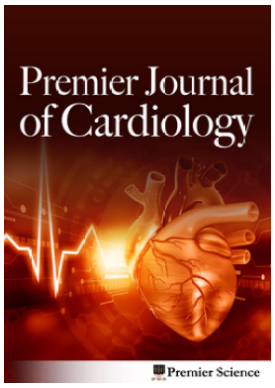


# Radiomics-Based Diagnosis in Cardiology: Advances and Prospects

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## ABSTRACT

With the increasing need for faster and more accurate diagnosis in cardiology, radiomics presents an innovative approach for assessing medical images and diagnosing clinical conditions. This review aims to highlight the applications of radiomics in the diagnosis of cardiovascular conditions. The development of a radiomic model typically progresses as follows: image acquisition and preprocessing, image segmentation, image processing, feature extraction, feature selection, and machine learning modeling and validation. Image data is commonly obtained from cardiac computed tomography angiography, cardiac magnetic resonance imaging, echocardiography, and nuclear imaging. Using machine learning frameworks such as decision trees, random forests, support vector machines, XGBoost, and deep learning, radiomics-based models demonstrated better performance for diagnosis and prediction of cardiovascular events than models designed using conventional clinical risk factors. Radiomics is applied in plaque and adipose tissue characterization to determine the degree of stenosis or predict plaque rupture. In cardiomyopathies, radiomics is employed to distinguish between healthy and diseased tissues. A notable challenge hindering the integration of radiomics in clinical practice is the lack of standardization of study protocols, including image acquisition and processing. Multiple studies also highlighted the need for high-quality images as well as validation of the radiomics model using data from multiple data collection centers. Findings from this study revealed that, while notable advancements have been recorded in radiology-based diagnosis in cardiology, there is a need for further research effort to harmonize evidence and enable the real-world clinical application of radiomics.

**Keywords:** Radiomics, Cardiovascular diagnosis, Machine learning, Coronary plaque characterization, Myocardial tissue characterization

## Highlights

- Radiomics combines the extraction of quantitative features with machine learning to analyze data and predict clinical outcomes
- Radiomics enables the detection of intricate quantitative features that may have been overlooked during visual inspection by radiologists
- Lack of standardization of study protocols limits the translation of reported findings to clinical settings

## Background

Cardiovascular diseases are associated with a high morbidity burden, and they may lead to even more serious complications and adverse health outcomes if not properly treated. Cardiovascular diseases, including coronary artery disease (CAD), stroke, and hypertensive heart disease, remain at the top of the list of killer diseases globally. CAD caused a total of 9 million deaths in 2021; this accounted for 13% of total deaths globally, making CAD the number one cause of death in that year.[1] To reduce the burden of cardiovascular diseases and promote optimal quality of life in patients with these conditions, accurate clinical diagnosis is essential. With the advent of big data technologies, including machine learning and deep learning, precision medicine has experienced significant advancements in clinical diagnosis and disease management.[2]

Radiomics is a recent development in medical imaging that utilizes advanced analytical techniques to extract quantitative features, such as shapes and signal intensities, from medical images. These features are then used to determine the presence of a clinical condition.[3] Medical imaging modalities in cardiology include coronary computed tomography angiography (CCTA), cardiac magnetic resonance imaging (CMR), echocardiography, and nuclear radiology, among others. Diagnoses based on these modalities traditionally involved a subjective assessment of imaging outputs by clinicians. However, given the heterogeneity of various cardiovascular conditions and variations in radiologists' clinical expertise, this method of diagnosis is challenging, and radiologists may fail to detect important diagnostic features.[4] A systematic review by Wong et al.,[5] which included more than 200,000 patients, revealed that heart failure misdiagnosis ranged from 16.1% to 68.5% in clinical settings. To address this, radiomics enables the detection of intricate quantitative features that may have been overlooked during visual inspection by radiologists. These features and patterns are then analyzed using machine learning algorithms for myocardial tissue characterization and adverse event risk assessments. Outcomes of radiomics-based diagnoses are used in designing individualized clinical interventions for patients with cardiovascular diseases.[6]

Artificial intelligence, particularly machine learning, plays a crucial role in radiomics. In addition to their roles in image segmentation and feature extraction, machine learning models are developed based on the extracted quantitative features and clinical data to provide predictions regarding clinical outcomes.[7] Machine learning algorithms identify complex relationships between radiomics features and provide predictions based on the analysis of these features. Common techniques employed by machine learning include supervised learning, unsupervised learning, and reinforcement learning.[6] In supervised learning, the algorithm is trained using labeled data, while in unsupervised learning, the training datasets



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are unlabeled, and the algorithm is expected to identify patterns independently.[8] In reinforcement learning, the machine learning algorithms receive rewards or penalties based on outcomes.[9] Choosing machine learning techniques depends on the nature of the problem and the characteristics of the available data. Machine learning algorithms include decision trees, support vector machines, random forests, and neural networks.[10] Deep learning, a subset of machine learning, utilizes neural networks and is commonly used in radiomics.

This review focuses on advances and prospects of radiomics in the clinical diagnosis of cardiovascular diseases. The paper explained the radiomic workflow, from image acquisition to machine learning modeling. Furthermore, specific applications of this approach, along with its challenges and limitations, were explained.

## Methods

This narrative review aimed to synthesize current literature on the application of radiomics in cardiology, with an emphasis on diagnostic performance, modality-specific advances, and prospects for clinical translation. We conducted a structured search of PubMed, Scopus, and IEEE Xplore for articles published between 2015 and 2025. Boolean terms were used to combine keywords, e.g., ("radiomics") AND ("cardiology" OR "cardiac imaging" OR "heart failure" OR "myocardial infarction" OR "coronary artery disease"). Studies were included if they evaluated radiomics in the context of cardiac structure, function, perfusion, or tissue characterization using cardiology imaging modalities. Key inclusion criteria were human or large-animal studies, reporting of diagnostic performance metrics (e.g., area under the curve [AUC], sensitivity, specificity), and clear methodology for feature extraction and modeling. Reviews, editorials, and non-English articles were excluded.

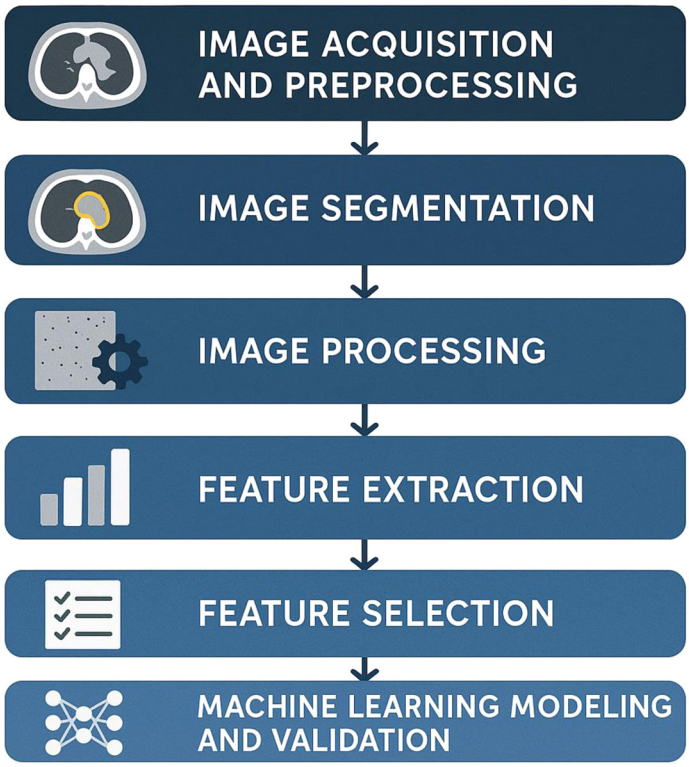


Fig 1 | Radiomics workflow in cardiology

## Radiomics Workflow in Cardiology

Radiomics workflow is divided into several steps, including image acquisition and preprocessing, image segmentation, image processing, feature extraction, feature selection, and machine learning modeling and validation (Figure 1).[4] The individual steps are interdependent, with the overall goal of developing an efficient and reliable diagnostic model.[11]

### Image Acquisition and Preprocessing

In cardiac imaging, image acquisition often relies on the fundamental technical principles of various imaging modalities, including cardiac computed tomography (CT), CMR, echocardiography, and nuclear imaging (single-photon emission CT/positron emission tomography). Images are acquired from scanners with varying image acquisition protocols, depending on the manufacturer, type, and machine settings.[12] The lack of standardized image acquisition protocols and parameters makes image acquisition challenging and affects analysis reproducibility. It is therefore imperative that standardized acquisition protocols are implemented to improve the radiomics workflow.[13] A proposed method of overcoming the bias of acquisition protocols is the test-retest analysis, which improves the reproducibility of radiomic features.[14] The use of standardized and high-quality images in the image acquisition process helps maintain robust radiomic features and eliminate unnecessary confounding variability. Image preprocessing steps include gray-level normalization, nonuniformity correction, voxel value discretization, and image reshaping.[15] The goal of image preprocessing is to ensure that the observed variations in brightness and contrast accurately reflect the differences in tissue characteristics, rather than differences in scale or matrix size.

### Image Segmentation

In image segmentation, acquired and preprocessed images are used to define one or more regions of interest (ROIs)/volumes of interest (VOIs). An ROI encompasses the anatomical region to be analyzed, including the left and right ventricles, left and right atria, coronary arteries, and myocardium.[16] Radiomics analysis is applied to the defined ROIs. Image segmentation can be achieved using either manual, semiautomatic, or fully automatic systems. The selection of the most appropriate cardiac phase for segmentation poses a challenge in cardiac image segmentation.[17] The traditional methods—manual and semiautomated segmentation systems—require user interaction, which may cause potential intraobserver and interobserver bias or variability.[4,6] Fully automated systems, however, are often recommended due to their higher reproducibility and


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accuracy. They also allow rapid segmentation of the entire cardiac phase, which would provide more information compared to the analysis of a single image or analysis at two points, such as at end-systole/diastole.[3]

### Image Processing

The goal of image processing is to ensure that images are homogeneous and consistent with respect to their pixel space, gray-level intensities, and bins of the gray-level histogram before radiomic features are extracted.[13] The image processing settings used have a significant impact on the test-retest robustness and reproducibility of the extracted radiomic features. The image processing framework comprises three steps: resampling to an isotropic voxel spacing, range resegmentation and image normalization, and image discretization.[18]

Resampling to an isotropic voxel spacing is crucial for most texture features and enhances reproducibility across different datasets. Range resegmentation and image normalization (intensity outlier filtering) are performed to remove pixels or voxels that fall outside a specified range of gray levels from the ROI or VOIs.[13] Range resegmentation is often required for CT and positron emission tomography data; however, it is not possible for data with arbitrary intensity units, such as MRI data, where intensity outlier filtering is applied.[14] The last image processing step, image discretization, is the process of grouping the original pixel or voxel gray-level values into predefined range intervals (bins). The process is conceptually similar to the creation of a histogram. Image discretization is characterized by three parameters: the range of the discretized quantity, the number of bins, and the width of each bin. The range of the discretized quantity is defined as the product of the bin number and the bin width; hence, only two of the three parameters can be freely set.[13]

### Feature Extraction

Once images have been segmented and processed, radiomic features are extracted from the predefined ROIs using sophisticated image analysis algorithms. Extracted features may be classified into three categories: shape and size, intensity, and textural features (Figure 2). Shape features quantify the three-dimensional size and shape of the ROI/VOIs and include indices such as the volume, maximum surface area, and dimensions in multiple planes.[19] They also describe the overall shape (such as compactness, sphericity, elongation, and flatness) of the segmented regions.

Intensity features are also known as first-order statistics features; they describe and assess the frequency distribution (such as the mean, minimum, standard deviation) of the gray-level value of the ROI/VOI.[20] Texture features describe the spatial distribution and relationships between pixel/voxel gray levels and characterize the texture and heterogeneity of the ROI; hence, they are more complex to understand. While shape and size features have not been often reported as useful in cardiac imaging, intensity-based and texture features are of high interest in cardiac radiomics as they add new insights into underlying tissue characteristics, such as myocardial tissue texture, that would indicate particular diseases.[21]

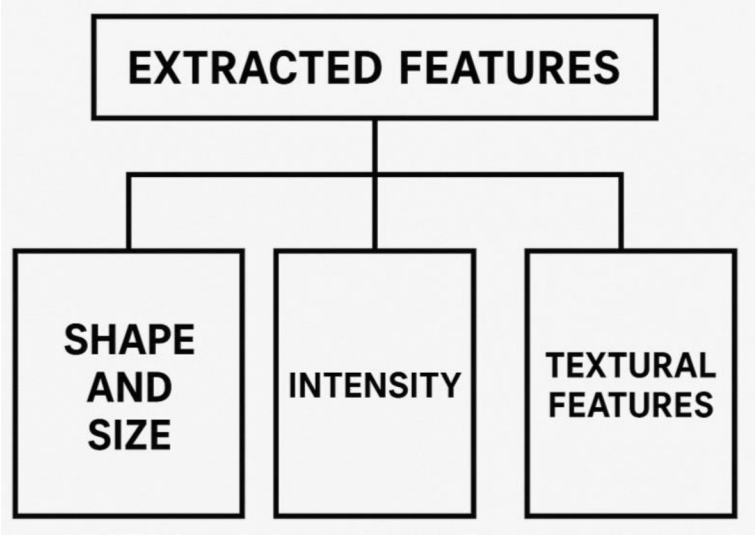


**Fig 2 | Categories of radiomics features**

### Feature Selection

Extracted features are used as predictor variables within a statistical model to classify disease or predict outcome. The process of feature extraction yields a large dataset consisting of hundreds to thousands of radiomic features, which often far exceeds the sample size of the cohorts used for model building.[22] Moderate sample sizes are often considered in cardiac imaging because using all the extracted features in a statistical model makes the model prone to overfitting.[23] Therefore, a major step in the radiomic workflow involves the selection of relevant features that are best performing, reproducible, and predictive of the outcome of interest. The goal of feature selection is to eliminate irrelevant features that may hinder the performance and generalizability of trained models.[24]

Feature selection is often performed using cluster analysis and principal component analysis. Cluster analysis is based on grouping similar radiomic features according to high cluster redundancy and low intercluster correlation, often illustrated as cluster heat maps. From each cluster, a feature is selected for further analysis. Principal component analysis involves the extraction of a small set of noncorrelated features (that explain the maximum variance in the data) from a large number of correlated features, often illustrated as score plots.[20]

### Machine Learning Modeling and Validation

Once the final set of informative radiomic features has been selected, the next step involves the development of models to evaluate the predetermined outcomes, such as diagnostic features, survival, disease-free progression, and therapeutic assessment. Models are built through various statistical and machine learning techniques, including linear regression, logistic regression, random forests, support vector machines, and deep

learning.[25] During validation, the selected features are used to train the model for the respective classification tasks and the prediction of target variables. Model validation involves the evaluation of the predictive power of the developed models using metrics such as accuracy, sensitivity, specificity, receiver operating characteristic curves, and AUC.[22] Developed models are trained and evaluated to ensure the generation of consistent and generalizable models.

The rapid development of machine learning algorithms in recent years has provided more options, aiding in the automatic extraction and selection of features and linking them to clinical parameters to better quantify and predict disease progression.[24] Finally, the model performance is evaluated on a predefined, independent dataset of patients to further demonstrate its generalization in clinical settings.

## Diagnostic Applications of Radiomics in Cardiology

This section describes applications of radiomics in different areas of cardiology (Figure 3).

### Coronary Plaque Radiomics

Plaque and adipose tissue accumulation in the coronary arteries is the hallmark clinical presentation of CAD and the cause of acute cardiovascular symptoms. Due to its noninvasiveness and accuracy compared to traditional angiography, CCTA is a common imaging modality employed in the assessment of coronary arteries and the screening for CAD.[26] Radiologists examine the CT scans and look for plaques and signs indicating rupture tendency, causing acute coronary syndrome. Plaque vulnerability signs include low attenuation, spotty calcification, positive remodeling, and the napkin-ring sign.[27] However, the accuracy of the diagnosis is dependent on the examiner's expertise. Additionally, interrater variability also causes variations in clinical judgments between radiologists and affects clinical interventions.

Radiomics offers an opportunity to automate and optimize this process and improve diagnostic accuracy. Chen et al.[28] assessed the utility of radiomics in identifying vulnerable plaques and the risk of major adverse cardiovascular events (MACE) using a CCTA radiomics model; intravascular ultrasound was used as the reference standard. With 16 radiomics features (2 shape and 14 textural features) and the XGBoost algorithm, the model was able to determine radiomic signatures from the medical images, which were highly predictive of plaque vulnerability (AUC: 0.81 and 0.75 for the training and validation datasets, respectively). Additionally, high radiomic signatures were also associated with the incidence of MACE (hazard ratio, 2.01; $P = 0.005$).

Similarly, in the study by Li et al.,[29] which utilized fractional flow reserve as the reference standard, parameters such as noncalcified plaque volume, napkin-ring sign, remodeling index, and spotty calcification were used in building a conventional model, while 14 radiomics features were used in building the radiomics model, which was based on random forest architecture. The radiomics model showed better performance than the conventional model in both the testing (AUC: 0.82 vs. 0.71) and validation (0.77 vs. 0.70) sets. Aside from XGBoost and random forest frameworks, deep learning is also utilized in building radiomics, yielding better performance compared to conventional algorithms.[30]

### Adipose Tissue Characterization

Several advances have been made recently in the imaging of adipose tissues surrounding the heart and coronary arteries, which are collectively referred to as epicardial adipose tissue. Specifically, adipose tissues surrounding coronary arteries are known as pericoronary adipose tissue (PCAT).[31] PCAT radiomics features are useful imaging markers for detecting structural alterations in adipose tissue and identifying vulnerable coronary plaque biomarkers for CAD risk assessment.[32] Given that the expression of certain genes is associated with the development of CAD, Li et al.[32] evaluated the correlation between radiomic features of PCAT and the expression of genes that could be indicative of CAD. This retrospective study involved the analysis of data from patients with CAD after undergoing coronary artery bypass grafting and CCTA. PCAT radiomic features, including texture and first-order features, were found to have strong correlations with the expression of inflammatory and vascular markers such as CD31 and MCP-1.[32] These findings confirmed that radiomics-based imaging is an innovative approach for identifying changes in adipose tissues that could indicate inflammation or the development of atherosclerosis, which may cause MACE.

In a similar study, the efficiencies of models developed with varying types of patient information were compared.[33] Data was obtained retrospectively from patients with CAD after undergoing CCTA. The study

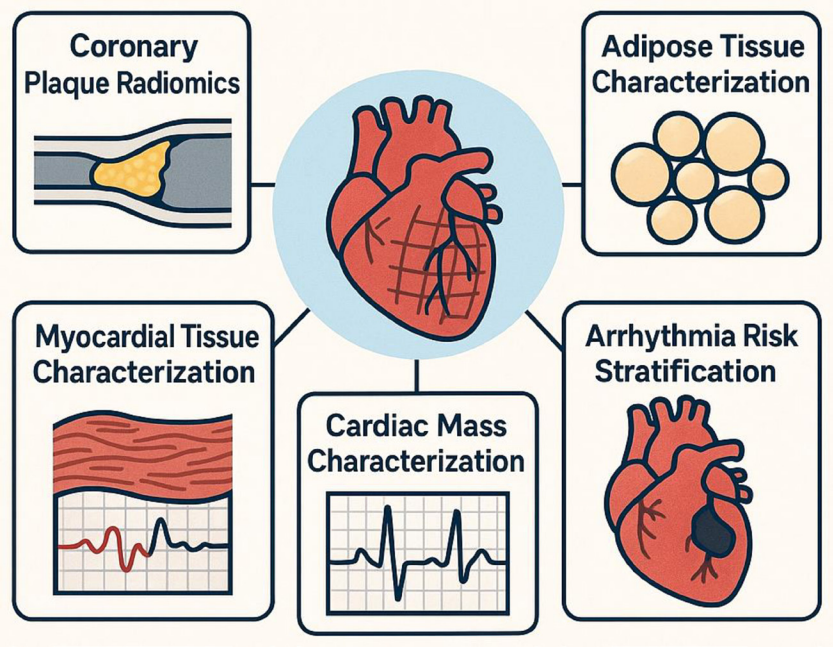


Fig 3 | Applications of radiomics in cardiology


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developed clinical radiomics and combined models using patients' clinical risk factors; radiomics scores specific for PCAT; a combination of clinical risk factors and radiomics scores; and finally, a combination of data from three previous models, respectively. The calculated radiomic score obtained from PCAT imaging data proved very effective in predicting the incidence of MACE (adjusted HR = 1.330, $P = 0.009$). Additionally, performances of the models were reported as C-indices: 0.639, 0.653, 0.698, and 0.718 for clinical, radiomics, clinical radiomics, and combined models, respectively, indicating the superior performances in radiomics-based models. Likewise, Miao et al.[34] employed a similar approach in patients with diabetes who were at a high risk of CAD. The study, which employed three algorithmic frameworks (support vector machines, decision trees, and random forests), reported superior performances in machine learning models that incorporated clinical data with radiomics data during modeling. The support vector machine-based model demonstrated better accuracy and specificity than other models.

### Myocardial Tissue Characterization

Cardiomyopathies are a group of clinical conditions that affect the heart muscle, resulting in complications and MACE. Radiomic models have been used in the evaluation of the myocardium and assessment of cardiac function. The incorporation of radiomics allows for the extraction and interpretation of visual data that is often unseen and uninterpretable by the eyes, leading to higher diagnostic accuracy and disease discrimination.[35] CMR is a widely used imaging modality in the assessment of the myocardium and screening for cardiomyopathies. Hence, radiomics-based innovations in cardiovascular imaging commonly utilize CMR data. Raisi-Estabragh et al.[36] utilized CMR data to distinguish between the anatomy of cardiac muscles in males and females, reporting larger ventricles and simpler textural features in males. Additionally, the study was able to demonstrate the correlations between vascular risk factors—hypertension, diabetes, dyslipidemia, and smoking status— and changes in the myocardium of patients. A notable finding from the assessment was the presence of smaller ventricles in hypertensive and diabetic patients.

Cardiac amyloidosis is a type of cardiomyopathy in which defective proteins (amyloids) accumulate in heart tissues and impair cardiovascular functions.[37] The application of radiomics in the assessment of this condition was reported in a previous study.[38] The study compared the performance of a radiomics model with that of myocardial CT attenuation. Designed with ten radiomics features from CT data, the radiomics model outperformed the myocardial CT attenuation for the detection of cardiac amyloidosis with AUCs of 0.95 (vs. 0.58, $P < 0.001$), 0.95 (vs. 0.59, $P < 0.001$), and 0.91 (vs. 0.64, $P < 0.001$) in training, testing, and validation cohorts, respectively. Additionally, radiomic scores correlated with NT-proBNP, a well-known biomarker for heart failure.

Both CCTA and CMR-based radiomics models have been investigated in clinical assessments for myocardial infarction.[39,40] Avard et al.[40] developed multiple machine learning models using radiomics features extracted from noncontrast cine CMR to detect myocardial infarction and distinguish MI from healthy myocardial tissues. The study highlighted logistic regression and support vector machine as the machine learning algorithms with the best performance based on the following indices: AUC: 0.93 and 0.92, accuracy: 0.86 and 0.85, and precision = 0.93 and 0.88, respectively. On the other hand, Chen et al.[39] developed multiple models using clinical, CMR, CMR+clinical, CCTA, and CCTA+ clinical data to predict adverse events following myocardial infarction. The CCTA model was found to have the most superior performance with AUC and C-index of 0.904 and 0.88, respectively, in the training cohort and 0.893 and 0.86, respectively, in the testing cohort.

### Arrhythmia Risk Stratification

The application of radiomics to improve risk stratification for ventricular tachycardia and ventricular fibrillation enables accurate diagnosis and prompt clinical management.[41,42] Left ventricular ejection fraction and myocardial scar are markers currently used to assess arrhythmic risk. Kotu et al.[43] applied radiomics as a tool to distinguish patients at high-risk and low-risk of fatal arrhythmias after myocardial infarction using quantitative discriminative features (size, location, and textural information concerning the scarred myocardium) extracted from late gadolinium-enhanced cardiac MRI. The study employed a combination of machine learning frameworks, such as k-nearest neighbor, support vector machine, decision tree, and random forest, to assess the discriminative power of the proposed features. For the stratification of risk of fatal arrhythmias in the patients, the developed model demonstrated an AUC of 0.965 and an accuracy of 94.4% in the initial experiment and an AUC of 0.921 and an accuracy of 92.6% in the validation experiment.

In another study, which aimed to predict arrhythmia in patients with dilated cardiomyopathy, left ventricular myocardial radiomic features from late gadolinium enhancement CMR images were used to develop prognostic logistic regression models.[41] While model 1 included only clinical risk factors and scar presence, model 2 combined model 1 with radiomics features. The study identified gray-level co-occurrence matrix autocorrelation as an independent predictor of ventricular tachycardia and fibrillation. Furthermore, the study reported that model 2 outperformed model 1 for the prediction of arrhythmia in this patient population with a higher C-statistic (training: 0.71 vs. 0.61 and validation: 0.70 vs. 0.61).

### Cardiac Mass Characterization

Cardiac CT provides cross-sectional imaging with high resolution for the assessment of the heart and surrounding structures. The differential diagnosis of cardiac masses is, however, challenging due to their

**Table 1 | A comparative performance table for selected machine learning models**

| Author | Sample Size | Study Design | Disease | Diagnostic Modality | Machine Learning | Use | AUC (Training, Validation) |
|---|---|---|---|---|---|---|---|
| Chen et al.[28] | 419 lesions from 225 patients | Retrospective | CAD | CCTA | XGBoost | Vulnerable plaque identification and risk prediction | 0.81, 0.75 |
| Li et al.[29] | 174 plaques of 149 patients | Retrospective | CAD | CCTA | Random forest | Coronary stenosis identification | 0.82, 0.77 |
| Meng et al.[38] | 378 patients | Retrospective | Cardiac amyloidosis | CT | Random forest | Detection of cardiac amyloidosis | 0.95, 0.91 |
| Chen et al.[39] | 236 patients | Retrospective | Myocardial infarction | CCTA | - | Adverse effects postmyocardial infarction | 0.904, 0.893 |
| Avard et al.[40] | 72 patients | Retrospective | Myocardial infarction | Noncontrast cine CMR imaging | Logistic regression<br>Support vector machine | Detection of myocardial infarction | 0.93, -<br>0.92, - |
| Kotu et al.[43] | 54 patients | Retrospective | Cardiac arrhythmias | Late gadolinium-enhanced CMR imaging | Combination: k-nearest neighbor, support vector machine, decision tree, and random forest | Risk stratification | 0.965, 0.921 |
| Nam et al.[45] | 39 periprosthetic masses in 34 patients | Retrospective | Suspected prosthetic valve obstruction | Cardiac CT | LASSO logistic regression model | Differentiation between pannus, thrombus, and vegetation | 0.876, - |
| Chun et al.[46] | 95 patients | Retrospective | Valvular heart disease | Cardiac CT | DeLong algorithm | differentiate the left atrial appendage thrombus from circulatory stasis | 0.76, 0.71 |

AUC, Area under the curve; LASSO, Least absolute shrinkage and selection operator.

significant heterogeneity in pathology and clinical presentation, as well as the reliance on imaging characteristics to make presumptive diagnoses.[44] In a study conducted by Nam et al.,[45] the performance of CT radiomic features for the differentiation between pannus, thrombus, and vegetation as potential causes of obstruction of prosthetic valves was assessed and compared with visual analysis alone. The standard clinical intervention for prosthetic valve replacement is reoperation and follow-up imaging. Hence, the study extracted radiomics features from the cardiac CT images and calculated radiomic scores for the identified cardiac masses. The radiomics score was found to be highly predictive of pannus compared to other masses with an AUC of 0.876. Additionally, findings from the study revealed that the combination of radiomics score with visual analysis resulted in better prediction of the cardiac masses than visual inspection of CT images alone.

Chun et al.[46] also demonstrated the ability of quantitative radiomic features from cardiac CT to differentiate the left atrial appendage thrombus from circulatory stasis in patients with valvular heart diseases. As reference standards, the ratio of Hounsfield units in the filling defects to those in the ascending aorta was calculated on early- and late-phase CT. The AUC of a radiomic feature termed "wavelet_LHL" for diagnosing the left atrial appendage thrombus (0.78) was higher than those of the Hounsfield units ratios in both early-phase CT (0.54) and late-phase CT (0.76). A similar finding was found in the validation cohort, demonstrating the importance of quantitative radiomics features in cardiac mass characterization.

Table 1 summarizes the comparative performance of some machine learning models used in the diagnosis of cardiovascular diseases.

## Discussion

Multiple studies have investigated the potential roles of radiomics in cardiology, particularly in image analysis, and many of these studies have reported favorable outcomes; however, the lack of standardization of study protocols and available evidence on the roles of radiomics across cardiovascular conditions and patient populations limits the translation of reported findings to clinical settings.[47] Likewise, image acquisition and processing protocols vary considerably across studies investigating radiomics models; this hinders the replication of studies and the comparison of findings across studies.[48] Therefore, there is a pressing need for consensus-driven guidelines and collaborative multicenter studies to enhance the reliability and clinical applicability of radiomics in this field.[12]

To ensure reliable and reproducible use of radiomics in cardiology, multicenter standardization must address imaging protocol harmonization, shared annotated datasets, reproducible feature selection, transparent model reporting, and robust data governance.[49,50] These steps are critical for minimizing variability across scanners and institutions, enabling external validation, and building clinical trust. Standardization is not just a technical necessity; it is foundational to translating radiomics from research settings into real-world cardiology practice at scale. The Image Biomarker Standardization Initiative provides a comprehensive framework to address standardization.[51] It defines radiomic features with precise mathematical formulations, standardizes filtering and discretization steps, and offers validated test phantoms for software benchmarking. By enabling reproducible and comparable radiomics workflows across centers and platforms, the initiative plays a critical role in supporting

multicenter validation, regulatory trust, and eventual clinical translation of radiomics-based tools in cardiovascular diagnostics.

The development of robust radiomics models relies on high-quality medical images from imaging modalities such as CT, CMR, and echocardiography. Given the advancements in machine learning, image preprocessing and optimization to remove noise and artifacts commonly involve the use of machine learning frameworks.[52] However, this process may introduce additional errors into the images that alter the intrinsic characteristics of the original image. Such alterations can significantly impact the reliability of radiomic features and the subsequent radiomics model. To mitigate these risks, it is crucial to implement standardized preprocessing workflows, conduct robustness analyses of radiomic features, and rigorously validate machine learning-based techniques using diverse, multi-institutional datasets.

A notable finding across studies on radiomics cardiology is the study designs, which are predominantly retrospective in nature. This study design offers lower quality evidence due to selection bias and limited control over the data collection process. Therefore, there is a need for prospective studies, especially randomized controlled trials, which represent a source of quality evidence. These prospective studies should aim to validate reported findings from previous replication studies. The validation studies may also involve validating existing models using datasets from other cohorts or institutions.

This study has some limitations. The absence of a systematic search process may introduce selection bias, and findings may be influenced by publication bias, particularly toward studies reporting positive radiomics outcomes. Additionally, the included literature spans a wide range of imaging modalities, feature extraction methods, and performance metrics, limiting direct comparability across studies. These factors should be considered when interpreting the generalizability of the reviewed radiomics-based diagnostic tools in cardiology.

## Conclusion

Cardiovascular diseases remain the top cause of death globally. Radiomics combines the extraction of quantitative features with machine learning to analyze data from cardiac CT, CMR, echocardiography, and other modalities, thereby predicting clinical outcomes. This review focused on applications of radiomics in the diagnosis of cardiovascular conditions. Radiomics workflow typically comprises image acquisition and preprocessing, image segmentation, image processing, feature extraction, feature selection, and machine learning modeling and validation. Radiomics models utilize machine learning architectures such as support vector machines, random forests, decision trees, and deep learning.

These models are applied in clinical investigations for CAD, where plaque and adipose tissue accumulation are assessed for vulnerability and degree of stenosis. Radiomics-based models may be used to detect signs of rupture to prevent adverse events. Furthermore, some models incorporate both clinical risk factors and radiomic features during their development. Numerous studies demonstrated that this combined approach leads to improved performance metrics, including AUC, accuracy, sensitivity, and specificity. Furthermore, radiomics is applied in the characterization of myocardial tissue, particularly after myocardial infarction, to distinguish between healthy tissue and infarct scar. It is also used to predict prognosis and health outcomes in patients with cardiomyopathies. Other reported areas of applications of radiomics included arrhythmia risk stratification and cardiac mass characterization.

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