort. The methodological characteristics of each study are summarised in Table 1.

### **MRI acquisition**

All studies used cine balanced Steady-State Free Precession (bSSFP) imaging as the index sequence, with the majority performed at 1.5 T; one study included both 1.5 T and 3.0 T scanners from multiple vendors. Where reported, cine coverage was a short-axis stack ( $\pm$  long-axis views) with typical temporal resolution of  $\sim$ 30–50 ms. LGE was performed in all studies to establish the reference standard; contrast type/dose and breath-hold/gating details were variably reported. MRI acquisition parameters are presented in Table 2.

### **Segmentation, feature processing, and modelling**

Segmentation approaches varied: three studies used fully manual Left Ventricle (LV) border delineation (3D Slicer or ITK-SNAP), and two applied semi-automated methods (e.g., cvi42) with manual correction. Most analyses targeted the whole LV myocardium in 2D or 3D, with scar/fibrosis regions defined from LGE. End-diastolic and/or end-systolic phases were analysed, and some combined features across slices or phases. Feature extraction, most often via PyRadiomics with Image Biomarker Standardisation Initiative (IBSI) compliance, followed pre-processing steps such as isotropic voxel resampling, grey-level discretisation (30–120 bins), intensity normalisation, and—in one study—Z-score normalisation. The reasons for specific preprocessing choices, such as bin numbers, were not explained in the studies. Extracted features included shape, first-order, and higher-order texture metrics (e.g., GLCM, GLRLM, GLSZM, NGTDM, wavelets). Feature selection methods included ICC filtering, RFECV, Boruta, and LASSO. Models ranged from logistic regression, SVM, random forest, and XGBoost to a hybrid deep learning–radiomics approach in one study. Full details are provided in Table 3.

### **Diagnostic performance**

Cine CMR radiomics demonstrated good to excellent discrimination for LGE-defined scar or fibrosis across all included studies.

In myocardial infarction cohorts, Avard et al. [15] and Baessler et al. [16] reported AUCs of 0.92–0.93 in internal validation, with sensitivities and specificities around 86% and 82%, respectively.

In hypertrophic cardiomyopathy, Fahmy et al. [17] achieved an AUC of 0.81 using a hybrid deep learning + radiomics model, while Pu et al. [19] reported an AUC of 0.906 for a purely radiomics-based approach. Pu et al. also performed external validation, which yielded a reduced but still clinically relevant AUC of 0.74 in an independent cohort.

In the ischaemic vs dilated cardiomyopathy setting, Lasode et al. [18] achieved AUCs of 0.915–0.956 for classification tasks including scar/no-scar detection, using repeated cross-validation. Radiologist cine reads, reported for context, had true-positive and false-positive rates of  $\sim$ 0.87 and 0.32 for ICM vs DCM discrimination, although no formal statistical comparisons (e.g., DeLong test) were provided.

Full performance metrics are provided in Table 4.

Table 1. Methodological characteristics.

Author (year)	Country	Study design (retrospective /prospective, single vs multicentre)	Patient population (disease type, inclusion/exclusion)	Sample size	Reference standard (visual or threshold-based LGE/cine)	Comparator	Primary outcome
Avard et al. (2022)	Iran	Retrospective, single-centre	Patients with prior MI – ischaemic cardiomyopathy. Non-contrast cine CMR	52 MI cases 20 Control	Visual assessment of scar on LGE (reference)	Radiologist visual read	Diagnostic accuracy of cine radiomics vs LGE for MI detection
Baessler et al. (2018)	Switzerland, Germany	Retrospective, single-centre	Patients with subacute or chronic MI confirmed on LGE	120 MI patients 60 Control	Visual assessment of scar on LGE (reference)	Radiologist visual read of cine MR images	Ability of cine texture analysis to identify subacute and chronic myocardial scar
Fahmy et al. (2022)	USA, Canada, Italy	Retrospective, multicentre	HCM patients with and without LGE-defined scar	759 patients (100 external validation)	Visual assessment of scar on LGE	Deep learning, combined radiomics + DL	Diagnostic accuracy of combined radiomics + DL cine model in identifying myocardial scar compared to LGE visual assessment
Lasode et al. (2025)	Thailand	Retrospective, single-centre	Patients with ICM or DCM, with/without scar	100 ICM (50 with scar, 50 without) 100 DCM (50 with scar, 50 without)	Visual assessment of scar and ICM vs DCM by LGE	Radiologist visual read	Differentiation of ICM vs DCM and scar detection
Pu et al. (2023)	China	Retrospective, single-centre	HCM patients with/without fibrosis	273 patients (Training n=191, Test n=82)	Visual assessment of scar by LGE	Radiologist visual read of LGE images	Diagnostic accuracy of cine radiomics model (alone and integrated with clinical variables) in detecting myocardial fibrosis, compared to the LGE visual standard.

Abbreviations: CMR, Cardiac Magnetic Resonance; DCM, Dilated Cardiomyopathy; DL, Deep Learning; HCM, Hypertrophic Cardiomyopathy; ICM, Ischaemic Cardiomyopathy; LGE, Late Gadolinium Enhancement; MI, Myocardial Infarction; USA, United States of America.

**Table 2.** MRI acquisition parameters.

Study (year)	Scanner vendor & field strength	Sequences used (cine bSSFP, LGE, T1, etc.)	Contrast agent (type, dose) if applicable	Slice coverage	Spatial & temporal resolution	ECG gating / breath-hold
Avard et al., Comput Biol Med (2022)	Siemens MAGNETOM Aera, 1.5 T	Cine bSSFP short-axis for LV function; LGE used for reference/labels.	GBCA used for LGE (type/dose NR).	Cine short-axis stack from base to apex.	Pixel size 1.37–1.68 mm <sup>2</sup> ; TR 43.35 ms; TE 1.22 ms; flip 65°; temporal resolution 30–40 ms.	Gated cine reported (ECG assumed but type NR); breath-hold NR.
Baessler et al., Radiology (2018)	Philips Achieva, 1.5 T; 5-element cardiac phased-array coil	Cine bSSFP short-axis for LV function; LGE (IR-GRE) for scar; T2-weighted black-blood for edema (exclusion).	Gadobutrol (Gadovist) 0.2 mmol/kg; LGE acquired ~15 min post-injection.	Cine: short-axis; LGE: whole LV stack.	NR in manuscript	Retrospective ECG-gated; breath-hold technique reported.
Fahmy et al., JCMR (2022)	Multi-vendor 1.5 T (Philips Achieva; GE Signa Genesis/Excite; Siemens Sonata/Avanto/Symphony/Verio). External test set: Philips Achieva 1.5 T.	Breath-hold ECG-gated cine bSSFP short-axis; LGE present (for labels only).	GBCA for LGE (type/dose NR).	Short-axis cine stack; LGE matched slices.	TR 2.5–3.6 ms; TE 1.1–1.7 ms; flip 39°–60°; pixel 0.6–1.4 mm; slice 8–10 mm; gap 8–10 mm; 17–30 cardiac phases.	Breath-hold; ECG-gated (gating mode NR).
Lasode et al., La Radiologia Medica (2025)	Siemens MAGNETOM Aera 1.5 T; Siemens MAGNETOM Skyra 3.0 T; Siemens MAGNETOM Vida 3.0 T; 16-element cardiac coil	Cine SSFP in 2-, 3-, 4-chambers and multislice short-axis; LGE used to identify fibrosis (non-contrast cine for radiomics).	LGE performed; GBCA type/dose NR.	Short-axis multislice stack from base to apex; plus long-axis cine views.	FOV 300–400 mm; spatial 1.5×1.5×8 to 2.0×2.0×8 mm; TR 3.0–4.0 ms; TE 1.5–2.0 ms; flip 50°–70°.	NR.
Pu et al., Eur Radiol (2023)	GE Signa Excite HD 1.5 T or Siemens MAGNETOM Avanto 1.5 T; phased-array body coil	Retrospective ECG-gated cine bSSFP (short-axis whole LV + long-axis 2/3/4-ch); LGE for fibrosis.	Gadopentetate dimeglumine 0.15–0.2 mmol/kg; LGE acquired 8–10 min post-injection.	Cine: whole LV short-axis stack + long-axis views; LGE: short- and long-axis.	Cine: slice/gap 8/2 mm; TR 3.5 & 2.64 ms; TE 1.5 & 1.11 ms; flip 45° & 56°; FOV 360×360 & 340×276 mm; matrix 224×224 & 192×125 (recon 512×512 & 192×156); temporal res ~49 & 47.5 ms. LGE parameters also reported.	Retrospective ECG gating; breath-hold NR.

Abbreviations: bSSFP, balanced steady-state free precession; CMR, cardiac magnetic resonance; DCM, dilated cardiomyopathy; ECG, electrocardiogram; FOV, field of view; GBCA, gadolinium-based contrast agent; GRE, gradient echo; HCM, hypertrophic cardiomyopathy; ICM, ischaemic cardiomyopathy; IR-GRE, inversion recovery gradient echo; JCMR, Journal of Cardiovascular Magnetic Resonance; LGE, late gadolinium enhancement; LV, left ventricle/left ventricular; mm, millimetres; ms, milliseconds; NR, not reported in manuscript; SSFP, steady-state free precession; TE, echo time; TR, repetition time.

Table 3. Segmentation, feature processing &amp; modelling.

Study	Segmentation method / software	Myocardial regions analysed	Phase(s)	Feature types extracted	Feature extraction tools / libraries	Preprocessing / feature processing	Feature selection methods	Modelling approach	Validation scheme	Software versions
<b>Avard 2022 (Computers in Biology &amp; Medicine)</b>	Manual 3D segmentation of the whole LV myocardium at end-diastole by two experts in consensus.	Whole LV myocardium (3D VOI).	End-diastole.	107 IBSI-compliant features: first-order, shape, and textures from GLCM, GLRLM, GLSZM, GLDM, NGTDM.	PyRadiomics (IBSI-compliant).	N4 bias-field correction; resampling to 1×1×1 mm (BSpline); discretization to 64 gray bins; features Z-score normalized for univariate analysis.	MSVM-RFE ranking followed by Spearman correlation filtering ( $R^2 > 0.80$ ).	Classical ML—tested LR, LDA, QDA, ET, RF, AdaBoost, KNN, Naïve Bayes, Linear SVM, MLP; best performance with LR/SVM.	Internal 10-fold CV repeated ×5; hold-out test set.	3D Slicer; PyRadiomics (IBSI-compliant, version NR); scikit-learn.
<b>Baessler 2018 (Radiology)</b>	Manual 2D ROI of LV myocardium on a single mid-ventricular short-axis cine slice at end-systole; trabeculations & epicardium excluded.	ROI within LV myocardium; patients: slice with largest LGE extent; controls: mid-ventricular slice.	End-systole (single time-frame).	Texture analysis features (total 286 across 5 groups). Final selected features included first-order (Perc.01, Variance), GLCM (S [5,5] SumEntropy), and higher-order (Teta1, Wavelet WavEnHH.s-3).	MaZda v4.6 (Institute of Electronics, Technical University of Lodz).	Gray-level normalization $m \pm 3\sigma$ prior to TA; intra-/inter-observer ICC filtering; dimension reduction with Boruta & RF-RFE; collinearity pruning.	ICC $\geq 0.75$ to retain reproducible features; Boruta and RF-based recursive feature elimination; correlation matrix pruning (retain highest Gini).	Machine learning (multiple logistic regression).	Internal 10-fold cross-validation.	MaZda v4.6.
<b>Fahmy 2022 (JCMR)</b>	LV borders automatically delineated in cvi42 then manually corrected; myocardium mask applied	Whole LV myocardium per short-axis slice.	End-diastole and End-systole.	2D radiomics: 14 shape + 93 texture per image; computed on original + 9 filtered images → 944 features/image.	PyRadiomics v3.0.1.	Resampled to 1×1 mm in-plane; normalized size 256×256; intensities scaled 0–1.	LASSO to select top features (best model with 10).	Radiomics: Logistic Regression (L1); Deep learning: CNN+FCN; Hybrid: combined DL	Internal 5-fold CV; independent external test set from separate site/vendor.	cvi42; PyRadiomics v3.0.1; TensorFlow/Keras.

	to SA cine slices.							+ radiomics probabilities.		
<b>Lasode 2025 (La Radiologia Medica)</b>	Manual segmentation in 3D Slicer v4.11 of LV myocardium, LV blood pool, RV blood pool.	LV myocardium, LV blood pool, RV blood pool.	End-diastole and End-systole.	PyRadiomics features in four groups: first-order (18), shape (14), texture (73), filter-based (1,092).	PyRadiomics v3.0.1.	Volume-wise Z-normalization; resampling to 2×2×2 mm; gray-level discretization to 30/40/60/120 bins.	Univariate AUC pre-ranking; RFECV with L2-LR.	Regularized logistic regression (L1/L2).	20 rounds of 5-fold stratified CV.	3D Slicer v4.11; PyRadiomics v3.0.1; scikit-learn.
<b>Pu 2023 (European Radiology)</b>	Manual delineation in ITK-SNAP v3.8 of (i) entire LV myocardium and (ii) maximal-wall-thickness slice.	Entire LV myocardium and MWT slice (short-axis).	End-diastole.	PyRadiomics features: first-order (18), shape (14), texture (75) + high-order (LoG/wavelet etc.).	PyRadiomics v3.0.1.	Resampling to 1×1×4 mm; intensity min-max normalization to 0–255; reproducibility screening.	ICC>0.85; Boruta to rank/keep top 100.	Machine learning (XGBoost).	Stratified 5-fold CV; internal only.	ITK-SNAP v3.8; PyRadiomics v3.0.1; XGBoost.

Abbreviations: 2D/3D = two-/three-dimensional; AUC = area under the receiver operating characteristic curve; BSpline = B-spline interpolation; CNN = convolutional neural network; CV = cross-validation; DL = deep learning; ED/ES = end-diastole/end-systole; ET = Extra Trees classifier; FCN = fully connected network; FOV = field of view; GBCA = gadolinium-based contrast agent; GLCM = gray-level co-occurrence matrix; GLDM = gray-level dependence matrix; GLRLM = gray-level run-length matrix; GLSZM = gray-level size zone matrix; IBSI = Image Biomarker Standardisation Initiative; ICC = intraclass correlation coefficient; ICM/DCM = ischemic/dilated cardiomyopathy; KNN = k-nearest neighbors classifier; L1/L2 = Lasso/Ridge regularization; LASSO = least absolute shrinkage and selection operator; LDA = linear discriminant analysis; LGE = late gadolinium enhancement; LoG = Laplacian of Gaussian filter; LR = logistic regression; ML = machine learning; MLP = multilayer perceptron;  $m\pm 3\sigma$  = gray-level normalization to mean  $\pm 3$  standard deviations; MSVM-RFE = multi-class support vector machine recursive feature elimination; MWT = maximal wall thickness; NGTDM = neighborhood gray-tone difference matrix; NR = not reported; PyRadiomics = open-source radiomics feature extraction library (Python); QDA = quadratic discriminant analysis; RF = random forest; RFECV = recursive feature elimination with cross-validation; ROI/VOI = region/volume of interest; SA = short-axis; SVM = support vector machine; TA = texture analysis.

**Table 4.** Feature assessment & diagnostic performance.

Study	Primary outcome	Cohort & split / CV	Primary metric (model)	Other metrics @ operating point	Comparator performance (visual/threshold)	Statistical tests for comparison	External validation?	Notes
Avard 2022 (Comput Biol Med)	MI detection	n=72 (MI=52, healthy=20); 10-fold cross-validation (multivariable models).	Best multivariable LR AUC 0.93 ± 0.03; SVM AUC 0.92 ± 0.05.	LR - Accuracy 0.86 ± 0.05; Recall 0.87 ± 0.10; Precision 0.93 ± 0.03; F1 0.90 ± 0.04.	None reported for cine; LGE used as reference labels.	Univariate p-values with FDR (q-values); no head-to-head vs visual cine.	No (authors note small sample; no external set).	Also reported univariate best feature AUC 0.88 (M2DS).
Baessler 2018 (Radiology)	Identify subacute and chronic myocardial scar	Patients with MI (120) vs controls (60); 10-fold cross-validation; subgroup analyses for small vs large scar.	AUC 0.92 (logistic regression on two features: Teta1 + Perc.01) for all MI vs controls.	Sensitivity 86%, Specificity 82%; cross-val accuracy ≈0.84.	None reported for cine; reference standard was visual LGE.	Group tests (t-tests/ANOVA); model selection by AIC; ROC/AUC reported.	No (internal CV only).	Also reported AUC 0.92 (small scar) and 0.93 (large scar).
Fahmy 2022 (JCMR) – HCM	Identification of myocardial scar in HCM	Development n=600 (5 CV runs) → internal test n=159; selected best models → external test n=100 (independent site/vendor).	Internal test AUC: DL-Radiomics 0.81 ± 0.02 (higher than DL or Radiomics alone). External test AUC: 0.74.	Operating at sensitivity ≥0.90. Internal specificity ~0.42; External specificity 0.28 (DL-Rad).	No cine-visual comparator; reference standard = LGE presence by visual read.	DeLong tests for AUC (e.g., external: DL-Rad vs Radiomics p=0.006; vs DL p=0.27).	Yes – independent external cohort (n=100).	Also report internal AUCs: Radiomics 0.75±0.03, DL 0.76±0.01; external AUCs: Radiomics 0.64, DL 0.71.
Lasode 2025 (La Radiologia Medica)	Differentiation of ICM vs DCM and scar detection	ICM vs DCM (n=100 each); within-group scar vs no-scar (n=50/50). Five-fold	Validation AUCs: ICM vs DCM 0.915; ICM-Scar 0.956; DCM-Scar 0.936 (logistic regression).	NR for sensitivity/specificity; AUCs also reported as mean±SD across	Radiologist on cine: TPR/FPR≈ 0.87/0.32 (ICM vs DCM), 0.76/0.16 (ICM-Scar), 0.36/0.22 (DCM-Scar).	Significant variation in AUC distributions across CV reps (p<0.0001);	No (repeated CV only).	Reference standard: LGE for scar; cine-radiomics compared with

		CV repeated 20× (≈100 repetitions).		repetitions (e.g., 0.918±0.040).		no formal DeLong vs radiologist.		radiologist performance qualitatively.
Pu 2023 (European Radiology) – HCM	Identification of myocardial scar in HCM	Training n=191, Test n=82 (internal split).	Test AUCs: R2 (radiomics whole- LV) 0.906; ICMR+R2 (integrated) 0.898.	ICMR+R2 test accuracy 89.02%, sensitivity 92.54%; R2 specificity 93.33%.	Comparator model = CMR-only; improvements shown by NRI/IDI; no cine-visual comparator.	Hosmer–Lemeshow calibration; NRI/IDI vs CMR model; ROC analyses.	No (internal split; multi- center cohort but no external hold-out).	Proposed strategy: use R2 to screen LGE(-), ICMR+R2 to flag LGE(+).

Abbreviations: AUC, area under the receiver operating characteristic curve; ACC, accuracy; SE, sensitivity; SP, specificity; CV, cross-validation; DL, deep learning; LGE, late gadolinium enhancement; LR, logistic regression; MI, myocardial infarction; HCM, hypertrophic cardiomyopathy; ICM, ischemic cardiomyopathy; DCM, dilated cardiomyopathy; NRI, net reclassification improvement; IDI, integrated discrimination improvement; ROC, receiver operating characteristic; TPR, true positive rate; FPR, false positive rate; NR, not reported.

### **Risk of bias and applicability (QUADAS-2)**

The QUADAS-2 assessment revealed several recurrent sources of bias. Patient selection was frequently high risk, particularly in Avard et al. [20] and Baessler et al. [21], which used case-control designs (e.g., MI vs healthy controls), potentially inflating diagnostic accuracy. The index test domain was high risk in Lasode et al. [23], where feature selection occurred before cross-validation, raising optimism bias concerns; in others, including Fahmy et al. [22] and Pu et al. [24], reporting was insufficient to determine whether modelling was fully nested within validation folds. Reference standard and flow/timing domains were generally low risk across all studies, as cine and LGE were acquired in the same session. Applicability concerns mainly reflected narrow patient populations or highly selective inclusion criteria.

### **Radiomics Quality Score (RQS)**

RQS totals ranged from 11 to 15 out of 36 (30.6%–41.7%). Strengths across studies included use of feature reduction, multiple testing correction, and some discussion of clinical utility. Common weaknesses were the absence of phantom or test-retest analyses, limited external validation (Pu et al. [24] being the only example), lack of model calibration or decision curve analysis, and minimal open science practices—only Pu et al. [24] shared code, and only Fahmy et al. [22] reported model calibration. No study performed cost-effectiveness analysis or prospective validation.

### **Synthesis and sources of heterogeneity**

Marked methodological heterogeneity was observed. Variations included reference standard type (visual vs threshold-based LGE), segmentation scope (single slice vs whole LV; 2D vs 3D), pre-processing protocols, feature extraction parameters, and modelling strategies. Validation approaches ranged from internal cross-validation (Avard et al. [20], Baessler et al. [21], Fahmy et al. [22], Lasode et al. [23]) to independent external datasets (Pu et al. [24]). Inconsistent reporting of operating-point metrics and 2×2 contingency data prevented pooled meta-analysis, so findings are presented narratively with structured tabulation to facilitate methodological and performance comparisons.

## **Discussion**

This systematic review synthesizes evidence on the diagnostic accuracy of cine CMR radiomics for myocardial scar and fibrosis detection. It uses visual or threshold-based LGE as the reference standard. Across five retrospective studies with 1,484 participants, cine CMR radiomics achieved good-to-excellent performance (AUC 0.74–0.96) in ischaemic and non-ischaemic cardiomyopathies [20–24]. Our findings suggest cine radiomics detects subtle myocardial changes not visible on standard assessment. This could enable scar and fibrosis evaluation without GBCAs.

The clinical impact of contrast-free scar detection is substantial. LGE CMR is the gold standard for focal scar. However, it faces limitations from GBCA contraindications, environmental concerns, and extra scan time [13,14]. Cine bSSFP sequences are routine and can be processed retrospectively for radiomics without workflow changes [8,10]. In patients with renal impairment or gadolinium hypersensitivity, cine radiomics offers a safer alternative. It may also help in resource-limited settings, where contrast access is restricted by cost or supply issues [24,25].

LGE limitations vary by disease. In ischaemic heart disease, it visualizes transmural scar well but requires contrast [11]. In hypertrophic cardiomyopathy, it often underestimates diffuse fibrosis [12]. Cine radiomics quantifies textural heterogeneity in non-contrast images. It reveals sub-visual changes. Thus, it complements LGE as a contrast-free screening tool. It may improve sensitivity to diffuse fibrosis in HCM and support scar detection in MI without gadolinium. Overall, cine radiomics expands detectable myocardial abnormalities.

However, our review highlights significant methodological heterogeneity across published studies. Key sources of variation included the type of reference standard (visual versus threshold-based LGE), segmentation scope (whole LV versus single-slice; 2D versus 3D), pre-processing pipelines (voxel resampling, grey-level discretisation, intensity normalisation), and feature extraction and selection strategies. The variation in preprocessing choices, such as grey-level discretisation bin numbers (30–120), was not justified in the included studies. This potentially impacts feature

robustness. Additionally, MRI acquisition parameters were variably reported, with some missing details that could affect reproducibility. Modelling approaches also differed widely, ranging from traditional classifiers (logistic regression, SVM) to hybrid deep learning–radiomics pipelines. This diversity hampers direct comparison, prevents meaningful meta-analysis, and may contribute to the variability in reported performance. Clinical heterogeneity was also evident, with study populations spanning myocardial infarction, hypertrophic cardiomyopathy, and dilated cardiomyopathy. Such differences in disease substrate complicate interpretation and restrict the generalisability of findings to any single clinical context.

Validation strategies represent another important limitation. Only one study (Pu et al.) [24] incorporated an independent external test set. Most relied solely on internal cross-validation, which is more prone to optimism bias, especially when feature selection is not nested within validation folds. The relatively modest Radiomics Quality Score (RQS) ratings (30–42% of the maximum) underscore persistent methodological shortcomings, such as the absence of phantom or test–retest analyses, inadequate reporting of model calibration, limited use of decision curve analysis, lack of cost-effectiveness evaluation, and minimal adoption of open science practices. Furthermore, the evidence base remains very narrow, with only five studies available, which constrains the robustness of conclusions and limits confidence in their broader generalisability. We recommend developing consensus guidelines for radiomics standardization in cardiac imaging to address these issues.

These limitations highlight the need for caution when interpreting the present diagnostic performance of cine CMR radiomics in a clinical context. While the diagnostic accuracy is encouraging, robust prospective studies with standardised pipelines and multicentre validation are required to confirm generalisability and reproducibility. Future research should assess whether cine radiomics offers added value beyond conventional functional parameters, and explore its prognostic significance and potential influence on clinical decision-making. Compared to other contrast-free techniques like native T1 and T2 mapping, which provide parametric tissue information, radiomics offers complementary textural analysis from routine cine sequences without extra scans. Incorporating head-to-head comparisons with emerging tissue characterisation techniques, such as native T1/T2 mapping and extracellular volume (ECV) quantification, will also be important to determine the relative and incremental value of radiomics in this setting.

## Conclusions

Cine CMR radiomics shows promising potential as a non-contrast, time-efficient method for myocardial scar and fibrosis detection, achieving high diagnostic accuracy when compared with LGE. However, the current evidence base is limited by methodological heterogeneity, small and selective study populations, and scarce external validation. Standardisation of radiomics workflows, transparent reporting, and rigorous multicentre prospective studies are essential to establish its clinical role. If validated, cine radiomics could complement LGE by providing contrast-free tissue characterization, and in selected cases, serve as an alternative, expanding the capabilities of routine CMR while reducing reliance on gadolinium-based contrast.

**Supplementary Materials:** The following supporting information can be downloaded at the website of this paper posted on Preprints.org. Radiomics Quality Score (RQS) details.

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