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Multimodality Imaging and Artificial Intelligence in Cardiovascular Disease: Advances, Integration, and Future Directions

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Abstract

A comprehensive review is essential to understand the evolving role of multimodality imaging and artificial intelligence (AI) in cardiovascular diseases (CVDs) diagnosis and management. This review highlights the integration of various imaging techniques and AI-driven advancements to enhance diagnostic accuracy, risk stratification, and personalized treatment approaches. By addressing current innovations, challenges, and future directions, this review provides a foundation for optimizing cardiovascular imaging and improving patient outcomes. This review explores the significance of multimodality imaging in CVDs, emphasizing its role in combining echocardiography, computed tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography (PET) for a more comprehensive assessment. The integration of AI in cardiovascular imaging is examined, particularly in automating image analysis, enhancing diagnostic precision, and facilitating risk prediction models. The review further discusses hybrid imaging techniques (HIT) and their ability to merge anatomical and functional data, improving disease detection and management. The application of multimodality imaging in personalized medicine, with a focus on patient-specific diagnostics and treatment strategies, is also addressed. Additionally, challenges such as accessibility, cost, and AI integration into clinical workflows are analyzed. The review concludes by outlining future research directions aimed at refining imaging technologies and AI applications for better cardiovascular care.

Keywords: Artificial intelligence, Cardiovascular disease, Diagnosis, Hybrid imaging, Multimodality imaging, Personalized medicine, Risk stratification

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Introduction

Multimodality Imaging in CVDs

Multimodality imaging in CVDs is a rapidly evolving field that leverages various imaging techniques to enhance the diagnosis, management, and risk stratification of cardiovascular conditions [1, 2]. This approach is particularly beneficial in complex cases where single-modality imaging may not provide comprehensive insights. Multimodality imaging combines data from different imaging techniques, such as echocardiography, CT, MRI, and PET, to offer a more holistic view of cardiovascular health (Table 1). This integration is crucial for early detection, accurate diagnosis, and effective management of CVDs, especially in populations with specific needs, such as cancer survivors, the elderly, and women [3, 4].

Multimodality imaging plays a crucial role in the evaluation and management of various CVDs. The use of multiple imaging modalities allows for a comprehensive assessment of cardiac structure and function, aiding in the diagnosis, treatment, and monitoring of patients with heart conditions (Figure 1) [5]. In the context of congenital heart disease, the ACC/AHA/ASE/HRS/ISACHD/SCAI/SCCT/SCMR/SOPE 2020 appropriate use criteria emphasizes the importance of multimodality imaging in the follow-up care of patients. This approach ensures a thorough evaluation of cardiac abnormalities and guides appropriate clinical decision-making [6]. The impact of multimodality imaging in the assessment of cardiovascular involvement in COVID-19 is highlighted in a study [7]. By utilizing various imaging techniques such as cardiac MRI and CT, researchers aim to identify cardiac pathophysiological mechanisms related to COVID-19 infections, providing valuable insights into the disease process [8, 9].

Furthermore, multimodality imaging has been instrumental in improving the definition and functional assessment of left ventricular non-compaction cardiomyopathy [10]. This approach allows for a more accurate characterization of cardiac abnormalities, leading to better management strategies for patients with this condition. In the realm of radiotherapy-induced cardiotoxicity, multimodality cardiovascular imaging plays a crucial role in screening for structural

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Table 1: Role of various imaging modalities in CVDs, highlighting their applications, strengths, and limitations.

Imaging modality	Primary applications	Advantages	Limitations
Echocardiography	Assessing cardiac structure, function, and hemodynamics	Non-invasive, widely available, real-time imaging	Limited by operator dependency and acoustic window
CT	Coronary artery disease detection, calcium scoring, plaque assessment	High-resolution imaging, fast acquisition	Radiation exposure, requires contrast agents
MRI	Myocardial tissue characterization, perfusion assessment, congenital heart disease evaluation	No radiation, superior soft tissue contrast	Expensive, time-consuming, contraindicated in some patients (e.g., those with certain implants)
PET	Myocardial viability, inflammation, and perfusion assessment	High sensitivity for metabolic and molecular imaging	High cost, radiation exposure, limited availability
SPECT	Myocardial perfusion imaging, ischemia detection	Widely available, cost-effective	Lower spatial resolution compared to positron emission tomography

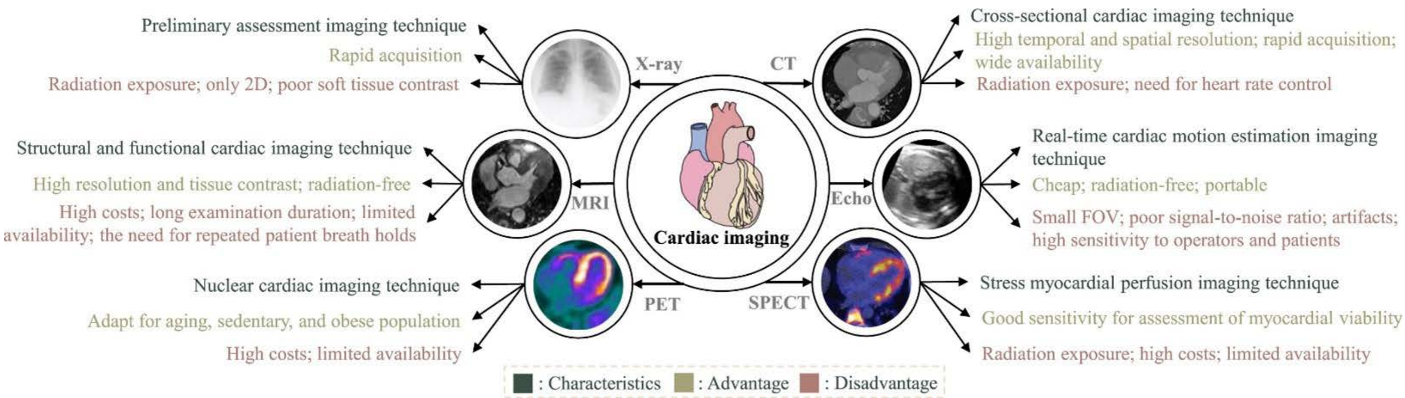

Figure 1: Various cardiac imaging techniques from different modalities with their characteristics, advantages and disadvantages [5].

and functional abnormalities secondary to radiation therapy [11]. By utilizing echocardiography, cardiovascular CT, cardiac MRI, and nuclear cardiology, clinicians can effectively monitor and manage cardiac complications in cancer patients undergoing radiotherapy [12, 13]. Overall, the integration of multimodality imaging in the evaluation and management of CVDs has proven to be essential. From assessing large-vessel vasculitis to guiding thoracoscopic cardiac surgery and monitoring Anderson-Fabry disease, the use of multiple imaging modalities provides valuable clinical information for healthcare providers [14-16].

Multimodality imaging is vital for detecting ischemic and valvular heart disease in cancer patients, who are at increased risk due to shared risk factors and treatment-related cardiovascular toxicity. This approach aids in individual risk stratification and multidisciplinary decision-making, ensuring timely intervention and management [17]. In elderly patients, combining multimodal imaging with biomarker detection significantly improves diagnostic accuracy for coronary heart disease. Techniques like coronary CT angiography (CCTA) and echocardiography, when used alongside biomarkers, enhance sensitivity and specificity in diagnosis [18]. Multimodality imaging helps in assessing cardiovascular changes associated with aging, such as arterial wall thickening and myocardial fibrosis. Techniques like CT and ultrasound are used to measure coronary artery calcium and carotid intima-media thickness, aiding in advanced risk stratification and preventive strategy formulation [19]. Recent advancements in imaging modalities, including CCTA and MRI, have improved the detection and quantification of atherosclerotic plaques. These techniques help assess plaque stability and predict adverse cardiovascular events, facilitating personalized patient care [20].

Multimodality imaging is crucial for the early diagnosis and follow-up of radiation-induced heart disease [21, 22]. Techniques such as speckle-tracking echocardiography and cardiac magnetic resonance myocardial strain assessment provide valuable insights into subclinical disease and guide preventive measures [21]. Advanced imaging techniques allow for a detailed evaluation of cardiac chamber volumes, ventricular function, and tissue structure in cardiomyopathies. This comprehensive assessment aids in identifying specific etiologies and guiding therapeutic decisions [23].

This comprehensive approach enhances diagnostic accuracy, improves treatment outcomes, and ensures optimal care for patients with various cardiac conditions. While multimodality imaging offers numerous advantages, it is essential to consider the challenges and limitations associated with its implementation [24]. These include the high cost and limited accessibility of advanced imaging technologies, which may restrict their widespread use. Additionally, the need for specialized training and expertise to interpret multimodal data can be a barrier in some healthcare settings [25]. Despite these challenges, the potential of multimodality imaging to transform cardiovascular care remains significant, warranting continued research and development in this field.

Integration of Imaging Techniques for Comprehensive Diagnosis

The integration of imaging techniques for comprehensive diagnosis in CVDs is a rapidly evolving field that leverages advanced technologies to enhance diagnostic accuracy and patient outcomes [26, 27]. This integration involves combining various imaging modalities, such as ultrasound, CT, MRI, and PET, with emerging technologies like AI and deep learning [28]. These advancements allow for a more detailed assessment of cardiovascular health, enabling early detection, precise diagnosis, and personalized treatment strategies.

Ultrasound and echocardiography are non-invasive techniques crucial for assessing cardiac structure and function. They provide real-time images of the heart, allowing for the evaluation of blood flow and heart valve function, which are essential for diagnosing various heart conditions [29, 30]. CT, particularly CCTA, are instrumental in visualizing coronary arteries and detecting atherosclerotic plaques. These techniques help in assessing plaque stability and predicting cardiovascular events [20]. MRI offers detailed images of cardiac anatomy and function without radiation exposure. It is particularly useful for evaluating myocardial perfusion and characterizing tissue properties [20, 31]. PET imaging is used to assess myocardial viability and perfusion, providing insights into metabolic activity and blood flow in the heart [20, 30].

Recent advancements in molecular imaging approaches, such as PET/CT and PET/MRI, have demonstrated their clinical utility in various aspects of cancer diagnosis, staging, and therapeutic response evaluation [32]. For instance, PET/MRI has been found to perform similarly to MRI but better than PET/CT in primary breast cancer assessment [32]. Additionally, deep learning algorithms have been proposed to estimate synthetic attenuation-corrected PET and CT images from non-attenuation corrected PET scans, potentially reducing the need for additional imaging in hybrid PET/CT and PET/MRI systems [33]. Furthermore, theranostic nanoparticles have emerged as a valuable tool for providing imaging contrast in CVDs, utilizing techniques such as MRI, PET, and CT [34]. These nanoparticles offer a multifaceted approach to diagnosis and treatment, aligning with the order of disease development in CVDs [34]. The use of PET imaging with PSMA-targeting radiopharmaceuticals has also been explored in the detection of hepatocellular carcinoma, showcasing the potential of PET in cancer diagnosis [35].

While the focus of imaging and staging has traditionally been on certain types of cancer, such as anal and rectal carcinomas, there is a growing interest in applying advanced imaging techniques to CVDs [36]. Current advances in nanotheranostics for molecular imaging and therapy of CVDs highlight the potential for integrating multiple imaging modalities for a comprehensive approach to diagnosis and treatment [37]. Additionally, multimodality imaging has been recognized as a valuable tool in assessing metabolic syndrome, further emphasizing the importance of combining different imaging techniques for a holistic evaluation [38]. In conclusion, the integration of CT, MRI, and PET imaging modalities holds great promise for the comprehensive diagnosis of CVDs. By leveraging the strengths of each modality and exploring innovative approaches, such as deep learning algorithms and theranostic nanoparticles, researchers are paving the way for more accurate and effective diagnostic strategies in the field of cardiovascular imaging.

HIT

HIT in diagnosing CVDs offer significant advantages by combining anatomical and functional data, leading to improved diagnostic accuracy and patient management (Table 2) [39, 40]. These techniques, such as the integration of CT with myocardial perfusion imaging (MPI), provide a comprehensive view of coronary artery disease (CAD) by assessing both the structure and function of the heart. The integration of coronary artery calcium scoring (CACS) with MPI enhances the diagnostic sensitivity for detecting obstructive CAD. This combination allows for better risk stratification and personalized management strategies, such as the initiation of statins and aspirin [41]. The combination of CACS with MPI significantly improves the diagnostic sensitivity for detecting obstructive CAD. This is particularly beneficial as it allows for better identification of patients at risk for cardiac events, even when traditional MPI results are normal. The addition of CACS has been shown to unmask silent coronary atherosclerosis in patients who may otherwise appear healthy based on MPI alone. This highlights the incremental diagnostic value of incorporating CACS into standard imaging protocols. CACS not only aids in diagnosing CAD but also plays a crucial role in predicting potential cardiac events. By assessing calcified plaque in the coronary arteries, CACS helps in stratifying patient risk more effectively, which is essential for personalized risk management. The paper emphasizes the evolving role of HI in guiding therapeutic decisions, particularly regarding the use of statins for cardiovascular prevention. The integration of CACS with MPI allows for a more tailored approach to treatment, optimizing patient care. While the results indicate significant benefits from combining CACS with MPI, the authors call for further research to fully establish the advantages of this HI strategy in clinical assessments of cardiovascular risk. In summary, the paper highlights that the incorporation of CACS into MPI protocols not only enhances the accuracy of CAD detection but also improves risk stratification and therapeutic decision-making, ultimately leading to better patient outcomes [41].

HIT, such as PET/CT and PET/MRI provide a comprehensive assessment by combining anatomical and functional data. These modalities are particularly beneficial in evaluating ischemic heart disease, where they improve diagnostic precision and guide therapeutic decisions [42, 43]. PET/MRI offers high-quality anatomical and functional assessments, with emerging applications in quantifying molecular parameters like metabolism and inflammation. This modality is increasingly used in clinical practice for myocardial tissue characterization [44]. However, despite these benefits, there

Table 2: Key HIT used in diagnosing CVDs, highlighting their applications, strengths, and limitations in clinical practice.

Imaging modality	Primary applications	Advantages	Limitations
PET/CT	Myocardial viability, inflammation, and perfusion assessment	Combines metabolic and anatomical data, high sensitivity	Radiation exposure, high cost, limited availability
PET/MRI	Myocardial tissue characterization, inflammation imaging	No radiation from MRI, superior soft tissue contrast	Expensive, longer scan times, limited accessibility
SPECT/CT	Myocardial perfusion imaging, ischemia detection, coronary artery assessment	Improved anatomical localization, enhanced accuracy	Radiation exposure, lower resolution than PET/CT
CT/MPI	CAD evaluation, ischemia detection	Combines anatomical and functional assessment, better risk stratification	Requires contrast agents, radiation exposure
CACS + MPI	Risk assessment in CAD, identifying silent atherosclerosis	Enhances diagnostic sensitivity, improves risk stratification	Limited availability, radiation exposure

are limitations, including cost, radiation exposure, and the need for specialized equipment and expertise.

A study compared the diagnostic accuracy of three imaging methods: single-photon emission CT (SPECT) alone, CTCA alone, and hybrid SPECT/CTCA imaging [45]. The results were as follows: (i) SPECT alone: Sensitivity with 73%, specificity with 61%, and accuracy with 67%. This indicates that while SPECT can identify some cases of CAD, it has limitations in specificity and overall accuracy. (ii) CTCA alone: Sensitivity with 96%, specificity with 44%, and accuracy with 67%. CTCA showed high sensitivity, meaning it was good at detecting the presence of disease, but its low specificity suggests many false positives. (iii) HI (SPECT/CTCA): Sensitivity with 95%, specificity with 75%, and accuracy with 84%. HI outperformed both SPECT and CTCA alone, providing a more balanced sensitivity and specificity, which is crucial for accurate diagnosis. One of the significant findings was that HI successfully diagnosed 47 vessels with severe calcification that CTCA alone could not evaluate correctly. This highlights the advantage of combining the two imaging modalities, as HI provides more comprehensive information on coronary stenosis and its hemodynamic significance. The study concluded that HI offers greater diagnostic accuracy than single-modality evaluations. This is particularly important for patients with suspected CAD, as it allows for better assessment and management of their condition (Figure 2). In summary, the results indicate that HI is a superior diagnostic tool for CAD, especially in complex cases with high levels of coronary calcification [45].

Recent advancements in imaging techniques have revolutionized the diagnosis and management of CVDs. Farber et al. [46] discussed the future of cardiac molecular imaging, highlighting the potential for improved diagnostic capabilities in CVDs. Badano et al. [47] emphasized the importance of advanced imaging techniques, such as three-dimensional echocardiography, for a comprehensive assessment of right ventricular anatomy and function without geometric assumptions.

Machine learning has also emerged as a valuable tool in the diagnosis of CVDs. Nogay and Adeli [48] reviewed the application of machine learning in the diagnosis of autism spectrum disorder using brain imaging techniques, including HI approaches. Similarly, Slart et al. [49] emphasized the role of AI in multimodality cardiovascular imaging, particularly in nuclear cardiology and CT techniques. Molecular imaging techniques, such as MRI, have been utilized for targeted imaging of CVDs. Vazquez-Prada et al. [50] discussed the use of iron oxide nanoparticles for molecular imaging of atherosclerosis, thrombosis, and myocardial infarction. Greulich et al. [51] highlighted the use of hybrid cardiac magnetic resonance/fluorodeoxyglucose PET for differentiating active from chronic cardiac sarcoidosis. AI has also found applications in cardiovascular MRI.

Argentiero et al. [52] provided a comprehensive review of AI applications in CMR imaging, covering image acquisition, reconstruction, segmentation, tissue characterization, diagnostic evaluation, and prognostication. Fukushima et al. [53] discussed the potential role of non-invasive HI, specifically cardiac PETMR, for assessing molecular function, tissue characterization, and hemodynamic performance in CVDs. Furthermore, the role of multimodality cardiac imaging in the diagnosis and management of left ventricular hypertrophy was addressed [54]. Finally, Nayfeh et al. [41] highlighted the benefits of HIT, such as CS and myocardial perfusion imaging, for a comprehensive assessment of CVDs. Overall, the integration of HIT, AI, and molecular imaging has significantly advanced the field of CVDs diagnosis and management, offering more precise and comprehensive evaluations for patients.

Advantages of HIT

- Enhanced diagnostic accuracy: HI such as SPECT/CT and PET/CT, combines anatomical and functional imaging, leading to higher diagnostic accuracy compared to single-modality imaging. For instance, hybrid SPECT/CTCA imaging has shown a sensitivity of 95% and specificity of 75% in detecting significant coronary artery stenosis, outperforming SPECT or CTCA alone [45].

- Comprehensive risk assessment: The integration of CACS with MPI enhances the detection of atherosclerosis and improves risk stratification, allowing for personalized treatment plans. This approach helps in identifying silent coronary atherosclerosis in patients with normal MPI results [41].

- Improved prognostic value: HI provides superior prognostic information by combining anatomical and functional data, which is crucial for assessing the risk of future cardiac events and guiding therapeutic decisions [55].

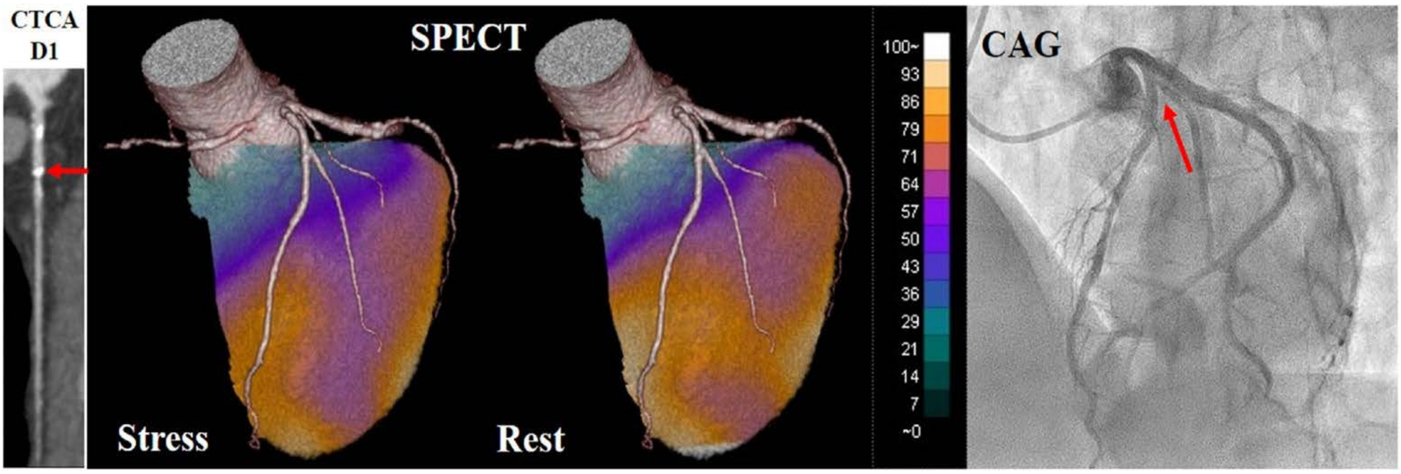

Figure 2: A representative case in which severe calcification in the diagonal branch complicated diagnosis through CTCA. However, a reversible perfusion defect was clearly identified on the hybrid image and later confirmed with coronary angiography (CAG) [45].

- Non-invasive nature: Techniques like multi-detector CT (MDCT) and MPI offer non-invasive alternatives to traditional invasive CAG, reducing the risk of complications such as myocardial infarction and stroke [56].

Limitations of HIT

- High costs and resource requirements: The implementation of HI systems requires significant investment in equipment and trained personnel, which can be a barrier for widespread adoption [57].

- Radiation exposure: Combining multiple imaging modalities can lead to increased radiation exposure, raising concerns about patient safety, especially in repeated examinations [57].

- Limited accessibility: The availability of HI is often restricted to specialized centers, limiting access for patients in remote or underserved areas [58].

- Complexity in interpretation: The integration of multiple data sets requires advanced software and expertise to accurately interpret the results, which can complicate the diagnostic process [55].

While HIT offers substantial benefits in diagnosing CVDs, it is essential to consider the balance between their advantages and limitations. The high costs and increased radiation exposure are significant concerns that need to be addressed to optimize their clinical utility. Additionally, the selection of patients who would benefit most from HI remains a topic of debate, emphasizing the need for further research to refine these techniques and establish clear guidelines for their use [57, 58].

Role of Multimodality Imaging in Personalized Medicine

Multimodality imaging combines various imaging techniques such as MRI, CT, PET, and molecular imaging to provide a detailed and holistic view of a patient's condition. This integration allows for more accurate diagnosis and assessment of diseases, particularly in complex cases like cancer and CVDs [59, 60]. By providing detailed insights into the anatomical and functional aspects of the heart, integrated imaging techniques facilitate personalized prevention strategies and treatment plans. This approach helps in tailoring interventions to individual patient needs, potentially improving outcomes [29]. The role of multimodality imaging in personalized medicine in CVDs is a rapidly evolving field that holds great promise for improving patient outcomes. Recent advancements in AI have revolutionized cardiovascular imaging, particularly in the realm of multimodality imaging. Xu et al. [61] provides a comprehensive review of the applications of AI in multimodality cardiovascular imaging, highlighting the state-of-the-art techniques that are enhancing diagnostic accuracy and treatment planning. Sex-related differences in CVDs, such as dilated cardiomyopathy, have been a focus of recent research. D'Amario et al. [62] discuss the implications of these differences, particularly in the context of chemotherapy-induced heart failure, and emphasize the importance of personalized medicine in managing these conditions. Understanding these sex-related disparities is crucial for tailoring treatment strategies to individual patients. Incorporating physics-based flow models into cardiovascular medicine has also shown promise in improving diagnostic capabilities.

Vardhan and Randles [63] explore the current practices and challenges associated with these models, highlighting their potential to enhance our understanding of CVDs and guide personalized treatment approaches. AI has also made significant strides in the realm of cardiac MRI. Cau et al. [64] provides an overview of the applications of AI in this field, emphasizing its ability to streamline image acquisition, reconstruction, and analysis. These advancements have the potential to reduce costs and improve decision-making processes for clinicians. Multi-modality cardiac imaging has emerged as a valuable tool in the management of diabetic heart disease. Wamil et al. [65] discuss the utility of these imaging techniques in characterizing both ischemic and non-ischemic causes of diabetic heart disease, highlighting their role in early detection and treatment planning. As the field of cardiovascular imaging continues to advance, it is essential to consider the unique needs of specific patient populations. Massalha et al. [66] focus on cardiovascular imaging in women, emphasizing the importance of tailored imaging approaches to address sex-related differences in CVDs.

While multimodality imaging significantly advances personalized medicine, it is important to consider the limitations and challenges associated with its implementation. The complexity of integrating diverse data types and the need for sophisticated computational tools can pose barriers to widespread adoption. Additionally, ensuring data privacy and security remains a critical concern as more sensitive patient information is utilized in personalized healthcare approaches. Addressing these challenges will be essential to fully realize the potential of multimodality imaging in personalized medicine. Furthermore, the integration of computational biology, AI, and multimodality imaging techniques holds great promise for personalized medicine in CVDs [67, 68]. By leveraging these cutting-edge technologies, clinicians can enhance diagnostic accuracy, tailor treatment strategies to individual patients, and ultimately improve patient outcomes.

Role of AI in Automating Image Analysis

The use of AI, particularly convolutional neural networks (CNNs), has shown promise in enhancing the accuracy of CVDs diagnosis. These models can analyze large datasets of cardiovascular images to predict disease presence with high precision, outperforming traditional methods [69, 70]. The integration of multimodal data is supported by advanced computational methods, including deep learning and multikernel learning, which enhance the ability to process and analyze complex datasets. These techniques facilitate the extraction of meaningful insights from diverse data sources, improving the generalization and transferability of medical models across different tasks (Table 3) [71, 72]. The development of frameworks like MarbliX, which integrates histopathology images with genomic data, exemplifies the potential of multimodal approaches to provide in-depth insights and reduce variability in diagnoses [73]. Integrating radiology images with electrocardiogram (ECG) data through AI-driven techniques allows for a comprehensive analysis of cardiovascular health, improving diagnostic accuracy and enabling early intervention [74].

The integration of AI with multimodal imaging enhances the prediction and diagnosis of CVDs. Techniques like deep multimodal fusion, which combine radiology and ECG data, have shown superior accuracy in detecting CVDs compared to traditional methods [74]. The research paper presents significant findings regarding the detection of CVDs through a novel approach that integrates radiology and ECG data using deep learning techniques. The proposed methodology demonstrated an impressive accuracy rate of 90.49% in diagnosing CVDs. This level of accuracy indicates that the model effectively distinguishes between healthy and diseased conditions, surpassing many existing methods in the field. The study emphasizes the importance of using multiple data sources, specifically X-ray images

Table 3: Overview of how AI enhances the detection, diagnosis, and monitoring of CVDs by automating the analysis of medical images, improving accuracy, efficiency, and patient outcomes.

Application area	Role of AI	Description
Cardiac imaging (MRI, CT, and ECG)	Heart disease detection and diagnosis	AI models analyze cardiac images to detect abnormalities such as coronary artery disease, heart failure, and myocardial infarction
Plaque detection in coronary arteries	Identifying plaque formation and stenosis	AI aids in detecting and quantifying plaque in coronary arteries, helping diagnose atherosclerosis and assess its severity
Automated measurement of cardiac structures	Quantifying cardiac dimensions	AI automates the measurement of heart chambers, valve structures, and other key dimensions in cardiac imaging, reducing human error and enhancing precision
Arrhythmia detection	ECG interpretation	AI algorithms analyze ECG data to detect arrhythmias (e.g., atrial fibrillation, ventricular tachycardia) and predict risks
Cardiac risk prediction	Predictive analytics for risk assessment	AI analyzes medical images, patient history, and other biomarkers to predict risks for heart attack, stroke, or other cardiovascular events
Heart function assessment	Ejection fraction and ventricular function	AI automatically assesses left ventricular ejection fraction and other functional parameters to evaluate heart function in heart failure patients
Automated image segmentation	Segmenting heart structures for diagnosis	AI performs image segmentation to identify and isolate specific heart structures (e.g., myocardium, blood vessels, etc.) to facilitate detailed analysis
Automated CTA	Analyzing coronary arteries for blockages	AI automates the analysis of CTA scans, detecting coronary artery blockages, and assessing the severity for better treatment planning
Cardiac MRI analysis	Scar tissue detection and myocardial infarction evaluation	AI detects myocardial scars and infarction areas from MRI scans, assisting in the diagnosis of heart attacks and chronic heart disease
3D cardiac imaging	Creating 3D models for personalized treatment	AI creates 3D models of the heart to assess complex heart conditions, allowing for personalized treatment plans or pre-surgical simulations
Coronary vessel analysis	Assessing blood flow and vessel health	AI evaluates coronary vessel health and blood flow patterns, aiding in the diagnosis of conditions like coronary artery disease and microvascular dysfunction
Monitoring heart disease progression	Tracking disease evolution over time	AI compares sequential heart images to track disease progression, such as the increase of artery stenosis or changes in heart function over time
Automated interpretation of echocardiograms	Analyzing heart valve function and cardiac output	AI automates the analysis of echocardiograms to detect issues with heart valves, such as stenosis or regurgitation, and assess overall cardiac output

and ECGs. By combining these modalities, the model can extract latent information that may not be apparent when using a single data source. This multimodal approach enhances the overall diagnostic capability. The results indicate that the proposed AI-driven approach outperforms other state-of-the-art methods currently used for CVDs detection. This suggests that integrating different types of medical data can lead to better diagnostic outcomes. The paper also highlights the challenges associated with traditional diagnostic methods, such as the limited accessibility of CT scans for the general public. By focusing on X-ray images and ECGs, which are more widely available, the study aims to improve early diagnosis and accessibility for patients. The findings support the potential of AI-driven biomarkers in enhancing the efficiency of CVDs diagnosis. This could lead to more timely interventions and better patient outcomes, addressing the growing health risks associated with CVDs. In summary, the results of this study indicate a promising advancement in the field of CVDs detection through the innovative use of deep multimodal fusion techniques, showcasing high accuracy and improved accessibility for patients [74].

A study by Zhang et al. [75] presented several significant findings regarding the predictive capabilities of the AI-ECG model for assessing the 10-year risk of atherosclerotic CVD (ASCVD). The AI-ECG model was developed using a large dataset of 1,163,401 ECGs from 189,539 patients in a secondary care population in the United States of America. The data was split into training/validation and hold-out test sets by patient ID to ensure robust model performance. The AI-ECG model achieved a C-index of 0.721 (with a confidence interval of 0.719 to 0.723) for predicting future ASCVD events, indicating good predictive accuracy. The 5-year AUC was reported as 0.761 (0.758 to 0.763). In comparison to the ACC/AHA pooled cohort equations (PCE), the AI-ECG model outperformed it with a C-index of 0.679 (0.651 to 0.708) versus PCE's 0.605 (0.577 to 0.634). When the AI-ECG predictions were combined with traditional ASCVD risk factors (like blood pressure, cholesterol levels, and diabetes), the predictive value improved further, yielding a C-index of 0.686 (0.657 to 0.715). The model was externally validated using the United Kingdom Biobank dataset, where it showed a C-index of 0.655 (0.637 to 0.673). Notably, it significantly outperformed the Stanford Estimator of ECG Risk model, which had a C-index of 0.547 (0.527 to 0.567). The findings suggest that AI-ECG models can provide accurate risk assessments for ASCVD, potentially aiding in the prevention of adverse cardiovascular events in high-risk individuals while avoiding unnecessary treatments in low-risk patients. These results highlight the potential of integrating AI with traditional ECG analysis to enhance cardiovascular risk prediction and improve patient outcomes [75].

The combination of advanced imaging technologies and AI enhances diagnostic precision, streamlines workflow, and supports research advancements in cardiology. This integration is crucial for accurate risk stratification and therapy guidance [76, 77]. While the integration of imaging techniques with AI in CVD diagnosis offers numerous benefits, it also presents challenges such as the need for specialized equipment and expertise, potential high costs, and the requirement for large datasets to train AI models effectively. Additionally, the accessibility of advanced imaging technologies may be limited in certain regions, posing a barrier to widespread implementation. Despite these challenges, the continued development and integration of these technologies hold significant promise for improving cardiovascular care and patient outcomes globally.

AI Driven Risk Prediction Models Using Imaging Data

AI-driven risk prediction models using imaging data in CVDs represent a significant advancement in medical diagnostics, offering enhanced accuracy and personalized care. These models leverage machine learning and deep learning techniques to analyze complex imaging data, such as cardiac CT, MRI, and retinal images, to predict cardiovascular risks and outcomes. By integrating diverse data sources, AI models can identify subtle patterns and abnormalities that traditional methods might miss, thus improving early diagnosis and intervention strategies. The section explores the various aspects of AI-driven risk prediction models using imaging data in CVDs.

AI models utilizing cardiac CT and MRI data have shown superior performance in predicting major adverse cardiovascular events (MACE) compared to traditional risk scores. For instance, a model incorporating both CCTA and stress cardiac MRI data achieved a higher area under the receiver operating characteristic curve area under the curve (AUC) of 0.86 for MACE prediction, outperforming existing scores like the Framingham Risk Score [78]. The study included 2,210 patients who underwent cardiac MRI, out of which 2,038 completed follow-ups. The mean age of these patients was 70 years, with a significant portion being female (53.5%). During the follow-up period, 281 patients (13.8%) experienced MACE, which included cardiovascular death and nonfatal myocardial infarction. The ML model, which utilized data from both stress cardiac MRI and CCTA, achieved an AUC of 0.86 for predicting MACE. This performance was significantly better than several traditional risk assessment tools: (i) European Society of Cardiology score: AUC 0.55, (ii) QRISK3 score: AUC 0.60, (iii) Framingham Risk Score: AUC 0.50, (iv) Segment involvement score: AUC 0.71, and (v) CCTA data alone: AUC 0.76. AUC 0.83, the p-values for these comparisons ranged from <0 .001 to 0.004, indicating strong statistical significance. The ML model also demonstrated good performance in two independent external validation datasets, achieving AUCs of 0.84 and 0.92, further confirming its robustness and reliability in predicting MACE. The study concluded that the ML model, which integrates both CCTA and stress cardiac MRI data, outperformed traditional methods and existing risk scores in predicting MACE for patients with newly diagnosed CAD, highlighting the potential of ML in enhancing cardiovascular risk stratification. These results underscore the importance of multimodality imaging and advanced analytical techniques in improving patient outcomes in cardiovascular care [78].

AI advancements have enabled the use of noncardiac CT scans for CACS, broadening access to cardiovascular screening [79]. The review highlights the successful application of AI models, particularly CNNs and U-Net architectures, in detecting coronary artery calcium from noncardiac CT scans. These models have shown promising results in improving the accuracy and efficiency of CACS, which is crucial for cardiovascular risk assessment. Broader Accessibility: One of the significant results discussed is the potential for AI to extend CACS detection beyond traditional cardiac CT scans to more widely available imaging modalities, such as those used in lung cancer screening. This advancement could democratize access to cardiovascular screening, allowing for earlier risk identification in a broader population. The incorporation of AI-driven CACS detection into routine clinical practice is expected to enhance preventive cardiology. The results suggest that this approach could lead to better healthcare resource optimization and improved patient outcomes by facilitating earlier identification of individuals at risk for CVDs. The paper also outlines several technical challenges that need to be addressed for successful implementation, including imaging variability, data privacy issues, and potential biases in AI models. These challenges highlight the need for ongoing research and development to ensure the reliability and fairness of AI applications in clinical settings. The review emphasizes the necessity for further research in standardization and validation of AI models across diverse populations. This is crucial to ensure that the benefits of AI-driven CACS detection are realized equitably and effectively in various clinical contexts. Overall, the results of the paper underscore the transformative potential of AI in enhancing CACS and expanding its application in preventive cardiology, while also addressing the challenges that must be overcome for successful integration into clinical practice [79].

Deep learning models analyzing retinal images can predict cardiovascular risk by detecting vascular changes linked to CVDs. These models, using CNNs, provide a non-invasive method for risk assessment, offering insights into the underlying pathological mechanisms of CVD progression [80]. The study highlights the ability of the proposed models to detect subtle vascular changes and abnormalities that are linked to cardiovascular risk factors. This capability is crucial for early intervention and prevention strategies in CVDs. The framework developed in this research aims to streamline the process of cardiovascular risk assessment. By utilizing retinal imaging, the study provides a more accessible method for evaluating cardiovascular health, which could lead to improved patient outcomes. The research not only focuses on risk prediction but also offers insights into the underlying pathological mechanisms that contribute to the progression of CVDs. This understanding can enhance personalized healthcare approaches and treatment plans. The paper emphasizes the importance of rigorous validation and performance assessments of the deep learning models. These evaluations are essential to ensure the reliability and accuracy of the predictive models developed for retinal image analysis. In summary, the results of this study indicate that deep learning-based retinal image analysis holds significant promise for improving cardiovascular risk prediction and enhancing personalized healthcare strategies. The findings underscore the potential of integrating advanced technology into routine clinical practice for better health outcomes [80].

A study by Vaishali et al. [81] presents significant findings regarding the effectiveness of an AI-powered prediction model for assessing the risk of CVDs. The AI model achieved an impressive accuracy rate of 92%. This indicates that the model correctly identified high-risk patients in a large majority of cases, showcasing its reliability in risk assessment. The model demonstrated an extraordinary AUC of 0.95. This score reflects the model's ability to distinguish between patients who are at risk of CVDs and those who are not, indicating a high level of predictive power. The AI algorithm outperformed traditional risk assessment tools, such as the Framingham risk score. This suggests that the AI model can identify patients at high risk more effectively than existing methods, which is crucial for timely intervention. The model was rigorously validated on a variety of datasets that included demographic, clinical, and lifestyle information. This diverse validation enhances the generalizability of the model's findings, making it applicable to different populations. The results indicate that the integration of AI in cardiovascular health care could lead to more personalized prevention strategies and improved patient outcomes. This transformation could also encourage funding for programs focused on early intervention and tailored treatment plans. In summary, the study highlights the potential of AI in revolutionizing CVDs risk assessment through high accuracy, superior performance compared to traditional methods, and the ability to provide personalized care. These results underscore the importance of leveraging advanced technologies in healthcare to enhance patient outcomes [81].

Challenges in Integrating AI into Clinical Workflows

Integrating AI into clinical workflows for CVDs presents numerous challenges, despite its potential to revolutionize diagnosis, treatment, and management. These challenges span technical, ethical, and practical domains, impacting the seamless adoption of AI technologies in healthcare settings. The integration of AI into clinical workflows requires addressing issues such as data quality, algorithm transparency, and the need for interdisciplinary collaboration. Below are the key challenges identified in the integration of AI into clinical workflows for CVDs.

Data quality and interoperability

- AI systems rely heavily on high-quality data from diverse sources such as electronic health records, imaging studies, and wearable devices. However, data quality and interoperability remain significant challenges, as inconsistent data formats and incomplete datasets can hinder AI performance and integration into clinical workflows [82, 83].

- The integration of multimodal AI systems, which utilize various data types, is still limited due to the complexity of managing and harmonizing these diverse data sources [84].

Ethical and privacy concerns

- Ethical issues, including patient privacy and data security, are paramount when integrating AI into healthcare. The potential for data breaches and misuse of sensitive health information poses significant risks that must be addressed to maintain patient trust and comply with regulatory standards [85].

- Algorithm bias and the lack of transparency in AI decision-making processes can lead to inequitable healthcare outcomes, necessitating the development of explainable AI models that clinicians and patients can trust [83, 85].

Technical and infrastructure challenges

- Implementing AI-driven solutions requires robust infrastructure and technological support, which may not be readily available in all healthcare settings. This includes the need for advanced computing resources and integration capabilities to support AI applications [86].

- The complexity of AI models, particularly deep learning algorithms, can make them difficult to interpret and validate, posing challenges for their acceptance and use in clinical practice [87, 88].

Regulatory and validation barriers

- Regulatory hurdles, including the need for rigorous validation and approval processes, can delay the deployment of AI technologies in clinical settings. Ensuring that AI models meet safety and efficacy standards is crucial for their integration into healthcare systems [82, 83].

- The lack of prospective human validation studies limits the evidence base for AI's effectiveness compared to traditional practices, which is necessary for gaining clinician and patient confidence [88].

Training and adoption by healthcare professionals

- The successful integration of AI into clinical workflows requires healthcare professionals to be adequately trained in using these technologies. The learning curve associated with new AI tools can be a barrier to their widespread adoption [85].

- Interdisciplinary collaboration among clinicians, researchers, and policymakers is essential to overcome these challenges and facilitate the effective use of AI in cardiovascular care [82].

While AI holds great promises for transforming cardiovascular healthcare, these challenges highlight the need for careful consideration and strategic planning in its integration. Addressing these issues requires a concerted effort from all stakeholders involved in healthcare delivery. Additionally, exploring alternative perspectives, such as the potential for AI to empower patients directly through self-monitoring and diagnosis, could offer new avenues for integrating AI into healthcare systems. This approach could alleviate some of the burdens on clinical workflows and enhance patient engagement in their own care [87].

Conclusions

The review comprehensively highlights the advancements and integration of multimodality imaging and AI in CVDs diagnosis and management. Multimodality imaging, encompassing ECG, CT, MRI, and PET, has revolutionized cardiovascular diagnostics by providing a holistic view of cardiac structure and function. The combination of these techniques enables early disease detection, precise risk stratification, and improved therapeutic decision-making. Furthermore, HI approaches, such as PET/CT and SPECT/CT, enhance diagnostic accuracy by merging anatomical and functional data, leading to better patient outcomes. Personalized medicine has also benefited significantly from multimodal imaging, allowing for tailored interventions based on patient-specific risk profiles and disease characteristics. However, challenges such as high costs, limited accessibility, and the need for specialized expertise continue to hinder the widespread adoption of these advanced imaging modalities.

The incorporation of AI into cardiovascular imaging has further optimized diagnostic precision, risk assessment, and workflow efficiency. AI-driven image analysis, deep learning algorithms, and predictive models have shown great potential in improving diagnostic accuracy and automating complex processes, reducing human error, and enhancing clinical decision-making. Additionally, AI-based risk prediction models utilizing imaging data have demonstrated superior performance in forecasting adverse cardiovascular events, ultimately aiding in preventive strategies. Despite these advantages, the integration of AI into clinical practice presents hurdles, including data standardization, regulatory constraints, ethical considerations, and the need for adequate clinician training. Addressing these challenges through ongoing research, technological advancements, and interdisciplinary collaboration will be crucial for harnessing the full potential of AI and multimodality imaging in transforming cardiovascular care.

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None.

Conflict of Interest

None.

References

1. Daubert MA, Tailor T, James O, Shaw LJ, Douglas PS, et al. (2021) Multimodality cardiac imaging in the 21st century: evolution, advances and future opportunities for innovation. Br J Radiol 94: 1-16. https://doi.org/10.1259/bjr.20200780

2. Sekar PK, Veerabathiran R (2024) Emerging technologies and applications in multimodality imaging for ischemic heart disease: current state and future of artificial intelligence. Exp Cardiol 2: 253-264. https://doi.org/10.37349/ec.2024.00038

3. Addissouky TA, El Sayed IE, Ali MM, Alubiady MH, Wang Y (2024) Recent developments in the diagnosis, treatment, and management of cardiovascular diseases through artificial intelligence and other innovative approaches. J Biomed Res 5: 29-40. https://doi.org/10.46439/biomedres.5.041

4. Velusamy R, Nolan M, Murphy A, Thavendiranathan P, Marwick TH (2023) Screening

for coronary artery disease in cancer survivors: JACC: cardiooncology state-of-the-art review. JACC Cardio Oncol 5: 22-38. https://doi.org/10.1016/j.jaccao.2022.12.007

5. Li L, Ding W, Huang L, Zhuang X, Grau V (2023) Multi-modality cardiac image computing: a survey. Med Image Anal 88: 102869. https://doi.org/10.1016/j.media.2023.102869

6. Sachdeva R, Valente AM, Armstrong AK, Cook SC, Han BK, et al. (2020) ACC/AHA/ASE/HRS/ISACHD/SCAI/SCCT/SCMR/SOPE 2020 appropriate use criteria for multimodality imaging during the follow-up care of patients with congenital heart disease: a report of the American College of Cardiology solution set oversight committee and appropriate use criteria task force, American Heart Association, American Society of Echocardiography, Heart Rhythm Society, International Society for Adult Congenital Heart Disease, Society for Cardiovascular Angiography and Interventions, Society of Cardiovascular Computed Tomography, Society for Cardiovascular Magnetic Resonance, and Society of Pediatric Echocardiography. J Am Coll Cardiol 75: 657-703. https://doi.org/10.1016/j.jacc.2019.10.002

7. Citro R, Pontone G, Bellino M, Silverio A, Iuliano G, et al. (2021) Role of multimodality imaging in evaluation of cardiovascular involvement in COVID-19. Trends Cardiovas Med 31: 8-16. https://doi.org/10.1016/j.tcm.2020.10.001

8. Gulsin GS, McVeigh N, Leipsic JA, Dodd JD (2021) Cardiovascular CT and MRI in 2020: review of key articles. Radiology 301: 263-277. https://doi.org/10.1148/radiol.2021211002

9. Afshar-Oromieh A, Prosch H, Schaefer-Prokop C, Bohn KP, Alberts I, et al. (2021) A comprehensive review of imaging findings in COVID-19-status in early 2021. Eur J Nucl Med Mol Imaging 48: 2500-2524. https://doi.org/10.1007/s00259-021-05375-3

10. Visoiu IS, Rimbas RC, Gheorghiu L, Antunes RD (2021) Functional assessment in left ventricular non-compaction cardiomyopathy in multimodality imaging era might improve the definition. Rom J Cardiol 31: 122-128.

11. Podlesnikar T, Berlot B, Dolenc J, Goričar K, Marinko T (2022) Radiotherapy-induced cardiotoxicity: the role of multimodality cardiovascular imaging. Front Cardiovasc Med 9: 887705. https://doi.org/10.3389/fcvm.2022.887705

12. Mahabadi AA, Rischpler C (2018) Cardiovascular imaging in cardio-oncology. J Thorac Dis 10: S4351. https://doi.org/10.21037/jtd.2018.10.92

13. Pepe A, Pizzino F, Gargiulo P, Perrone-Filardi P, Cadeddu C, et al. (2016) Cardiovascular imaging in the diagnosis and monitoring of cardiotoxicity: cardiovascular magnetic resonance and nuclear cardiology. J Cardiovasc Med 17: 45-54. https://doi.org/10.2459/jcm.0000000000000380

14. Tarkin JM, Gopalan D (2023) Multimodality imaging of large-vessel vasculitis. Heart 109: 232-240. http://orcid.org/0000-0002-9132-120X

15. Jiang Q, Huang K, Yin L, Zhang B, Wang Y, et al. (2024) Multimodality cardiovascular imaging for totally video-guided thoracoscopic cardiac surgery. Rev Cardiovasc Med 25: 181. https://doi.org/10.31083/j.rcm2505181

16. Cameli M, Pieroni M, Pastore MC, Brucato A, Castelletti S, et al. (2025) The role of cardiovascular multimodality imaging in the evaluation of Anderson-Fabry disease: from early diagnosis to therapy monitoring a clinical consensus statement of the ESC working group on myocardial & pericardial diseases and the European association of cardiovascular imaging of the ESC. Eur Heart J Cardiovasc Imaging 4: jeaf038. https://doi.org/10.1093/ehjci/jeaf038

17. Hugelshofer S, Giacomuzzi-Moore B, Auberson D, Tzimas G, Kamani CH, et al. (2024) Multi-modality imaging to detect ischemic and valvular heart disease in adult cancer patients. Echocardiography 41: e70030. https://doi.org/10.1111/echo.70030

18. Liu X, Li Y, Li W, Zhang Y, Zhang S, et al. (2024) Diagnostic value of multimodal cardiovascular imaging technology coupled with biomarker detection in elderly patients with coronary heart disease. Br J Hosp Med 85: 1-10. https://doi.org/10.12968/hmed.2024.0123

19. Hrabak Paar M, Muršić M, Bremerich J, Heye T (2024) Cardiovascular aging and risk assessment: how multimodality imaging can help. Diagnostics 14: 1947. https://doi.org/10.3390/diagnostics14171947

20. Dhole R, Borse D, Ahire R, Sharma A, Marathe P (2024) Cardiovascular imaging: recent advances in atherosclerosis diagnosis. Pathophysiol 2: 3048-4626. https://doi.org/10.55522/ijti.v2i5.0077

21. Du Z, Lan C, Shen L, Tian Z, Hu H, et al. (2024) Advances in multimodality imaging and the application of new cardiac imaging technologies for radiation-induced heart disease. iRadiology 2: 285-304. https://doi.org/10.1002/ird3.72

22. Quintero-Martinez JA, Cordova-Madera SN, Villarraga HR (2021) Radiation-induced heart disease. J Clin Med 11: 146. https://doi.org/10.3390/jcm11010146

23. Güler GB, Gürsoy MO, Kürklü TS, Tülüce SY, Özer PK, et al. (2024) Multimodality imaging in cardiomyopathies. Tur Kardiyol Dern Ars 52: 1-206. https://doi.org/10.5543/tkda.2024.13636

24. Azam MA, Khan KB, Salahuddin S, Rehman E, Khan SA, et al. (2022) A review on multimodal medical image fusion: compendious analysis of medical modalities, multimodal databases, fusion techniques and quality metrics. Comput Biol Med 144: 105253. https://doi.org/10.1016/j.compbiomed.2022.105253

25. Acosta JN, Falcone GJ, Rajpurkar P, Topol EJ (2022) Multimodal biomedical AI. Nat Med 28: 1773-1784. https://doi.org/10.1038/s41591-022-01981-2

26. Ali A (2023) Innovations in cardiovascular imaging techniques: a state-of-the-art review. Pak J Med Cardiological Rev 1: 31-48.

27. Olawade DB, Aderinto N, Olatunji G, Kokori E, David-Olawade AC, et al. (2024) Advancements and applications of artificial intelligence in cardiology: current trends and future prospects. J Med Surg Public Health 3: 100109. https://doi.org/10.1016/j.glmedi.2024.100109

28. Najjar R (2023) Redefining radiology: a review of artificial intelligence integration in medical imaging. Diagnostics 13: 2760. https://doi.org/10.3390/diagnostics13172760

29. Trimarchi G, Pizzino F, Paradossi U, Gueli IA, Palazzini M, et al. (2024) Charting the unseen: how non-invasive imaging could redefine cardiovascular prevention. J Cardiovasc Dev Dis 11: 245. https://doi.org/10.3390/jcdd11080245

30. Sirajuddin A, Mirmomen SM, Kligerman SJ, Groves DW, Burke AP, et al. (2021) Ischemic heart disease: noninvasive imaging techniques and findings. Radiographics 41: 990-1021. https://doi.org/10.1148/rg.2021200125

31. Netala VR, Teertam SK, Li H, Zhang Z (2024) A comprehensive review of cardiovascular disease management: cardiac biomarkers, imaging modalities, pharmacotherapy, surgical interventions, and herbal remedies. Cells 13: 1471. https://doi.org/10.3390/cells13171471

32. Ming Y, Wu N, Qian T, Li X, Wan DQ, et al. (2020) Progress and future trends in PET/CT and PET/MRI molecular imaging approaches for breast cancer. Front Oncol 10: 1301. https://doi.org/10.3389/fonc.2020.01301

33. Hu Z, Li Y, Zou S, Xue H, Sang Z, et al. (2020) Obtaining PET/CT images from non-attenuation corrected PET images in a single PET system using Wasserstein generative adversarial networks. Phys Med Biol 65: 215010. https://doi.org/10.1088/1361-6560/aba5e9

34. Wu Y, Vazquez-Prada KX, Liu Y, Whittaker AK, Zhang R, et al. (2021) Recent advances in the development of theranostic nanoparticles for cardiovascular diseases. Nanotheranostics 5: 499-514. https://doi.org/10.7150/ntno.62730

35. Rizzo A, Racca M, Albano D, Dondi F, Bertagna F, et al. (2022) Can PSMA-targeting radiopharmaceuticals be useful for detecting hepatocellular carcinoma using positron emission tomography? an updated systematic review and meta-analysis. Pharmaceuticals 15: 1368. https://doi.org/10.3390/ph15111368

36. Congedo A, Mallardi D, Danti G, De Muzio F, Granata V, et al. (2023) An updated review on imaging and staging of anal cancer—not just rectal cancer. Tomography 9: 1694-1710. https://doi.org/10.3390/tomography9050135

37. Setia A, Mehata AK, Priya V, Pawde DM, Jain D, et al. (2023) Current advances in nanotheranostics for molecular imaging and therapy of cardiovascular disorders. Mol Pharm 20: 4922-4941. https://doi.org/10.1021/acs.molpharmaceut.3c00582

38. Kalisz K, Navin PJ, Itani M, Agarwal AK, Venkatesh SK, et al. (2024) Multimodality imaging in metabolic syndrome: state-of-the-art review. Radiographics 44: e230083. https://doi.org/10.1148/rg.230083

39. Rizvi A, Han D, Danad I, ó Hartaigh B, Lee JH, et al. (2018) Diagnostic performance of hybrid cardiac imaging methods for assessment of obstructive coronary artery disease compared with stand-alone coronary computed tomography angiography: a meta-analysis. JACC Cardiovasc Imaging 11: 589-599. https://doi.org/10.1016/j.jcmg.2017.05.020

40. Juarez-Orozco LE, Martinez-Manzanera O, Nesterov SV, Kajander S, Knuuti J (2018) The machine learning horizon in cardiac hybrid imaging. Eur J Hybrid Imaging 2: 1-5. https://doi.org/10.1186/s41824-018-0033-3

41. Nayfeh M, Sayed A, Alwan M, Alfawara M, Al Rifai M, et al. (2024) Hybrid imaging: calcium score and myocardial perfusion imaging. Semin Nucl Med 54: 638-647. https://doi.org/10.1053/j.semnuclmed.2024.04.003

42. Biondi-Zoccai G, D'Ascenzo F, Giordano S, Mirzoyev U, Erol Ç, et al. (2025) Artificial intelligence in cardiology: general perspectives and focus on interventional cardiology. Anatol J Cardiol 29: 152. https://doi.org/10.14744/AnatolJCardiol.2025.5237

43. Caobelli F, Dweck MR, Albano D, Gheysens O, Georgoulias P, et al. (2025) Hybrid cardiovascular imaging. A clinical consensus statement of the European association of nuclear medicine (EANM) and the European association of cardiovascular imaging (EACVI) of the ESC. Eur J Nucl Med Mol Imaging 52: 1095-1118. https://doi.org/10.1007/s00259-024-06946-w

44. Kazimierczyk R, Kaminski KA, Nekolla SG (2024) Cardiac PET/MRI: recent developments and future aspects. Semin Nucl Med 54: 733-746. https://doi.org/10.1053/j.semnuclmed.2024.05.007

45. Hachiya S, Kosuge H, Fujita Y, Hida S, Chikamori T (2022) Performance of hybrid imaging in the diagnosis of coronary artery disease. Am J Cardiol 174: 34-39. https://doi.org/10.1016/j.amjcard.2022.02.043

46. Farber G, Boczar KE, Wiefels CC, Zelt JG, Guler EC, et al. (2020) The future of cardiac molecular imaging. Semin Nucl Med 50: 367-385. https://doi.org/10.1053/j.semnuclmed.2020.02.005

47. Badano LP, Addetia K, Pontone G, Torlasco C, Lang RM, et al. (2020) Advanced imaging of right ventricular anatomy and function. Heart 106: 1469-1476. http://orcid.org/0000-0002-0379-3283

48. Nogay HS, Adeli H (2020) Machine learning (ML) for the diagnosis of autism spectrum disorder (ASD) using brain imaging. Rev Neurosci 31: 825-841. https://doi.org/10.1515/revneuro-2020-0043

49. Slart RH, Williams MC, Juarez-Orozco LE, Rischpler C, Dweck MR, et al. (2021) Position paper of the EACVI and EANM on artificial intelligence applications in multimodality cardiovascular imaging using SPECT/CT, PET/CT, and cardiac CT. Eur J Nucl Med Mol Imaging 48: 1399-1413. https://doi.org/10.1007/s00259-021-05341-z

50. Vazquez-Prada KX, Lam J, Kamato D, Xu ZP, Little PJ, et al. (2021) Targeted molecular imaging of cardiovascular diseases by iron oxide nanoparticles. Arterioscler Thromb Vasc Biol 41: 601-613. https://doi.org/10.1161/ATVBAHA.120.315404

51. Greulich S, Gatidis S, Gräni C, Blankstein R, Glatthaar A, et al. (2022) Hybrid cardiac magnetic resonance/fluorodeoxyglucose positron emission tomography to differentiate active from chronic cardiac sarcoidosis. Cardiovasc Imaging 15: 445-456. https://doi.org/10.1016/j.jcmg.2021.08.018

52. Argentiero A, Muscogiuri G, Rabbat MG, Martini C, Soldato N, et al. (2022) The applications of artificial intelligence in cardiovascular magnetic resonance—a comprehensive review. J Clin Med 11: 2866. https://doi.org/10.3390/jcm11102866

53. Fukushima K, Ito H, Takeishi Y (2023) Comprehensive assessment of molecular function, tissue characterization, and hemodynamic performance by non-invasive hybrid imaging: Potential role of cardiac PETMR. J Cardiol 82: 286-292. https://doi.org/10.1016/j.jjcc.2023.06.004

54. Moura B, Aimo A, Al-Mohammad A, Keramida K, Ben Gal T, et al. (2023) Diagnosis and management of patients with left ventricular hypertrophy: role of multimodality cardiac imaging. A scientific statement of the heart failure association of the European society of cardiology. Eur J Heart Fail 25: 1493-1506. https://doi.org/10.1002/ejhf.2997

55. Costantino MF, Cortese F, D'Addeo G, Nicoletti A, Mancino S, et al. (2025) Diagnostic modalities for ischemic heart disease: evaluating the role of stress echocardiography, cardiac CT, and myocardial perfusion scintigraphy in guiding coronary angiography. Expl Cardiol 3: 101243. https://doi.org/10.37349/ec.2025.101243

56. Ahmed R, Carver C, Foley JR, Fent GJ, Garg P, et al. (2022) Cardiovascular imaging techniques for the assessment of coronary artery disease. Br J Hosp Med 83: 1-11. https://doi.org/10.12968/hmed.2022.0176

57. Barragán AC, Leiva VV (2021) Coronary artery calcium and hybrid imaging in ischemic heart disease. In Mesquita CT, Rezende MF (eds) Nuclear Cardiology. Springer, pp 203-223.

58. Upadhyay D, Kakkar M (2025) Emerging frontiers: innovations and trends in medical imaging. In Computer-Assisted Analysis for Digital Medicinal Imagery. IGI Global, pp 63-76.

59. Salih S, Elliyanti A, Alkatheeri A, AlYafei F, Almarri B, et al. (2023) The role of molecular imaging in personalized medicine. J Pers Med 13: 369. https://doi.org/10.3390/jpm13020369

60. Ties D, van Dorp P, Pundziute G, Lipsic E, van der Aalst CM, et al. (2022) Multi-modality imaging for prevention of coronary artery disease and myocardial infarction in the general population: ready for prime time?. J Clin Med 11: 2965. https://doi.org/10.3390/jcm11112965

61. Xu B, Kocyigit D, Grimm R, Griffin BP, Cheng F (2020) Applications of artificial intelligence in multimodality cardiovascular imaging: a state-of-the-art review. Prog Cardiovasc Dis 63: 367-376. https://doi.org/10.1016/j.pcad.2020.03.003

62. D'Amario D, Camilli M, Migliaro S, Canonico F, Galli M, et al. (2020) Sex-related differences in dilated cardiomyopathy with a focus on cardiac dysfunction in oncology. Curr Cardiol Rep 22: 1-11. https://doi.org/10.1007/s11886-020-01377-z

63. Vardhan M, Randles AJ (2021) Application of physics-based flow models in cardiovascular medicine: Current practices and challenges. Biophys Rev 2: 011302. https://doi.org/10.1063/5.0040315

64. Cau R, Cherchi V, Micheletti G, Porcu M, Mannelli L, et al. (2021) Potential role of artificial intelligence in cardiac magnetic resonance imaging: can it help clinicians in making a diagnosis?. J Thorac Imaging 36: 142-148. https://doi.org/10.1097/rti.0000000000000584

65. Wamil M, Goncalves M, Rutherford A, Borlotti A, Pellikka PA (2022) Multi-modality cardiac imaging in the management of diabetic heart disease. Front Cardiovasc Med 9: 1043711. https://doi.org/10.3389/fcvm.2022.1043711

66. Massalha S, Kennedy J, Hussein E, Mahida B, Keidar Z (2024) Cardiovascular imaging in women. In Seminars in Nuclear Medicine. WB Saunders, pp 191-205.

67. Xu X, Li J, Zhu Z, Zhao L, Wang H, et al. (2024) A comprehensive review on synergy of multi-modal data and ai technologies in medical diagnosis. Bioeng 11: 219. https://doi.org/10.3390/bioengineering11030219

68. Srinivasan SM, Sharma V (2025) Applications of AI in cardiovascular disease detection-a review of the specific ways in which AI is being used to detect and diagnose cardiovascular diseases. In AI in Disease Detection: Advancements and Applications. Wiley Online Library, pp 123-146.

69. Gupta A, Kumar V, Nakhale A (2025) A comprehensive review of cardiac image analysis for precise heart disease diagnosis using deep learning techniques. In Wellness Management Powered by AI Technologies. Wiley Online Library, pp 133-155.

70. Azariya DSS, Mohanraj V, Jothi G, Emilyn JJ, Akilandeswari J (2023) Cardiac image analysis for accurate heart disease diagnosis using deep learning techniques: a comprehensive review. In International Conference on Soft Computing and Signal Processing. Springer Nature, Singapore, pp 57-67.

71. Tan Z, Yang X, Pan T, Liu T, Jiang C, et al. (2024) Personalize to generalize: towards a universal medical multi-modality generalization through personalization. arXiv preprint. https://doi.org/10.48550/arXiv.2411.06106

72. Qoku A, Katsaouni N, Flinner N, Buettner F, Schulz MH (2023) Multimodal analysis methods in predictive biomedicine. Comput Struct Biotechnol J 21: 5829-5838. https://doi.org/10.1016/j.csbj.2023.11.011

73. Alsaafin A, Shafique A, Alfasly S, Tizhoosh HR (2024) Personalized 2D binary patient codes of tissue images and immunogenomic data through multimodal self-supervised fusion. arXiv preprint. https://doi.org/10.48550/arXiv.2409.13115

74. Rajanandhini C, EugeneBerna I, Megala N, Chandrasekaran R, Begam J, et al. (2024) Revolutionizing cardiovascular diagnostics: advancements in heart disease identification through multimodal data fusion and deep learning CNN algorithm. In 2024 International Conference on Knowledge Engineering and Communication Systems (ICKECS).

75. Zhang H, Sau A, Patlatzoglou K, Pastika L, Sieliwonczyk E, et al. (2024) Artificial intelligence-enhanced electrocardiography predicts 10-year risk of atherosclerotic cardiovascular disease. Eur Heart J 45: ehae666-3499. https://doi.org/10.1093/eurheartj/ehae666.3499

76. Linte CA, Pop M (2023) Applied sciences—special issue on emerging techniques in imaging, modelling and visualization for cardiovascular diagnosis and therapy. Appl Sci 13: 984. https://doi.org/10.3390/app13020984

77. Balakiruba J, Santhanamari G Usha S (2023) Advancements in imaging technologies for enhanced cardiac diagnostics: a comprehensive review. In 2023 International Conference on Intelligent Technologies for Sustainable Electric and Communications Systems. IEEE, pp 501-506.

78. Pezel T, Toupin S, Bousson V, Hamzi K, Hovasse T, et al. (2025) A machine learning model using cardiac CT and MRI data predicts cardiovascular events in obstructive coronary artery disease. Radiology 314: e233030. https://doi.org/10.1148/radiol.233030

79. Vivekanandan DD, Singh N, Robaczewski M, Wyer A, Canaan LN, et al. (2024) Artificial intelligence-driven advances in coronary calcium scoring: expanding preventive cardiology. Cureus 16: e74681. https://doi.org/10.7759/cureus.74681

80. Hu W, Yii FS, Chen R, Zhang X, Shang X, et al. (2023) A systematic review and meta-analysis of applying deep learning in the prediction of the risk of cardiovascular diseases from retinal images. Transl Vis Sci Technol 12: 14-27. https://doi.org/10.1167/tvst.12.7.14

81. Vaishali S, Mohan T, Navaneethan S (2024) AI-powered prediction models for cardiovascular disease risk assessment. In 7th International Conference on Contemporary Computing and Informatics.

82. Kok CL, Koh YY, Ho CK, Thanh NTC Teo TH (2024) Artificial intelligence in cardiology. In IEEE 17th International Symposium on Embedded Multicore/Many-core Systems-on-Chip (MCSoC).

83. Doolub G, Khurshid S, Theriault-Lauzier P, Lapalme AN, Tastet O, et al. (2024) Revolutionising acute cardiac care with artificial intelligence: opportunities and challenges. Can J Cardiol 40: 1813-1827. https://doi.org/10.1016/j.cjca.2024.06.011

84. Jaltotage B, Lu J, Dwivedi G (2024) Use of artificial intelligence including multimodal systems to improve the management of cardiovascular disease. Can J Cardiol 40: 1804-1812. https://doi.org/10.1016/j.cjca.2024.07.014

85. Ahmad A, Husnain A, Shiwlani A, Hussain A, Gondal MN, et al. (2024) Ethical and clinical implications of AI integration in cardiovascular healthcare. World J Adv Res Rev 23: 2479-2501. https://doi.org/10.30574/wjarr.2024.23.3.2907

86. Lüscher TF, Wenzl FA, D'Ascenzo F, Friedman PA, Antoniades C (2024) Artificial intelligence in cardiovascular medicine: clinical applications. Eur Heart J 45: 4291-4304. https://doi.org/10.1093/eurheartj/ehae465

87. Quer G, Topol EJ (2024) The potential for large language models to transform cardiovascular medicine. Lancet Digital Health 6: 767-771. https://doi.org/10.1016/S2589-7500(24)00151-1

88. Moosavi A, Huang S, Vahabi M, Motamedivafa B, Tian N, et al. (2024) Prospective human validation of artificial intelligence interventions in cardiology: a scoping review. JACC Advances 3: 101202.