

Quantum Computing for Cardiovascular Imaging: A Review of Emerging Applications, Challenges and Future Perspectives

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Abstract—Quantum computing is being investigated as a computational approach for medical image analysis, but its potential role in cardiovascular imaging remains unclear. This review examines gate-based, quantum annealing, and hybrid quantum-classical techniques for cardiovascular image enhancement, image reconstruction, image segmentation, image feature extraction, and image-based disease classification, and it treats quantum-inspired classical algorithms as a separate category. The literature was identified through a structured search of four bibliographic databases and one preprint server, using stated eligibility criteria and study-level data extraction. Applications are considered in echocardiography, computed tomography, cardiac magnetic resonance imaging, nuclear imaging, and coronary angiography, and direct cardiovascular evidence is distinguished from methods developed for other medical imaging tasks. One adjacent cardiac study based on chest radiography is reported separately because it falls outside these five modalities. For each study, the imaging data, qubit count, encoding strategy, execution on a simulator or physical hardware, classical baseline, and validation design are tabulated. The review also defines the forms of quantum advantage that a study could claim, quantifies the qubit and state-preparation costs of common image encodings for realistic cardiac image sizes, and compares quantum methods with classical machine learning and deep learning in terms of computational requirements, training, interpretability, and reported performance. The existing evidence is exploratory and relies mostly on small datasets, compressed image representations, and quantum simulators. Some results are encouraging, but no consistent advantage over well-tuned classical approaches has been established. The key obstacles are image encoding, hardware noise, circuit depth, trainability, end-to-end computational cost, and the lack of external validation. Hybrid designs offer a practical setting for testing selected quantum components within current imaging pipelines. Future progress requires reproducible cardiovascular benchmarks, evaluation on physical quantum devices, and staged clinical validation. Quantum computing is therefore an emerging field of study whose role in cardiovascular imaging has to be defined through rigorous technical and clinical comparison.

Keywords—Quantum computing; cardiovascular imaging; quantum machine learning; hybrid quantum-classical computing; medical image analysis

I. INTRODUCTION

Even though cardiovascular diseases (CVDs) rank among the leading causes of morbidity and mortality worldwide, there is an urgent need for early diagnosis, early risk assessment, and easy intervention planning [1]. Medical imaging is integral to cardiovascular care, providing not only anatomical information but also functional information [2].

Most commonly used modalities include echocardiography, which allows real-time evaluation of cardiac structure and function; computed tomography (CT), which gives detailed coronary anatomy; cardiac magnetic resonance imaging (CMR), which characterizes myocardial tissue and ventricular function; and nuclear imaging, including positron emission tomography (PET) and single-photon emission computed tomography (SPECT), which evaluate myocardial perfusion and metabolism and uncover myocardial viability. Also, invasive coronary angiography is of critical importance for evaluation of coronary artery disease and for interventional planning. As a whole, these modalities have significantly aided in diagnosis and treatment of cardiovascular diseases [3].

As the use and complexity of cardiovascular imaging has increased, computational challenges have also become more prevalent. In modern imaging technologies, a huge amount of multidimensional and sometimes multimodal data is generated, which needs to be reconstructed, enhanced, registered, segmented, features extracted, classified, and interpreted. In addition, images of the cardiovascular system are difficult due to cardiac and respiratory motion, anatomical variations, vascular complexity, and varying acquisition protocols. There has been a resulting growth in the number of image processing applications that have been automated using deep learning and machine learning methods and that assist in the diagnosis of diseases. However, imaging data and models have become increasingly complex, further demanding efficient and effective processing and optimization techniques [4].

Quantum computing has recently emerged as a possible approach to selected computational problems involving complex and high-dimensional data. In medical imaging, quantum algorithms and quantum machine learning (QML) methods have been investigated for image processing,

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segmentation, feature selection, classification, and diagnostic tasks, although most applications remain experimental and are commonly evaluated with simulators or hybrid quantum-classical approaches [5]. Current evidence also indicates that a consistent quantum advantage over classical machine-learning methods has yet to be demonstrated, with recurring limitations related to data encoding, scalability, noisy quantum hardware, and small experimental datasets [6].

Several reviews have already addressed parts of this field. Yan et al. [4] surveyed quantum-enabled algorithms for medical image processing across imaging modalities and organ systems, Gupta et al. [6] systematically reviewed QML across digital health applications and data types, and Ayyad et al. [7] discussed the promise and limitations of artificial intelligence and quantum computing across cardiovascular medicine. To our knowledge, none of these works appraises cardiovascular imaging studies individually by modality, qubit count, encoding strategy, execution platform, and validation design. This structured narrative review addresses that gap and makes four contributions. First, it applies a stated search and selection protocol and separates direct cardiovascular imaging evidence from transferable non-cardiac evidence. Second, it distinguishes gate-based, annealing-based, hybrid, and quantum-inspired classical methods, which are often grouped in the literature. Third, it defines the forms of quantum advantage that a study could claim and quantifies the qubit and state-preparation costs of image encoding for realistic echocardiographic, CT, CMR, angiographic, and nuclear imaging data. Fourth, it outlines a staged pathway for clinical validation, together with the reporting items needed to judge whether an observed benefit can be attributed to the quantum component.

The remainder of this study is organized as follows. Section II describes the review methodology. Section III outlines the computational challenges of cardiovascular imaging, and Section IV introduces the fundamentals of quantum computing and QML, including the classes of methods considered, image encoding, and the definition of quantum advantage. Section V reviews applications by image-analysis task, and Section VI considers each cardiovascular imaging modality in turn. Section VII compares classical and quantum approaches and summarizes the extracted evidence. Sections VIII and IX discuss current limitations and future directions for clinical translation, and Section X concludes the review.

II. REVIEW METHODOLOGY

A. Search Strategy

This review was designed as a structured narrative review, and its search and selection steps are reported with reference to the PRISMA 2020 statement [8]. A formal meta-analysis was not attempted because the included studies differed widely in task, data, quantum method, and outcome measures. PubMed/MEDLINE, Scopus, Web of Science Core Collection, and IEEE Xplore were searched for articles published between January 2015 and [month] 2026. The arXiv repository was also searched because much of the quantum computing literature first appears as preprints, and preprints are identified as such wherever they are cited. The search combined three groups of terms with Boolean operators. The quantum group included “quantum computing”, “quantum machine learning”, “quantum

neural network”, “variational quantum”, “quantum kernel”, “quantum support vector”, “quantum annealing”, “QUBO”, and “Grover”. The imaging group included “medical imaging”, “image segmentation”, “image reconstruction”, “image classification”, and “radiomics”. The cardiovascular group included “cardiac”, “cardiovascular”, “heart”, “coronary”, “echocardiography”, “cardiac magnetic resonance”, “CT angiography”, “myocardial perfusion”, “SPECT”, “PET”, and “angiography”. A representative PubMed string was (“quantum comput*” OR “quantum machine learning” OR “quantum neural network*” OR “variational quantum” OR “quantum kernel” OR “quantum annealing”) AND (imag* OR radiomic* OR segmentation OR reconstruction) AND (cardi* OR heart OR coronar* OR echocardiograph* OR myocard* OR angiograph*), and it was adapted to the syntax of each database. To identify transferable methods, the quantum and imaging groups were also searched without the cardiovascular group. The reference lists of included articles and of the reviews by Yan et al. [4], Gupta et al. [6], and Ayyad et al. [7] were screened by hand for additional studies.

B. Eligibility Criteria

Studies were eligible for the evidence synthesis if they 1) applied a gate-based quantum algorithm, a quantum annealing formulation, or a hybrid quantum-classical model to medical images or to features derived from medical images, 2) reported a quantitative evaluation on patient data or on phantoms, and 3) were published in English as a peer-reviewed journal article, a full conference paper, or a preprint with sufficient methodological detail. A study was classified as direct cardiovascular evidence when its images or image-derived features came from the heart or the vasculature. Studies of non-cardiac images were classified as transferable evidence and were retained only when their method could be mapped onto one of the five cardiovascular modalities considered here. Quantum-inspired algorithms that run entirely on classical hardware were not counted as quantum evidence, because they use no quantum resources, and they are discussed separately where they appear as comparators or are described as quantum methods in the literature. Studies that used only tabular clinical data, such as the Cleveland heart-disease dataset, were excluded from the imaging evidence tables and are mentioned in Section V only for context. Quantum sensing and quantum-optical imaging hardware, editorials, abstracts without results, and studies without any quantitative evaluation were also excluded.

C. Study Selection and Data Extraction

Two reviewers screened titles and abstracts independently and then assessed the full texts against the eligibility criteria. Disagreements were resolved by discussion, and a third reviewer was consulted when needed. The search returned twelve records, of which eight remained after removal of duplicates. After title and abstract screening, eight full texts were assessed, and two studies met the inclusion criteria, comprising three direct cardiovascular imaging studies and four transferable studies.

For each included study, one reviewer extracted the imaging modality and task, dataset size and source, quantum paradigm, qubit count, encoding strategy, execution on a simulator or on physical hardware, classical comparator, validation design, and main results, and a second reviewer checked the extracted data.

Items that a study did not report were recorded as not specified. The extracted data are summarized in Tables II and III in Section VII.

III. CARDIOVASCULAR MEDICAL IMAGING AND COMPUTATIONAL CHALLENGES

Cardiovascular imaging generates diverse and increasingly complex data that require substantial computational processing before meaningful clinical information can be obtained. Depending on the modality, cardiovascular examinations may involve two-dimensional images, volumetric three-dimensional datasets, dynamic image sequences, or multiparametric information. Common activities of these data analyses involve image reconstruction, image enhancement, image registration, image segmentation, quantitative measurement, feature extraction, and disease classification. With the advancement of new imaging modalities such as echocardiography, CMR, CT, and nuclear imaging over the last few years, there is now more information available on the anatomy and function of tissues that can be assessed clinically, but they also place more demands on the ability to process and analyze images quickly and automatically [9][10].

Segmentation is one such computation task, especially critical, as the segmentation of the cardiac chambers, myocardium, coronary vessels, plaques, and other anatomical parts of interest is often necessary and is a prerequisite for generating quantitative measurement values or diagnostic features. In practice, however, the segmentation of the heart is difficult, as there is considerable variation in cardiac anatomy among subjects, and cardiac motion, image noise, low contrast, irregular anatomy, and acquisition protocol differences may impact the imaging. These challenges are particularly pertinent in the context of small and complex vessels, where the accuracy of the Segmentation procedure might impact the quantitative assessment of the vessel's diameter, luminal stenosis, plaque burden, or arterial wall thickness [11]. The same holds in CMR, where image acquisition is slow and prone to cardiac and respiratory motion, so fast reconstruction and motion-tolerant processing are key research topics [12].

To overcome these challenges, machine learning and deep learning have been applied increasingly. Current applications span automated segmentation, image reconstruction, anatomical and functional quantification, feature extraction, disease detection, and risk prediction in the various imaging modalities of cardiovascular image analysis [13]. However, these strategies remain subject to the need for large and representative cohorts, heavy computational power, and accurate generalization from model to data across scanners, institutions, and patients. Finally, multimodal cardiovascular imaging adds additional complexity in that the data derived from CT, CMR, echocardiography, and other modalities may vary in terms of spatial resolution, acquisition characteristics, and representation of cardiac anatomy and function [14]. These modalities can be used together for procedural guidance, e.g., in the case of transcatheter aortic valve implantation, and require accurate registration of different techniques used to obtain images [15]. Because of the surge of larger, more heterogeneous datasets from cardiovascular imaging, an interest in alternative computations has emerged that may provide additional

information to complement the current “classic” computation. This can serve as a foundation for the exploration of quantum computing and QML for specific cardiovascular image-processing/diagnostic problems.

IV. FUNDAMENTALS OF QUANTUM COMPUTING AND QUANTUM MACHINE LEARNING

A. Qubits, Quantum Circuits, and the NISQ Era

Quantum computing processes information using quantum bits, or qubits, rather than conventional binary bits. While a classical bit is represented as either 0 or 1, a qubit can exist in a superposition of both states until it is measured. Multiple qubits may also become entangled, meaning that their joint state cannot be described as a combination of independent single-qubit states. Computation is performed by applying quantum gates to qubits in a defined sequence, forming a quantum circuit. The final quantum state is then measured and converted into classical information. Because each measurement returns a single outcome, a circuit is usually executed many times, and the number of repetitions, or shots, contributes directly to the run time. Each measurement only gives one result, so a circuit is typically repeated many times, and the number of times each is repeated is the number of shots and a direct factor of runtime. This is due to the properties that quantum systems can perform the representation and manipulation of information in different ways than classical computers and have encouraged their study for solving problems which require a significant amount of computational power, such as medical image processing and analysis [16].

In general, today's quantum computers are in the noisy intermediate-scale quantum (NISQ) phase, with a small number of qubits, in which gate errors and decoherence are dominant and circuit depth is constrained [17]. These limitations make it difficult to work with large medical data on quantum hardware. Consequently, the most recent approaches adopt hybrid (quantum-classical) computation, where data is preprocessed, features are extracted, or parameters are optimized by classical hardware, but select computation steps are performed on a quantum processor, or, in most cases, on a classical simulation of it. This framework is normally based on variational quantum circuits, where the parameters of the circuit are updated in an iterative fashion based on measured output of the circuit using a classical optimizer [18]. The mixed design is especially interesting for medical image processing, as quantum hardware currently cannot be effectively used for high-resolution imaging.

B. Quantum Machine Learning Models

QML extends these concepts by integrating quantum computation with machine-learning algorithms. Several QML approaches have been investigated for medical image analysis, including variational quantum classifiers, quantum neural networks (QNNs), quantum kernel methods, and quantum support vector machines (QSVMs). In a variational quantum model, classical input data are first encoded into a quantum state before passing through a parameterized quantum circuit. QNNs use a similar trainable circuit structure, in which repeated quantum operations act as the learning layers of the model. Quantum kernel approaches instead map classical data into a quantum feature space and estimate similarities between

quantum states, which can subsequently be used by classical kernel-based classifiers such as support vector machines [19][20].

For medical imaging, these methods are mainly being investigated as components of hybrid pipelines rather than as complete replacements for classical deep-learning models. Classical convolutional neural networks or other feature-extraction methods may first reduce image dimensionality, followed by a quantum classifier for the final prediction stage. Reviews of QML in medical imaging and digital health show that hybrid models are currently among the most commonly investigated approaches, while most studies remain small in scale and are performed on simulators rather than on fault-tolerant quantum systems [6][21]. QML should therefore be considered at present an emerging computational framework whose practical value in cardiovascular imaging still requires validation.

C. Classes of Quantum and Quantum-Related Methods

The label “quantum” is applied in the imaging literature to methods that differ fundamentally in the resources they use, and this review separates them into four classes (Fig. 1). Gate-based methods run quantum circuits under the circuit model of computation. They include variational classifiers, QNNs, quantum kernel methods, and search algorithms such as Grover’s algorithm, and they can be executed on physical gate-based processors or on classical simulators. Quantum annealing methods instead express a task as the minimization of an Ising or quadratic unconstrained binary optimization (QUBO) objective [22] and solve it on an annealing device. The D-Wave systems used by Felefly et al. [23] and by Lee and Jun [24] are examples. Annealers are not universal quantum computers, and commercial hybrid solvers combine annealing with classical heuristics, so the share of the work performed by the quantum device is often not reported. Hybrid quantum-classical methods combine either kind of quantum component with classical preprocessing, feature extraction, or optimization, and they account for most of the imaging studies reviewed here. Quantum-inspired algorithms, finally, borrow concepts such as superposition-based representations or quantum-behaved optimization but run entirely on classical hardware [25]. They can be useful classical methods, but they provide no evidence about the performance of quantum devices and are therefore not counted as quantum evidence in this review. Within the quantum classes, results obtained on noiseless simulators, noisy simulators, and physical hardware should also be distinguished, because simulator performance does not guarantee the same performance on a device.

D. Encoding Classical Images into Quantum States

Before a quantum model can process an image, the pixel values must be loaded into a quantum state, and the choice of encoding determines both the number of qubits and the cost of state preparation [26]. Four families of schemes are relevant to medical imaging. Basis encoding writes each value as a binary string in the computational basis, so loading all N pixels of an image with q -bit intensities at once would require qN qubits. Angle encoding maps each feature to the rotation angle of a single-qubit gate. It needs only shallow circuits but uses one qubit per feature, which is why the hybrid models in Tables II

and III encode between 2 and 16 compressed features rather than raw pixels. Amplitude encoding stores a normalized vector of N values in the amplitudes of only $\lceil \log_2 N \rceil$ qubits, which is the source of the frequently cited exponential compression. Preparing an arbitrary amplitude-encoded state, however, requires several two-qubit gates that grow linearly with N , of the order of 2^n CNOT gates for n qubits, and a correspondingly deep circuit [27]. Quantum image representations were developed specifically for pictures. The flexible representation of quantum images (FRQI) stores the intensity of each pixel in the rotation angle of a single color qubit entangled with $\lceil \log_2 N \rceil$ position qubits [28], whereas the novel enhanced quantum representation (NEQR) stores a q -bit intensity in q basis qubits, giving $\lceil \log_2 N \rceil + q$ qubits in total [29]. NEQR allows exact retrieval of pixel values, while FRQI requires repeated measurements to estimate each angle, and the preparation cost of both representations grows at least linearly with the number of pixels [30].

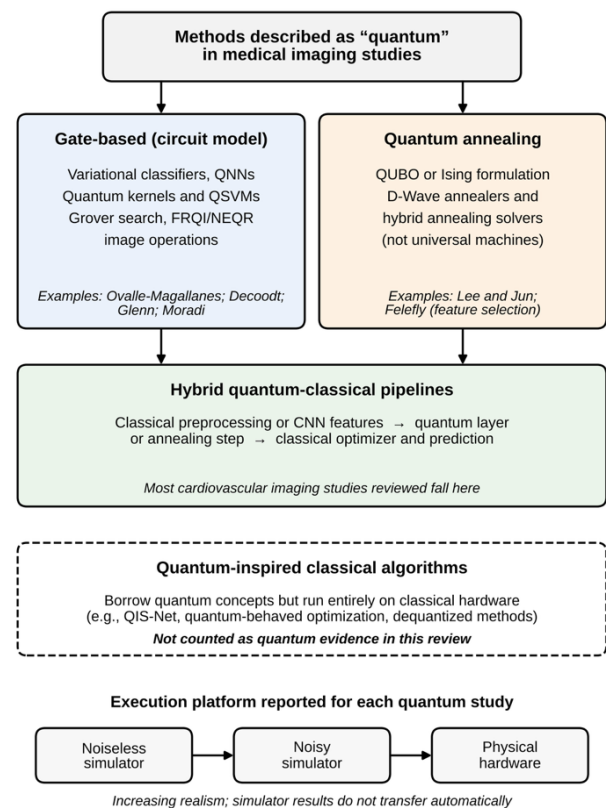


Fig. 1. Classes of quantum and quantum-related methods considered in this review, with representative imaging studies and the execution platforms on which quantum methods are evaluated. Quantum-inspired classical algorithms are shown separately because they use no quantum resources.

Table I applies these scalings to typical cardiovascular data. A single 112×112 echocardiographic frame, the resolution used in the EchoNet-Dynamic dataset [31], would require 12,544 qubits under angle encoding but only 14 qubits under amplitude encoding. The amplitude-encoded state, however, would need on the order of 10^4 CNOT gates to prepare. For a $512 \times 512 \times 256$ coronary CT angiography volume, amplitude encoding requires 26 qubits and is of the order of 10^7 CNOT gates, and NEQR with 12-bit attenuation values requires 38 qubits. Circuits of this depth exceed what current NISQ devices can execute

reliably by several orders of magnitude. Reading information back out is also costly, because estimating N output amplitudes to a precision ϵ requires a number of shots of the order of N/ϵ^2 . An end-to-end speed-up is therefore plausible only when the data are already available in quantum form, when an efficient loading routine exists for the structure of the data, or when the task requires only a small number of output values rather than a

full image [32]. These costs explain why current cardiovascular studies compress images into a handful of classical features before encoding. They also identify the main risk of this strategy, which is that compression may discard clinically relevant information such as small coronary lesions or subtle regional wall-motion abnormalities.

TABLE I. QUBIT AND STATE-PREPARATION REQUIREMENTS OF COMMON ENCODINGS FOR REPRESENTATIVE CARDIOVASCULAR IMAGE SIZES

Imaging data (assumed bit depth q)	Dimensions (padded)	Values, N	Angle encoding, qubits	Amplitude encoding, qubits	Amplitude preparation, CNOT gates (order of 2^n)	FRQI, qubits	NEQR, qubits
Echocardiography frame ($q = 8$)	112×112 (128×128)	12,544	12,544	14	1.6×10^4	15	22
Echocardiography clip, 32 frames ($q = 8$)	$112 \times 112 \times 32$	401,408	401,408	19	5.2×10^5	20	27
X-ray coronary angiography frame ($q = 8$)	512×512	262,144	262,144	18	2.6×10^5	19	26
Cardiac CT slice ($q = 12$)	512×512	262,144	262,144	18	2.6×10^5	19	30
CCTA volume ($q = 12$)	$512 \times 512 \times 256$	67,108,864	67,108,864	26	6.7×10^7	27	38
CMR cine stack, 10 slices $\times$ 25 phases ($q = 12$)	$256 \times 256 \times 10 \times 25$ ($256 \times 256 \times 16 \times 32$)	16,384,000	16,384,000	24	1.7×10^7	26	37
SPECT myocardial perfusion volume ($q = 8$)	$64 \times 64 \times 64$	262,144	262,144	18	2.6×10^5	19	26

^a Angle encoding assumes one value per qubit. Amplitude encoding uses $n = \lceil \log_2 N \rceil$ qubits, and the CNOT count is the order of magnitude for preparing an arbitrary state [27]. FRQI and NEQR position registers use the dimensions padded to powers of two, with one color qubit for FRQI [28] and q intensity qubits for NEQR [29]. Basis encoding of all values simultaneously would require qN qubits. Values are illustrative and exclude ancilla qubits and error correction.

E. Defining Quantum Advantage

Claims of quantum advantage in medical imaging are often made without stating what is being compared. Following recent discussions in the QML literature [33][34], this review distinguishes three forms of advantage. Computational advantage means a quantum algorithm solves the same task with lower asymptotic or measured resource cost than the best-known classical algorithm, including the costs of data loading, repeated measurement, error mitigation, and classical optimization. Predictive advantage means that a quantum or hybrid model achieves better performance on held-out data than strong, well-tuned classical models trained on the same inputs and data partitions, supported by appropriate statistical testing and, ideally, by external validation. Resource advantage means that a model reaches comparable performance with fewer trainable parameters, fewer training samples, or lower energy use, measured for the whole pipeline. For hybrid models, the most informative comparison is an ablation in which the quantum layer is replaced by a classical layer of similar size, because this isolates the contribution of the quantum component. Huang et al. [34] showed that classical models with access to training data can match quantum models on many learning problems, so a predictive advantage on classical data cannot be inferred from the size of the quantum feature space alone. None of the cardiovascular studies reviewed here establishes a computational advantage, and the reported predictive differences are small, metric-dependent, and obtained without external validation. In the remainder of this review, the term quantum advantage is used only in these defined senses.

V. QUANTUM COMPUTING APPLICATIONS IN CARDIOVASCULAR MEDICAL IMAGING

Quantum computing is beginning to attract interest in medical imaging because several image-analysis tasks involve large search spaces, high-dimensional representations, and computationally demanding optimization problems. Current applications include image preprocessing, segmentation, feature extraction, classification, and, more recently, tomographic reconstruction. However, direct applications to cardiovascular imaging remain limited compared with other areas such as brain MRI and oncological imaging. Evidence from broader medical imaging research is therefore useful for identifying techniques that may eventually be adapted to echocardiography, cardiac CT, CMR, PET and SPECT, and angiographic imaging [4][7]. In each subsection below, the quantum paradigm of the cited work is stated according to the classes defined in Section IV-C.

A. Quantum Image Processing and Enhancement

Image preprocessing is an important stage in cardiovascular imaging because subsequent measurements and diagnostic analysis can be affected by noise, poor contrast, motion artifacts, and indistinct anatomical boundaries [9][12]. Quantum and quantum-related approaches have been investigated for several preprocessing operations, including filtering, edge detection, noise reduction, and contrast enhancement. Two strands of this work should be separated. In the first, gate-based quantum image representations such as FRQI and NEQR are used to implement edge detection and morphological operations as quantum circuits [30]. In the second, quantum-inspired optimization algorithms, which run on classical computers, are used to determine the parameters of conventional image-enhancement techniques. Yan et al. [4] reviewed both strands

and noted applications to noise removal, edge detection, contrast enhancement, and texture analysis in medical images. The conceptual workflow presented in Fig. 2 illustrates the integration of cardiovascular imaging data, classical preprocessing, quantum-assisted enhancement, image-quality assessment, and subsequent clinical and artificial intelligence tasks.

These approaches may be relevant to cardiovascular imaging, where clear representation of anatomical boundaries is important for identifying structures such as the myocardium, ventricular walls, coronary vessels, and vascular lesions. In echocardiography, for example, speckle noise and variable image quality may influence the visibility of endocardial boundaries, while cardiac CT and CMR can be affected by motion and reconstruction artifacts. Nevertheless, most published quantum-enhanced preprocessing studies have not yet been validated specifically on cardiovascular datasets, and most gate-based demonstrations use very small images on simulators because of the encoding costs described in Section IV-D. Their current importance is therefore mainly methodological. They provide possible tools that could later be incorporated into cardiovascular image-analysis pipelines, but they have not demonstrated an established clinical advantage [4].

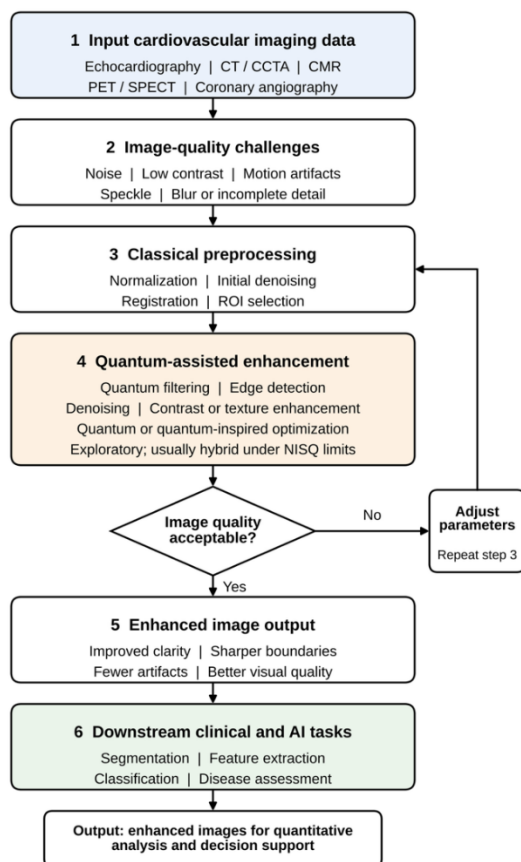


Fig. 2. Conceptual workflow of quantum-enhanced image processing for cardiovascular medical imaging, integrating classical preprocessing, quantum-assisted enhancement, image-quality assessment with parameter adjustment, and downstream clinical and artificial intelligence tasks. Under current NISQ constraints, the quantum step is exploratory and is usually implemented within a hybrid quantum-classical pipeline.

B. Quantum-Based Image Reconstruction

Image reconstruction is one of the most computationally intensive stages in tomographic imaging. CT, MRI, PET, and SPECT require measurements acquired in the physical domain to be transformed into images suitable for clinical interpretation. Reconstruction becomes particularly challenging when acquisition data are incomplete, undersampled, noisy, or affected by patient motion. These problems can be formulated as inverse or optimization problems, which makes them an area of interest for quantum optimization methods.

Recent work has begun to examine the feasibility of quantum-assisted tomographic reconstruction. Lee and Jun [24], for example, proposed a quantum annealing reconstruction framework in which a low-resolution image is first reconstructed from a downsampled sinogram and then refined region by region, with each local reconstruction problem expressed as a QUBO and solved with a D-Wave hybrid quantum-classical solver while the surrounding image is kept fixed. By reducing the size of the image from 100×100 to 50×50 , the maximum number of binary variables per subproblem was reduced to 2500 for the case of a binary phantom and 7500 for a problem with 4 intensity levels for the entire phantom. Evaluation was carried out on Shepp-Logan phantoms as well as on the chest CT slice in both “dense-view” and “sparse-view” acquisition. Most evaluation was based on the difference between the QUBO energy achieved in the experiment and the theoretical minimum achievable by the QUBO, and on visual inspection, not standard image quality measures based on the comparison with classical iterative reconstruction.

While this work was developed without the purpose of cardiac CT, the problem becomes relevant for cardiovascular imaging. Coronary CT reconstruction tries to manage small anatomic details, fast cardiac motion, noise, and, at least in some cases, limited datasets or less than ideal dose in the acquisition. The same computational problem situations will be encountered in accelerated CMR and in nuclear cardiac imaging. Thus, quantum optimization may prove useful for some reconstruction problems, especially those for which a mathematical description exists as a discrete optimization problem. At the moment, however, the evidence is mostly obtained from an experimental reconstruction environment, phantoms, or small image examples, and it is not yet possible to make the claim that quantum reconstruction is beneficial for standard cardiovascular imaging.

C. Quantum and QML for Image Segmentation

Segmentation plays a pivotal role in quantitative cardiovascular image analysis because most measurements rely on proper delineation of the anatomy. Some examples are segmentation of the left and right ventricles, myocardium, atria, coronary arteries, vessel lumen, atherosclerotic plaque, and myocardial scar. Although conventional deep-learning approaches like U-Net architectures have been effective in these tasks, they may be time-consuming to train and require a significant amount of data and computing power.

Different approaches for segmenting with quantum assistance have been investigated, such as Quantum Optimization, Quantum Clustering, Search with Grover, Quantum morphological operations, and hybrid quantum-

classical networks. In particular, Glenn et al. [35] tested quantum contouring liver segmentation on abdominal MRI for 34 patients. The U-Net was the first model to learn to find the candidate liver pixels, which were subsequently used as the target states for the Grover search in their gate-based method. The hybrid approach gave the median Dice coefficient of 0.9309, and 0.9307 for the U-Net alone (within one standard deviation) was not statistically different. The two quantum-inspired comparators did much worse, with Dice coefficients of 0.31 and 0.25, respectively.

All quantum algorithms were run on a classical simulator without a noise model, and the authors estimated that a 64×64 image would require at least 12 qubits under their encoding [35]. The study illustrates how a classical model and a quantum search procedure can be combined within the same segmentation workflow, but it does not show a benefit from the quantum step. Quantum-inspired clustering and optimization approaches have also been investigated for medical image segmentation, although their performance is often evaluated on relatively small datasets and, as noted in Section IV-C, they use no quantum hardware [4].

In cardiovascular imaging, similar approaches could potentially be adapted for ventricular chamber segmentation, myocardial delineation, vessel extraction, and plaque segmentation. However, direct studies applying quantum segmentation to these cardiovascular structures remain scarce. For this reason, the current evidence should be viewed as proof of feasibility for medical image segmentation rather than as evidence that quantum segmentation is superior to established cardiovascular segmentation networks.

D. Quantum-Based Feature Extraction and Dimensionality Reduction

Medical images contain considerably more information than can be processed directly by current quantum computers. Feature extraction and dimensionality reduction therefore have an important role in QML pipelines. Rather than encoding an entire CT or MRI volume into a quantum circuit, classical algorithms can first extract a smaller set of informative features, which are subsequently encoded into qubits. Quantum feature maps may then transform these data into a quantum feature space in which nonlinear relationships can be represented before classification.

Quantum approaches have also been investigated for feature selection. Felefly et al. [23] used a quantum-annealing-based mutual-information method to select radiomic features before classification with a variational QNN for MRI-based tumor differentiation. The study initially considered 423 patients, of whom 201 were retained after exclusion, comprising 72 patients with high-grade gliomas and 129 with large brain metastases. From 1,813 extracted radiomic features, 10 were selected through a QUBO formulation solved on a D-Wave quantum annealer. These features were subsequently encoded into a two-qubit QNN, evaluated in simulation, to distinguish large brain metastases from high-grade gliomas [23]. The study therefore combines two quantum paradigms, an annealing step for feature selection and a simulated gate-based classifier. Although this application is neurological rather than cardiovascular, the methodology may be relevant to cardiovascular radiomics,

where numerous texture, shape, and intensity features can be extracted from cardiac CT and CMR images of the myocardium, coronary plaques, and surrounding vascular structures [36]. Epicardial adipose tissue is one such target, as its attenuation on cardiac CT has been associated with cardiovascular risk factors in high-risk patients [37].

Dimensionality reduction is particularly important under current NISQ constraints because classical imaging datasets usually need to be reduced before they can be encoded into small-scale quantum circuits (Section IV-D). Common preprocessing approaches include feature selection, cropping, principal component analysis, and linear discriminant analysis [6]. Consequently, many current medical-imaging QML models adopt a hybrid structure in which classical computation reduces the imaging data to a manageable feature representation, while a quantum circuit performs feature transformation or classification.

E. Quantum Machine Learning for Classification and Cardiovascular Disease Diagnosis

Classification is currently one of the most frequently studied QML applications in healthcare. In medical imaging, hybrid quantum models have been investigated for distinguishing normal from abnormal images, identifying disease classes, and assisting diagnostic prediction. Ajlouni et al. [38] developed an adaptive hybrid quantum convolutional neural network for medical image diagnosis. Their model combined parameterized quantum circuits with classical neural-network components and was evaluated on a brain-image dataset containing more than 7,000 images. The hybrid model performed favorably compared with its conventional CNN counterpart, although the results were obtained on a non-cardiovascular dataset. Other recent hybrid quantum networks have similarly been investigated for MRI brain-tumor classification, reflecting a growing interest in incorporating parameterized quantum circuits into image-classification architectures [21].

More importantly for cardiovascular imaging, direct QML applications are beginning to appear. Decoodt et al. [39] investigated classical-quantum models for classifying left ventricular ejection fraction into reduced, mid-range, and preserved categories directly from echocardiographic videos in the EchoNet-Dynamic dataset, without prior delineation of the left ventricle. They combined a MoViNet video network with PennyLane-based quantum layers and used the original training, validation, and test split of the dataset. A soft-voting ensemble built on the outputs of all classifiers reached a micro-averaged ROC-AUC of 0.96 on the test set, and the ROC-AUC and balanced accuracy for reduced ejection fraction against the other categories were 0.96 and 0.89 [39]. This study is one of the clearer examples of QML applied directly to cardiovascular image data rather than only to clinical tabular variables. Because the best results were obtained with an ensemble of classical and hybrid classifiers, however, the separate contribution of the quantum layers cannot be determined from the summary metrics. In an earlier study, Decoodt et al. [40] developed hybrid transfer-learning models that combined a pretrained DenseNet-121 with parameterized quantum circuits for cardiomegaly detection on 2,436 chest radiographs from CheXpert. Chest radiography lies outside the five modalities that are the focus of

this review, so that study is reported separately as adjacent cardiac evidence in Section VII.

QML has also been investigated for cardiovascular disease prediction using non-imaging clinical data. For example, hybrid quantum neural networks, QSVMs, and quantum-assisted ensemble methods have been tested for heart-disease and coronary heart-disease classification [41], while Kumar et al. [42] combined classical and quantum-inspired techniques that run entirely on classical hardware. Verdone et al. [43] combined a classical autoencoder for dimensionality reduction with a variational QNN for cardiovascular disease classification and reported an accuracy of up to 90.98% on the Cleveland heart-disease dataset of 303 patients, obtained in simulation with up to nine qubits. Similarly, Rao et al. [44] reported that a QSVM with a quantum kernel reached 93.90% accuracy, compared with 92.50% for its classical SVM baseline, on a UCI-derived cardiovascular dataset.

These results indicate increasing interest in QML for cardiovascular diagnosis, but they should not be interpreted as evidence of quantum advantage in cardiovascular imaging. Most cardiovascular QML studies still use small, structured clinical datasets rather than raw CT, MRI, PET, SPECT, or angiographic images. Large multicenter imaging studies comparing QML with well-optimized classical deep-learning models are therefore still required.

F. Hybrid Quantum-Classical Approaches

At present, hybrid quantum-classical models are the most practical approach for medical imaging because current quantum hardware cannot efficiently accommodate full-resolution medical images. A typical hybrid pipeline begins with classical image preprocessing, segmentation, or feature extraction. The resulting low-dimensional feature vector is then encoded into a quantum circuit, processed by a parameterized or variational quantum layer, and returned to a classical computer for optimization or final prediction. This structure allows researchers to investigate quantum learning while retaining established classical methods for computationally demanding image operations.

Several medical-imaging studies have adopted this strategy. Ajlouni et al. [38] combined classical neural-network processing with parameterized quantum circuits for image classification, while Ovalle-Magallanes et al. [45] and Decoodt et al. [40][39] used pretrained classical networks for feature extraction followed by quantum circuits for classification. The same principle has been applied to segmentation, in which classical U-Net contouring was followed by Grover search [35]. Cardiovascular QML studies based on clinical data have also adopted hybrid architectures, because dimensionality reduction is necessary before clinical or imaging features can be processed with a limited number of qubits [43].

For cardiovascular imaging, a realistic near-term workflow is therefore unlikely to replace established CT, MRI, echocardiographic, or nuclear imaging software with a fully quantum system. Initially, however, quantum algorithms could be used as special modules in an otherwise classical pipeline, such as to help with feature selection, optimization, classification, or selected reconstruction problems. This

interpretation fits well in the current NISQ context and is in line with recent quantum computing assessment in cardiovascular medicine that highlights not only its promise but also the significant amount of technical and clinical validation to be done before mainstream usage can become a reality [7].

VI. APPLICATION ACROSS CARDIOVASCULAR IMAGING MODALITIES

Quantum computing might be useful to different extents depending on the modality of imaging and the sort of information needed to make clinical decisions. One of them is to impact the quality of echocardiograms, segmentation of cardiac boundaries, or classification of ventricular function from a series of images. Most directly to date, Decoodt et al. [39] explored the use of QML for classification of left ventricular EF categories, using echocardiographic videos. Other applications (e.g., speckle reduction using quantum assistance; chamber segmentation) should be viewed as research areas that still need to be validated. Finally, it is clear from the presentation of the problem with the echo that, even for a recent and low number of features, the number of components, at the time of encoding, is already of the order of 400,000 elements (Table I), so any "near-term" quantum component must operate on top of features extracted by a classical network.

A quantum approach could be explored to reconstruct the image and select features for coronary plaque and classification for CT, CCTA (Coronary CT Angiography). Lee and Jun [24] have developed a quantum annealing reconstruction method, which splits an image into smaller regional optimization problems, resulting in fewer variables at each step of the process. They conducted experiments on phantoms and a chest CT slice. Further work would be needed to assess the coronary details, cardiac motion, and realistic image size in adaptation of this method for cardiac CT, and published results haven't proven its performance in CCTA.

Possible applications of CMR in this context include myocardial tissue characterization/classification with features derived from the cine images or derived from tissue-characterization sequences. Felefly et al. presented a methodological example of an MRI radiomics workflow that used quantum annealing for feature selection coupled with a variational QNN [23]. But that research was on brain tumors. In myocardial disease, such a procedure would involve cardiac feature selection, appropriate reference myocardial diagnoses, and comparison with known classical myocardial models.

For PET and SPECT, candidate applications include reconstruction and the analysis of features describing myocardial perfusion or tracer distribution. Moradi et al. [46] evaluated QML on PET radiomics datasets using simulators and a gate-based quantum processor with error mitigation. Their study involved cancer cohorts, so its relevance to cardiac nuclear imaging is methodological. Whether such approaches can support the assessment of myocardial ischemia or viability remains a question for future research, particularly for SPECT, which was not evaluated in that study.

X-ray coronary angiography is the modality with the most direct experimental evidence. Ovalle-Magallanes et al. [45] developed a hybrid classical-quantum convolutional neural

network for stenosis detection in which a pretrained classical network was combined with a distributed variational quantum circuit, and a hyperbolic tangent layer bounded the features passed to the quantum stage. On a small dataset of 250 angiographic image patches, the hybrid model reached an accuracy of 91.8%, a recall of 94.9%, and an F1-score of 91.8%, which the authors reported as improvements of 9%, 20%, and 11% over classical transfer learning [45]. A more recent preprint by Xia [47] added a four-qubit parameterized circuit to a ResNet-18 backbone and reported an accuracy of 0.950 and a ROC-AUC of 0.987 on public angiography datasets, compared with 0.910 and 0.920 for ResNet-18 alone. That work has not been peer-reviewed and reports single-run results without confidence intervals. For both studies, the quantum part was embedded in an already existing image-classification pipeline and simulated. However, further studies should be performed to determine the validity of those methods in other acquisition systems, at different image qualities and in different patient cohorts for routine assessment of the coronary arteries.

VII. COMPARISON OF CLASSICAL AI AND QUANTUM APPROACHES

The primary benchmarks for quantum approaches are those of classical machine learning and classical deep learning. Conventional classifiers can be trained based on the selected radiomic features, while the deep networks can be trained based on the image itself. Most existing hybrid QML implementations retain a classical feature extractor and replace only the final classification step with a quantum circuit. A small quantum component therefore does not imply a smaller or less computationally demanding model overall. When comparing, all of the steps involved in the pipeline- classical preprocessing, feature extraction, quantum encoding of information, circuit operations, and measurements should be taken into account [6][18].

This is also a consideration for the cost of computing, which depends on how the imaging data is input into the quantum model. While it is a compact way of describing the high-dimensional information, the preparation of that state and extraction of an output may incur a significant amount of overhead, as quantified in Table I. Overall training or inference speed is thus not necessarily faster than the one algorithmic step with a theoretical speed-up. While classical models can be run on existing CPU and GPU platforms, quantum implementations of the models need special processors or classical simulators. In simulated imaging studies, an extra few tens of qubits causes a 30-qubit state to take nearly 17 GB of double-precision memory, and increases by a factor of two with each additional qubit. Although simulator results may be helpful for evaluation of algorithms, the simulator runtimes do not show quantum advantage in the form of experimentation in hardware. There are additional resource considerations on physical devices such as the number of layers (circuit depth), noise in the system, repeated measurements, and error mitigation. Of the cardiovascular studies in Table II, few report both the time taken to train the whole network as well as the time taken for inference,

both relative to a classical baseline, for purposes of concluding computational advantage.

The prerequisites and the training are interpretive aspects as well. The amount of training data with labels required is great in deep networks trained from scratch, although it can be reduced using transfer learning. For smaller datasets, classical feature-based methods can also work well: This should not be construed as quantum models necessarily requiring fewer patients in small cohorts, however. Many imaging data sets are also compressed prior to encoding in the qubits, which may cause useful information to be lost and thus impact the comparison to classical methods. Variational models additionally depend on classical optimizers and can encounter vanishing gradients, including barren plateaus [48]. Reporting both trainable parameter counts and the resources required for optimization would make comparisons more informative.

Interpretability is not an automatic property of either approach. Some classical models permit direct inspection of feature contributions, while deep and quantum models often require additional explanation methods. Felefly et al. [23] used Shapley values to interpret an MRI radiomics QNN. Their results also illustrate why performance should be examined across several metrics. The QNN achieved a slightly higher test balanced accuracy than the classical comparators (0.74 against 0.73 and 0.72), whereas XGBoost achieved a higher test ROC-AUC (0.79 against 0.76). In an adjacent cardiac application on chest radiographs, Decoodt et al. [40] reported hybrid cardiomegaly classifiers with ROC-AUC values of up to 0.93, comparable to a classical DenseNet-121 reference, and found that Grad-CAM++ heatmaps focused on the heart more often for the hybrid models. In ten-fold cross-validation, however, three hybrid configurations had a significantly lower ROC-AUC than the classical reference. These findings support further investigation but do not establish general quantum superiority. Table II summarizes the cardiovascular imaging studies identified in this review, including the adjacent chest radiography study, and Table III summarizes transferable evidence from non-cardiac imaging. Both tables report qubit count, encoding, execution platform, and validation design, so that each comparison can be judged against the definitions given in Section IV-E.

Taken together, the extracted data show a consistent pattern. Where qubit counts were reported, the gate-based cardiovascular studies used between 4 and 10 qubits operating on features produced by a classical network. None reported execution of the quantum layer on physical hardware, and none reported validation on an external cohort. Classical baselines were usually the same backbone without the quantum layer, which is a reasonable ablation, although the tuning of these baselines was rarely described in detail. Differences between hybrid and classical models were generally within a few percentage points and depended on the metric reported. Among the classification studies in Table III, only Moradi et al. [46] ran classifiers on gate-based hardware, and error mitigation was needed to improve the hardware results.

TABLE II. CARDIOVASCULAR IMAGING STUDIES OF QUANTUM OR HYBRID MODELS COMPARED WITH CLASSICAL AI, INCLUDING ONE ADJACENT CHEST RADIOGRAPHY STUDY

Study	Modality and task	Quantum paradigm and method	Qubits and encoding	Execution	Dataset	Classical comparator	Validation design	Main findings and limitations
Ovalle-Magallanes et al. [45]	X-ray coronary angiography; stenosis detection (direct)	Gate-based hybrid; pretrained CNN with a distributed variational quantum circuit	NS; tanh-bounded CNN features used as circuit inputs	Simulation (PennyLane)	250 image patches, balanced between stenosis and non-stenosis	Classical transfer-learning CNN	Single small dataset; no external validation reported	Accuracy 91.8%, recall 94.9%, F1-score 91.8%; reported gains of 9%, 20%, and 11% over the classical model. Very small patch-level dataset; no hardware execution.
Xia [47] (preprint)	X-ray coronary angiography; stenosis classification (direct)	Gate-based hybrid; ResNet-18 features fused with a PQC of depth 2 with data re-uploading	4; angle encoding	Simulation (PennyLane, CPU)	Public DSSS, ADSD, and P-ADSD datasets; sample counts: NS	ResNet-18; classical CNN; pure quantum CNN	Patient-independent 80:20 split; single run; no external validation	Accuracy 0.950 and ROC-AUC 0.987 versus 0.910 and 0.920 for ResNet-18. Not peer-reviewed; no confidence intervals.
Decoodt et al. [39]	Echocardiography video; LVEF category (reduced, mid-range, preserved) (direct)	Gate-based hybrid; MoViNet video network with PennyLane quantum layers; soft-voting ensemble	NS	Simulation (PennyLane); no hardware reported	EchoNet-Dynamic [31]	Classical MoViNet models	Original EchoNet training, validation, and test split; no external validation	Ensemble micro-averaged ROC-AUC 0.96; reduced EF versus rest ROC-AUC 0.96 and balanced accuracy 0.89. Ensemble mixes classifiers, so the quantum contribution is not isolated.
Decoodt et al. [40]	Chest radiography; cardiomegaly detection (adjacent, outside the five core modalities)	Gate-based hybrid transfer learning; DenseNet-121 with a PQC	4 (Qiskit) and 4 to 10 (PennyLane); Hadamard layer followed by R_y angle encoding	Simulation (Qiskit Aer state vector; PennyLane)	2,436 balanced frontal radiographs from CheXpert	DenseNet-121 transfer learning (ROC-AUC 0.931, accuracy 0.863 in 10-fold CV)	70/30 split and 10-fold CV; single source; no external validation	ROC-AUC up to 0.93 and accuracy up to 0.87, comparable to the classical model; three hybrid configurations had significantly lower ROC-AUC in 10-fold CV. Heatmap focus does not establish clinical reliability.

^b. NS, not specified in the source. CV, cross-validation. EF, ejection fraction. LVEF, left ventricular ejection fraction. PQC, parameterized quantum circuit. Direct indicates cardiovascular image data within the five modalities covered by this review, and adjacent indicates a cardiac task on another modality.

TABLE III. TRANSFERABLE EVIDENCE FROM NON-CARDIAC IMAGING STUDIES WITH POTENTIAL METHODOLOGICAL RELEVANCE TO CARDIOVASCULAR IMAGING

Study	Modality and task	Quantum paradigm and method	Qubits and encoding	Execution	Dataset	Classical comparator	Validation design	Main findings and limitations
Lee and Jun [24]	CT reconstruction; possible relevance to cardiac CT	Quantum annealing; region-wise QUBO refinement	2,500 to 7,500 binary variables per 50×50 region; binary pixel encoding	D-Wave hybrid quantum-classical solver	100×100 Shepp-Logan phantoms; one chest CT slice	No classical reconstruction baseline reported	Dense-view (100 angles) and sparse-view (50 angles) settings	QUBO energy gaps of about 10^{-7} and visually accurate reconstructions. Small images; no standard image-quality metrics; annealer contribution within the hybrid solver not separated.
Felefly et al. [23]	Contrast-enhanced brain MRI radiomics; metastasis versus glioma; possible relevance to	Quantum annealing feature selection followed by a gate-based variational QNN	2 qubits; 10 selected features	D-Wave annealer for selection; QNN in simulation	201 patients; 1,813 features reduced to 10	DNN and XGBoost on the same 10 features	Held-out internal test set; no external cohort	Test ROC-AUC 0.76 (QNN), 0.75 (DNN), and 0.79 (XGBoost); balanced accuracy 0.74, 0.73, and 0.72. Shared features do not isolate the benefit of quantum selection.

	cardiac radiomics							
Moradi et al. [46]	PET radiomics; glioma, prostate, and lung cancer; possible relevance to cardiac nuclear imaging	Gate-based quantum kernel classifiers, QNN, and quantum distance classifier	Scaled with 8 or 16 selected features	Simulation and selected IonQ hardware runs with error mitigation	Three cancer cohorts; 18 dataset variants	SVM, Gaussian process, neural network, and k-NN	Cross-validation; hardware runs on first-fold experiments only	With 16 features, mean simulated balanced accuracy 70% (QML) versus 69% (classical); with 8 features, classical ML about one point better. Results depend on feature count and dataset.
Glenn et al. [35]	Abdominal MRI; liver contouring; possible relevance to cardiac segmentation	Gate-based Grover search after U-Net; quantum-inspired comparators (QIS-Net, QCuts)	At least 12 qubits estimated for a 64×64 image; NAQSS image representation	Classical simulator (MATLAB); no noise model	34 patients, 102 scans; single institution	PocketNet U-Net alone	Internal single-institution evaluation	Median Dice 0.9309 versus 0.9307 for U-Net alone, not significant; QIS-Net 0.314 and QCuts 0.253. No hardware execution; no measurable gain from the quantum step.

^c. DNN, dense neural network. k-NN, k-nearest neighbors. NAQSS, normal arbitrary quantum superposition state. QUBO, quadratic unconstrained binary optimization. Quantum-inspired comparators run entirely on classical hardware.

VIII. CURRENT CHALLENGES AND LIMITATIONS

The scope of evidence of quantum computing in cardiovascular imaging is not very large. A few papers have studied tasks on cardiac images; the majority of the literature is on non-cardiac images or structured clinical data. Without further testing, these findings cannot directly be translated to echocardiography, coronary CT, or CMR [4]. Reported improvements are also somewhat hard to interpret with small data sets and limited external data validation, and some differences in preprocessing and classical comparators. Gupta et al. [6] did not find any consistent evidence of an empirical advantage of QML over classical methods in their systematic review of QML for digital health.

The second big difficulty is image encoding. As in Section IV. As seen in D and Table I, a state preparation circuit to load a full cardiac image is either very large or very deep, and this can outweigh any gains in subsequent processing steps. Due to the few available qubits and the small circuit depth, heavy compression or classical feature extraction is thus required in order to use quantum processing. The resulting measurements suffer from hardware noise and decoherence [48], and variational models can also face barren plateaus, where the gradients go too small for training. These remain problems for the manner in which an architecture is designed, in particular the way that encoding is performed; more qubits by themselves are no help [18].

The results of the simulations must also be carefully interpreted. There are no guarantees that the performance of a simulator corresponds to that of a real quantum processor. There are increased costs due to repeated measurements, error mitigation, data preparation, and classical optimization. Difficulties arise in the field of reproducibility when studies lack information regarding data partitions, parameter tuning, circuit construction, or hardware conditions. There are therefore a series of standards for cardiovascular measurements and reporting, which is desirable in order to ascertain that improvements observed could be replicated and could be due to the quantum part.

Additional requirements are added with the clinical adoption. Most quantum processors are accessed via cloud services [20], and thus proper consent, secure data handling, access control, and monitoring of external computing services remain relevant considerations in quantum processing. Predictions should also be interpretable to facilitate clinical review and error analysis. A system under consideration for deployment would need to demonstrate evidence to support its use, such as external validation, patient safety evaluations, and relevant regulatory reviews. While specific to quantum computing, the FUTURE-AI guideline can be used as a reference for these all-encompassing necessities of healthcare AI [49].

IX. FUTURE DIRECTIONS AND CLINICAL TRANSLATION

Future research should begin with a clear definition of the cardiovascular imaging problems in which a quantum component can be tested against a robust classical alternative. Candidate tasks include radiomic feature selection, classification with compact image features, and selected reconstruction problems that can be written as discrete optimization tasks. Hybrid models provide a convenient means of exploring these applications without abandoning established deep-learning methods for image processing. More robust and reliable hardware, along with efficient encoding, will be important, but research should also determine whether the compression needed for encoding preserves clinically relevant information.

Shared cardiovascular datasets with agreed tasks, patient-level data partitions, and independent test cohorts would also be valuable. Reports of quantum and hybrid models should state, at a minimum, the quantum paradigm, qubit count, encoding, circuit depth, number of shots, execution platform and noise model, the classical baseline and how it was tuned, the result of an ablation in which the quantum layer is replaced by a classical layer, and confidence intervals for all metrics. Reports should also include training time, inference time, and the resources needed by the entire pipeline. Multimodal studies might test the hypothesis that quantum models add value when combining compact features from echocardiography, CT, CMR, or nuclear imaging. Such studies should explicitly test the contribution of

the quantum component rather than attributing the performance of a whole hybrid model to quantum processing.

Clinical translation will require evidence to be built in stages, as for any imaging AI system. The first stage is technical validation on public and institutional datasets, reported with the items listed above. The second is retrospective evaluation on external, multicenter cohorts that include different vendors, acquisition protocols, and patient populations, reported according to TRIPOD+AI [50] and the CLAIM checklist for artificial intelligence in medical imaging [51]. The third is early clinical evaluation, in which clinicians use the system under realistic conditions and workflow, human factors, and safety are examined, as described in the DECIDE-AI guideline [52]. Only after these steps could prospective comparative studies, and randomized trials where appropriate, show whether a quantum-enabled system improves diagnostic accuracy, clinical decision-making, or patient outcomes compared with the best classical alternative. At each stage, the key question is whether the quantum component provides a benefit that justifies its additional cost and complexity, which is a stricter test than whether the hybrid system as a whole performs well.

Federated quantum-classical learning might also be considered as a means for institutions to collaborate while keeping images on site. This should be treated as a research direction, because keeping data at the originating center does not by itself guarantee privacy. Collaboration among cardiologists, imaging scientists, AI researchers, quantum specialists, and data-governance teams will be necessary throughout development and evaluation. These priorities are consistent with the lifecycle approach proposed by FUTURE-AI [49].

X. CONCLUSION

An investigation of quantum computing can help explore approaches for image processing in the cardiovascular domain for reconstruction, segmentation, feature selection, and classification. The current evidence, however, is exploratory, based on a limited number of direct cardiovascular studies mostly evaluated in simulation, and is not conclusive as to any computational advantage or any consistent predictive advantage over classical approaches. The main technical challenge is image encoding, which would not be cost-effective in quantum states at present on NISQ devices to load real cardiac images. However, if we want to pursue this in real devices, we can consider hybrid quantum-classical ones, but it is important to also consider what the contribution of the quantum component is, and how much computation it costs. The path towards clinical use will require reproducible cardiovascular benchmarks, realistic hardware evaluation, and successive clinical validation with eventual prospective evidence of clinical benefit.

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