IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 25 January 2026, accepted 6 February 2026, date of publication 10 February 2026, date of current version 23 February 2026.

Digital Object Identifier 10.1109/ACCESS.2026.3663498

SURVEY

Quantum Machine Learning in Medical Image Analysis: From Diagnostics to Surgery Planning

AYAN SAR[1], (Student Member, IEEE), ANKIT KUMAR[2], SAMPURNA ROY[1], (Student Member, IEEE), ANURAG KAUSHISH[1], TANUPRIYA CHOUDHURY[1], (Senior Member, IEEE), MINAKSHI[3], (Senior Member, IEEE), SAAD SAEED ALQAHTANI[4], (Member, IEEE), AND AJITH ABRAHAM[5,6]

[1]School of Computer Science, University of Petroleum and Energy Studies (UPES), Dehradun, Uttarakhand 248007, India
[2]School of Computing Science and Engineering, Galgotias University, Greater Noida, Uttar Pradesh 203201, India
[3]College of Computer Science, King Khalid University, Abha 62521, Saudi Arabia
[4]Department of Clinical Pharmacy, College of Pharmacy, King Khalid University (KKU), Abha 62521, Saudi Arabia
[5]School of Artificial Intelligence, Sai University, Chennai, Tamil Nadu 603104, India
[6]Center for Artificial Intelligence, Innopolis University, 420500 Innopolis, Russia

Corresponding authors: Ajith Abraham (abraham.ajith@gmail.com) and Tanupriya Choudhury (tanupriya@ddn.upes.ac.in)

The study was supported by the Ministry of Economic Development of the Russian Federation (agreement No. 139-10-2025-034 dd. 19.06.2025, IGK 000000C313925P4D0002).

ABSTRACT Quantum Machine Learning (QML) is an emerging, powerful paradigm at the intersection of quantum computing and artificial intelligence, with the potential to enhance medical image analysis. We compared their performance with classical counterparts, while critically examining the gap between theoretical quantum advantages and the practical constraints of current Noisy Intermediate-Scale Quantum (NISQ) implementations. This review explored the current landscape of QML-based methodologies applied to key medical imaging modalities - Magnetic Resonance Imaging (MRI), Computed Tomography (CT), X-rays, and histopathology. We systematically analyzed how quantum-enhanced models were employed for critical tasks such as image classification, segmentation, and reconstruction, and we compared their performance with that of classical counterparts. The review delved into the architectural innovations that enabled these quantum approaches, including hybrid quantum-classical frameworks, variational quantum circuits, and quantum convolutional neural networks. Particular emphasis was given to the clinical relevance of QML applications, from early diagnostics to real-time surgery planning, and how quantum advantage might influence data efficiency, interpretability, along computational scalability. Finally, we highlighted current challenges in data encoding, noise resilience, and hardware limitations, and discussed promising future directions that could enable the practical deployment of QML in healthcare settings. This comprehensive review aimed to serve as a foundational reference for researchers and practitioners looking to harness quantum computing in medical imaging and precision medicine.

INDEX TERMS Hybrid quantum-classical models, medical image reconstruction, quantum convolutional neural networks, quantum image segmentation, quantum machine learning (QML), variational quantum circuits.

I. INTRODUCTION

A. MOTIVATION AND SCOPE

Medical imaging has always been a cornerstone of modern healthcare, playing a vital role in disease diagnosis [1], treatment planning [2], [3], and surgical navigation [4]. The explosion of imaging data from modalities such as Magnetic Resonance Imaging (MRI) [5], Computed Tomography (CT) [6], X-Rays, and Histopathology [7] has necessitated the development of advanced computational techniques for automated image analysis. Classical machine learning and deep learning approaches [8], [9] have significantly

The associate editor coordinating the review of this manuscript and approving it for publication was Kumaradevan Punithakumar.

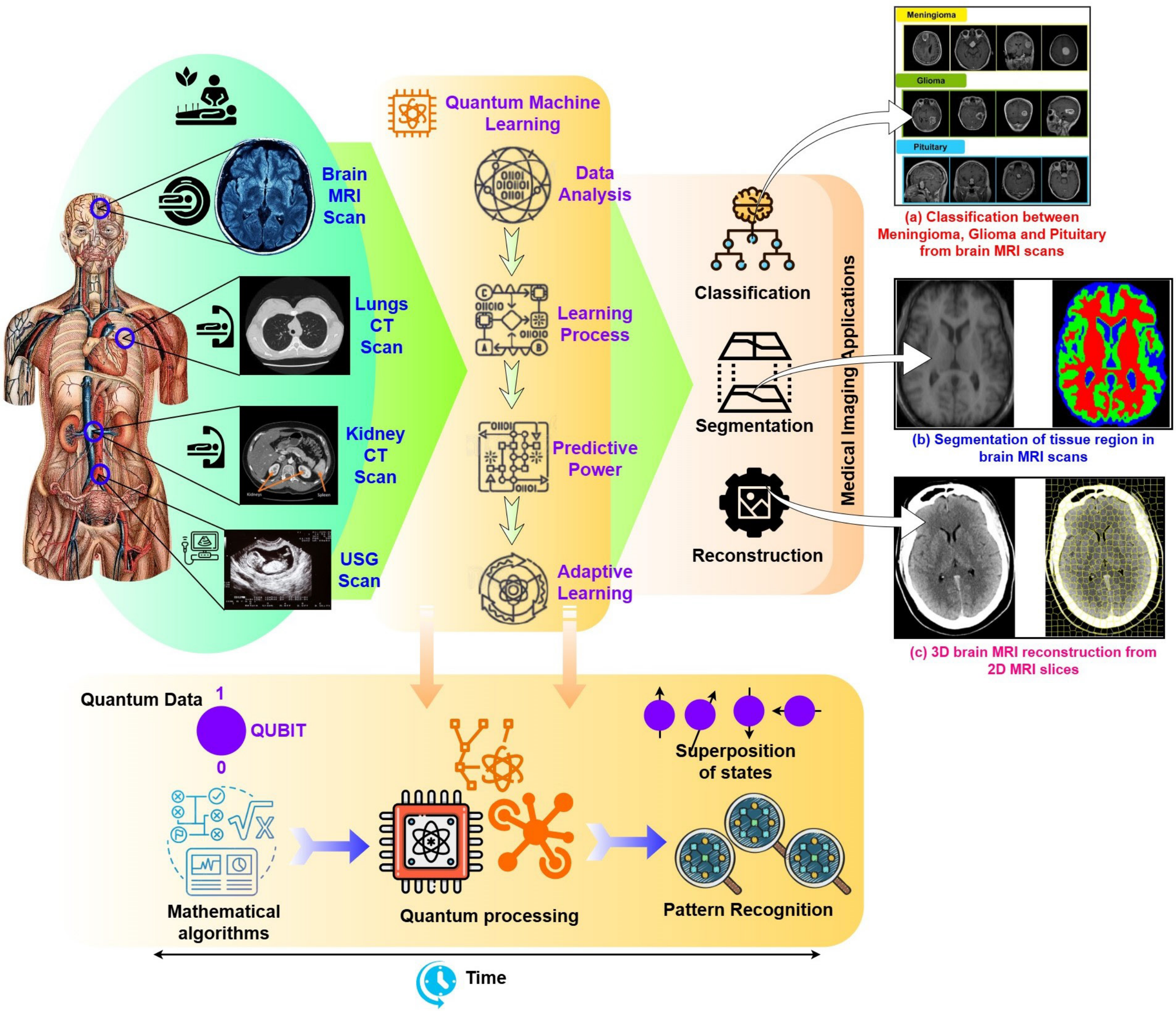


FIGURE 1. The potential integration of quantum machine learning (QML) with medical imaging for enhanced diagnostic and analytical capabilities. From the left, various medical imaging modalities generate complex medical data, including Brain MRI Scan, Lungs CT Scan, Kidney CT Scan, and USG Scan. This data serves as input for quantum machine learning algorithms. The QML process, depicted in the central section, leverages quantum data represented by qubits and undergoes mathematical algorithms within a quantum processing unit. The inherent properties of quantum mechanics, such as superposition of states, enable sophisticated pattern recognition. This advanced analysis leads to improved data analysis, a more efficient learning process, enhanced predictive power, and adaptive learning capabilities. On the right side, the medical imaging applications of this integrated approach are highlighted. These applications include (a) improved classification between different types of brain tumors (Meningioma, Glioma, and Pituitary) from brain MRI scans, (b) precise segmentation of tissue regions within brain MRI scans, and (c) high-quality 3D brain MRI reconstruction from 2D MRI slices. The overall diagram emphasizes the temporal progression from data acquisition through quantum processing to advanced medical image analysis, suggesting a future where QML significantly enhances the accuracy, efficiency, and detail achievable in medical imaging. In the figure, blue-colored labels denote medical data acquisition and classical preprocessing stages (e.g., imaging modalities and input data representations), whereas red-colored labels highlight quantum-enhanced learning components and clinical output tasks (e.g., classification, segmentation, and reconstruction). The color coding is used solely for conceptual differentiation and does not imply performance hierarchy.

advanced the field; however, they are increasingly limited by computational complexity, data dimensionality, and energy efficiency.

Over the past two decades, the integration of artificial intelligence (AI), especially deep learning (DL), has revolutionized medical image analysis. These AI models have achieved impressive accuracy in image classification, lesion segmentation, anomaly detection, and image reconstruction [10], [11]. However, these classical models often require massive datasets [12], [13], substantial computational resources, and long training times [14], [15]. Moreover, challenges such as model interpretability, susceptibility to overfitting in low-data regimes, and scalability constraint persists, particularly in real-time or resource-constrained clinical settings [16], [17].

Quantum Machine Learning (QML), a hybrid paradigm that synergistically integrates quantum computing with classical artificial intelligence models, has emerged as a promising extension of AI-driven medical image analysis. QML leveraged quantum mechanical principles - such as superposition, entanglement, and parallelism - for potential acceleration of training, enhancement of pattern recognition, and improvement in generalization in complex image analysis tasks [18], [19] [20], [21]. This made QML particularly appealing for medical imaging applications where precision, speed, and scalability are critical factors [22]. The convergence of three critical trends drives the motivation behind this review:

- Explosive growth of medical imaging data, with increasing resolution, frequency, and variety.
- Emergence of scalable and programmable quantum hardware and quantum simulators.
- The rising interest in the application of quantum-enhanced models to real-world problems in life sciences, where classical approaches are reaching their computational limits.

Current Maturity and Limitations: While the theoretical advantages of QML—such as exponential state space capacity—are compelling, it is critical to acknowledge that the field is currently in an experimental ''proof-of-concept'' phase. As this review will highlight, clinically validated systems operating at a real-world scale are extremely rare. The majority of ''success stories'' in the current literature rely on downsampled data or simulations on classical hardware, meaning that claims of superior speed or accuracy must be interpreted as projections of future capability rather than descriptions of current clinical utility.

It is important to note that the application of Quantum Machine Learning in medicine and biomedical imaging is not entirely new. Several recent studies have systematically explored hybrid quantum–classical learning paradigms, feasibility on NISQ devices, and the practical limitations of quantum-enhanced medical analytics. For instance, recent reviews and experimental studies have analyzed QML-based frameworks for biomedical data processing and medical image analysis, highlighting both their promise and current constraints [23], [24]. These works further motivate the need for a consolidated, modality-aware, and clinically grounded review of QML in medical imaging.

B. MEDICAL IMAGING MEETS QUANTUM COMPUTING

Artificial Intelligence (AI), particularly machine learning and deep learning, has played a transformative role in medical imaging over the past decade. AI-driven models have demonstrated remarkable success in diagnostic tasks such as tumor detection, organ and lesion segmentation, disease classification, and prognostic assessment across modalities, including MRI, CT, X-ray, and histopathological imaging. Beyond diagnosis, AI has contributed significantly to treatment planning and clinical decision-making, enabling image-guided radiotherapy, surgical navigation, therapy response prediction, and personalized treatment optimization. Convolutional Neural Networks (CNNs), transformer-based architectures, and multi-modal learning frameworks have become integral components of modern computer-aided diagnosis (CAD) systems, substantially improving diagnostic accuracy, efficiency, and reproducibility in clinical workflows.

Despite these advances, classical AI models often face challenges related to computational scalability, energy consumption, data efficiency, and optimization complexity when applied to increasingly large and high-dimensional medical imaging datasets. Quantum computing (QC) introduces fundamentally new computational principles—such as superposition, entanglement, and quantum parallelism—that offer the potential to augment and accelerate AI-driven image analysis. Quantum Machine Learning (QML) thus emerges as a natural convergence of QC and AI, where quantum circuits are integrated with classical learning pipelines to enhance feature representation, optimization, and inference in medical imaging tasks.

Medical imaging technologies have evolved remarkably over the past few decades, enabling clinicians to visualize anatomical structures and physiological functions with increasing precision and clarity [25]. Modalities such as MRI, CT, X-Rays, and Histopathology generate high-dimensional, information-rich data critical for diagnosis, treatment planning, and surgical decision-making [26]. However, medical images' sheer volume and complexity have created significant challenges regarding manual interpretation [27], [28] [29], data storage [30], feature extraction [31], and diagnostic accuracy [32]. This led to the adoption of machine learning (ML) and deep learning (DL) techniques for automating and enhancing image analysis. Despite their success, classical DL/ML models faced inherent limitations, which included

1) High training times and large resource requirements create computational complexity, especially with 3D imaging data [33], [34].
2) There is difficulty scaling models for large datasets and multi-modal imaging fusion [35], [36].
3) Overfitting in low-data regimes is common in rare diseases or specialized clinical cases [37], [38].
4) Closed-box models hinder clinical trust and regulatory acceptance and create interpretability issues [39], [40].
5) Deep learning models are power-hungry, which poses challenges for sustainable deployment.

These limitations sparked interest in quantum computing as a transformative enabler in computational medicine. Quantum computing operates on the principle of quantum mechanics, which offers new computational paradigms:

1) Unlike classical bits, qubits could exist in superpositions of 0 and 1, which enabled massive parallelism.
2) Correlation between qubits allowed simultaneous processing of interdependent data.
3) Analogous to logic gates in classical computing, quantum gates and circuits operate under unitary transformations.

4) Information retrieval involved collapsing qubits to classical states, which impacted model design and interpretability.

These principles provided the theoretical foundation for quantum algorithms that could exponentially accelerate certain machine learning tasks.

1) RISE OF QUANTUM MACHINE LEARNING (QML)

Quantum machine learning merges quantum computing with classical machine learning to enhance model performance and learning efficiency. There are two primary categories:

1) **Pure-quantum models**: Fully quantum implementations of ML algorithms (e.g., quantum support vector machines, quantum k-means).
2) **Hybrid Quantum-Classical models**: Combine quantum subroutines (e.g., variational quantum circuits) with classical neural networks for optimizing performance while remaining compatible with current hardware (NISQ devices).

In recent years, frameworks such as Qiskit (IBM), PennyLane (Xanadu), Tensorflow Quantum (Google), and Cirq have democratized access to QML development, even allowing simulations on classical hardware. The convergence of QML and medical imaging is a natural progression that offers quantum-enhanced solutions to long-standing challenges in the field [41]. Some specific use cases included

1) Quantum image classification, where tumors, fractures, or anomalies are detected with enhanced accuracy and robustness [42].
2) Quantum segmentation models do the localization of regions of interest, such as cancerous tissues or internal bleeding [43].
3) Quantum reconstruction improves the image quality in low-dose CT scans or fast-scan MRI by reducing artifacts and preserving detail [44].

Moreover, quantum feature encoding allowed for a more compact and efficient representation of high-dimensional image data, which makes it suitable for models with fewer trainable parameters.

2) BRIDGING THE GAP: FROM THEORY TO CLINICAL PRACTICE

Initial research has demonstrated that quantum-enhanced neural networks could match or surpass classical models in small, noise-prone, or feature-sparse datasets - a common scenario in medical diagnostics. The key studies have applied QML for the classification of lung and breast cancer from CT/MRI scans [45], as well as the segmentation of brain tumors [46], [47] using hybrid quantum architectures and the reconstruction of histopathological images for faster cancer screening [48]. While these models are still largely in the experimental phase, they provided strong proof-of-concept for the future of this field. Despite promising results, several barriers must be overcome to bring QML into routine clinical use:

1) Hardware readiness should be done where decoherence, gate errors, and qubit count limit current quantum computers.
2) Data encoding should be done as translating classical image data into quantum states is computationally intensive.
3) It should be ensured that QML models are aligned with medical standards, explainability requirements, and regulatory frameworks.

Nonetheless, with continuous improvements in quantum processors, error correction, and hybrid model design, QML is gradually transitioning from academic curiosity to clinical feasibility.

C. OBJECTIVE AND CONTRIBUTIONS

The primary objective of this review is to investigate and synthesize the current advancements in Quantum Machine Learning (QML) as applied to medical image analysis. We aim to evaluate how QML methods perform across various imaging tasks and modalities, assess their potential for clinical translation, and identify the remaining technological gaps. We aimed to provide a clear roadmap for researchers and practitioners looking to integrate QML into healthcare workflows. In this review, we present the following novel contributions:

1) We systematically examined the role of QML across four major medical imaging modalities - MRI, CT, X-Rays, and Histopathology, and highlighted specific use cases, challenges, and opportunities unique to each modality.
2) We analyzed how QML techniques have been applied to core image processing tasks, including image classification, segmentation, and reconstruction. Each task is examined in the context of quantum model performance versus classical baselines.
3) We explored cutting-edge architectural innovations in QML such as variational quantum circuits (VQCs), quantum convolutional neural networks (QCNNs), and hybrid quantum-classical models. We compared these with classical deep learning architectures regarding computational complexity, data efficiency, and performance.
4) We assessed the practical implications of QML in healthcare, particularly for early diagnostics and real-time surgery planning, and evaluated the readiness of these technologies for clinical deployment.
5) We identified and discussed pressing challenges in the field, such as quantum data encoding, hardware noise, scalability, and interpretability, which currently hinder widespread adoption.
6) We proposed future directions, including integration with fault-tolerant quantum hardware, multi-modal

quantum learning, and privacy-preserving quantum federated learning, to accelerate QML's adoption in medical imaging and precision medicine.

This review consolidates current research in QML-based medical image analysis and offers a strategic outlook on how the field could evolve towards practical and scalable quantum healthcare solutions.

D. ORGANIZATION OF THE MANUSCRIPT

This manuscript is organized as follows: Section II introduces Quantum Machine Learning (QML): the basics of quantum computing, the outlined QML concepts, and the specific QML advantages and limitations compared to conventional machine learning understanding in imaging tasks. In Section III, primary medical imaging modalities are discussed, i.e., MRI, CT, X-ray, and histopathology: their clinical relevance and challenges in medical image analysis. Section IV applies QML techniques to critical imaging tasks such as imaging of image classification, segmentation, and reconstruction, with comparative insights to classical methods. Section V discusses architectural innovations in QML, including quantum feature encoding techniques, quantum neural networks (QNNs), hybrid quantum-classical models, and benchmarking strategies. Finally, Section VI lists the limitations and challenges of QML in healthcare, including quantum data encoding, hardware noise, and model interpretability. Section VII proposes future research directions and current opportunities to improve QML's use in clinical practice further. Finally, in the conclusion, Section VIII summarizes the discussion concerning key findings and identifies the potential of QML to revolutionise precision medical image analysis.

II. FUNDAMENTALS OF QUANTUM MACHINE LEARNING

Quantum machine learning is a novel computational paradigm that integrates principles of quantum mechanics with machine learning techniques for solving problems that are classically intractable or computationally expensive. We covered the core theoretical and practical foundations of QML here in a structured way.

A. QUANTUM COMPUTING

In classical computing, information is encoded using bits, which can take 0 or 1. The computation proceeded through logic gates (AND, OR, NOT, XOR), and the performance is bound by Moore's law, which is slowing down due to physical limitations [49]. Here, quantum computing comes into the picture where information is encoded using qubits (quantum bits), which can exist in superpositions of states. The computation utilizes quantum gates operating on qubits, which form quantum circuits [50]. This also offers exponential speedup in solving specific class problems (e.g., factorization, linear algebra, optimization) [51]. A qubit is the fundamental unit of quantum information, where it is represented as a vector in a two-dimensional complex

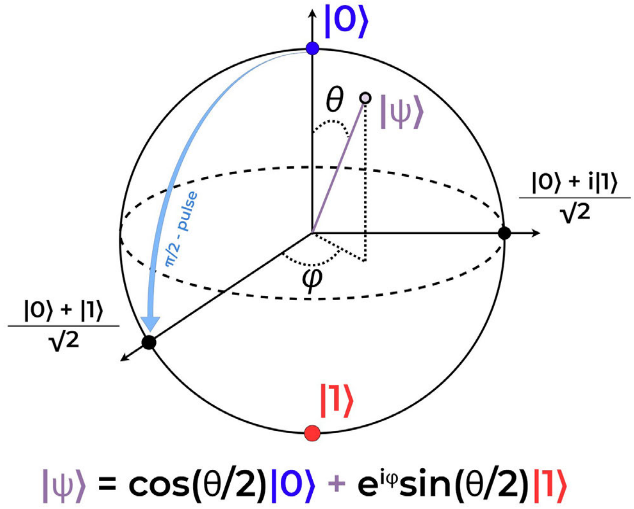


FIGURE 2. **Bloch sphere, a geometric representation of a qubit's pure states in quantum computing. The north pole represents the basis state $|0\rangle$, and the south pole represents $|1\rangle$. Any pure qubit state $|\psi\rangle$ can be visualized as a point on the surface of this sphere, defined by the polar angle θ and the azimuthal angle ϕ. The image also illustrates the effect of a $\pi/2$-pulse, which rotates the qubit state from $|0\rangle$ to the superposition state $(|0\rangle + |1\rangle)/\sqrt{2}$ along the equator of the Bloch sphere. The general form of a qubit state is given by $|\psi\rangle = \cos(\theta/2)|0\rangle + e^{i\phi}\sin(\theta/2)|1\rangle$.**

TABLE 1. **Quantum gates along with matrix representation and function.**

Gate	Symbol	Matrix	Function
Hadamard	H	$\frac{1}{\sqrt{2}}\begin{bmatrix}1 & 1\\ 1 & -1\end{bmatrix}$	Creates superposition of states
Pauli-X	X	$\begin{bmatrix}0 & 1\\ 1 & 0\end{bmatrix}$	Bit-flip gate (quantum NOT)
Pauli-Y	Y	$\begin{bmatrix}0 & -i\\ i & 0\end{bmatrix}$	Bit and phase-flip
Pauli-Z	Z	$\begin{bmatrix}1 & 0\\ 0 & -1\end{bmatrix}$	Phase-flip gate
CNOT	$\oplus$	*Two-qubit gate*	Controlled-NOT gate; creates entanglement between qubits

Hilbert space [52]. This is mathematically represented below by Eq. 1.

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle \quad \textit{where} \quad \alpha, \beta \in \mathbb{C}, \quad |\alpha|^2 + |\beta|^2 = 1 \tag{1}$$

Here, $|0\rangle$ and $|1\rangle$ are basis states, α and β are probability amplitudes. Upon measurement, the qubit collapses to $|0\rangle$ with probability $|\alpha|^2$ or to $|1\rangle$ with probability $|\beta|^2$. A qubit's state can be visualized on the Bloch sphere (see Figure 2), a 3D unit sphere where any point corresponds to a valid qubit state [53]. The superposition feature allows quantum systems to explore multiple computational paths in parallel.

Entanglement is a non-classical correlation between two or more qubits such that the state of one qubit depends on the state of another, regardless of the distance between them [54]. It is important to note that many of the fundamental principles cited in this section (e.g., quantum state preparation, interference, and general circuit design) originate from core quantum physics and general computer

TABLE 2. Quantum speedup comparison between classical time and quantum time. Here, $O(\cdot)$ denotes Big-O notation representing upper-bound time complexity, and n refers to the input size of the problem (e.g., matrix dimension in linear systems, number of elements in a search space, or problem scale).

Task	Classical Time	Quantum Time
Matrix inversion (HHL)	$O(n^3)$	$O(\log n)$
Search (Grover)	$O(n)$	$O(\sqrt{n})$
Factorization (Shor)	Exponential	Polynomial

science literature [49], [50], [51], [52], [53], [54], [55]. While these studies do not address medical imaging directly, they establish the necessary mathematical and algorithmic ground truths (such as unitarity and entanglement entropy) that are subsequently applied to the medical domain in Section IV. Readers should view these as the theoretical "building blocks" rather than clinical applications. One such example is Bell State shown in Eq. 2.

$$|\Phi^+\rangle = \frac{1}{\sqrt{2}}(|00\rangle + |11\rangle) \tag{2}$$

This measure of one qubit instantaneously determines the state of the other. It also enables non-local interactions, crucial for quantum communication and quantum-enhanced neural networks [56]. Entangled layers in Quantum convolutional neural networks (QCNNs) improve the feature representation and correlation modelling in medical images (e.g., symmetry in brain MRIs) [57]. Now, talking about quantum gates and circuits, just as classical computing uses logic gates, quantum computing uses quantum gates for manipulating qubit states. These are unitary matrices that preserve the norm of qubit vectors. Table 1 shows the basic quantum gates.

Quantum circuits are mainly sequences of gates applied to qubits. For machine learning, circuits can be parameterised (e.g., rotation gates with trainable angles) and optimised using classical optimisers [58]. In QML, these circuits form the foundation of variational quantum algorithms [59]. A quantum system can process 2^n states simultaneously for n qubits through superposition. For example, a 10-qubit register encodes $2^{10} = 1024$ states simultaneously. Constructive and destructive interference among amplitudes can amplify correct outputs and cancel the incorrect ones [55]. This can be used in QML to optimise cost functions and improve classification performance. Quantum computing also promises exponential improvements over classical counterparts in selected domains [60], as shown in Table 2.

Quantum computational advantage has been rigorously demonstrated for a limited class of problems under well-defined assumptions. For example, Shor's algorithm provides an exponential speedup for integer factorization compared to the best-known classical algorithms, while Grover's search algorithm achieves a quadratic speedup for unstructured search problems. Similarly, the Harrow–Hassidim–Lloyd (HHL) algorithm offers an exponential improvement in solving certain sparse and well-conditioned linear systems, which are foundational to machine learning and image reconstruction pipelines. These examples illustrate that quantum computing can outperform classical computing in specific algorithmic regimes; however, it is important to note that such advantages are often conditional on data structure, error-free execution, and sufficient qubit resources, which remain challenging for current NISQ-era hardware.

In the context of medical imaging, these theoretical advantages motivate the exploration of quantum-enhanced subroutines—such as optimization, kernel evaluation, and dimensionality reduction—within hybrid quantum–classical frameworks, rather than direct replacement of full classical imaging pipelines. Large matrices from MRI/CT scans, high-dimensional segmentation masks, and nonlinear registration tasks are computationally intensive. Quantum algorithms (like Quantum PCA, quantum clustering, and QSVMs) can handle such tasks more efficiently, especially when deployed in hybrid mode. Due to noise and decoherence, quantum devices fall under the NISQ (Noisy Intermediate-Scale Quantum) category [61]. Examples of hardware platforms include IBM Quantum (Superconducting qubits) - Qiskit [62], D-Wave (Quantum annealing) for combinatorial optimization [63], IonQ (Trapped-ion quantum computer) for high fidelity [64], and Rigetti, Xanadu for variational quantum models [65]. Some scalability challenges are shown below.

1) Current devices support 20-100 qubits, but require error correction for reliable QML deployment.
2) Error mitigation and short-depth circuits are key medical image QML pipelines strategies.

Quantum computing introduces new dimensions to computational intelligence. Unique concepts such as superposition, entanglement, and quantum inference hold the potential for redefining the process of analyzing and interpreting medical imaging data.

B. KEY CONCEPTS IN QUANTUM MACHINE LEARNING (QML)

A quantum circuit composed of a series of quantum gates applied to qubits is at the heart of any quantum algorithm [66]. These gates manipulate qubits in a way that alters their probability amplitudes and phase relationships, which is fundamentally different from logical gates in classical computers [67]. The basic quantum gates (see Figure 3) consists of:

- **Pauli Gates**
  - **X (NOT Gate):** Flips the qubit state ($|0\rangle \leftrightarrow |1\rangle$).
  - **Y,Z Gates:**This performs rotations around different Bloch sphere axes.
- **Hadamard Gate (H):** This places a qubit in superposition using $H|0\rangle = \frac{1}{\sqrt{2}}(|0\rangle + |1\rangle)$.
- **CNOT Gate (Controlled-NOT):** A two-qubit gate that flips the second qubit (target) if the first qubit (control) is $|1\rangle$; this creates entanglement.

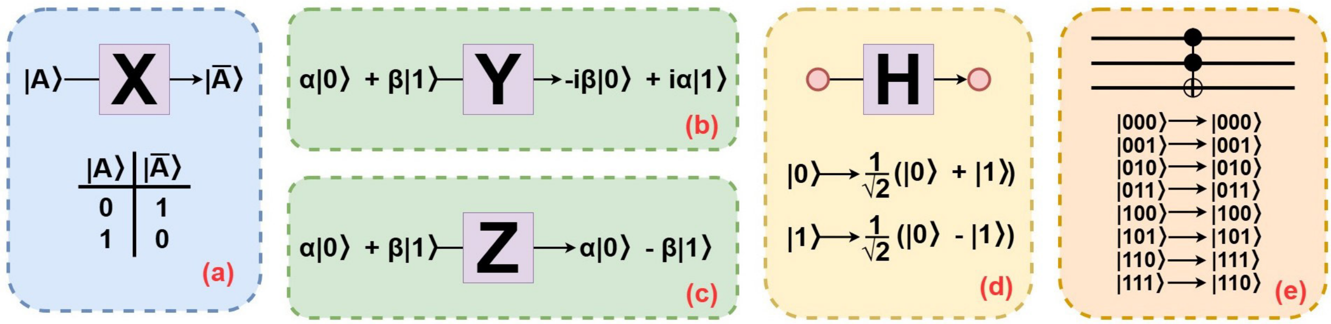


FIGURE 3. This image illustrates fundamental quantum logic gates and their operations on qubits. Section (a) depicts the Pauli-X (NOT) gate, showing its action on basis states and a qubit $|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$. Sections (b) and (c) similarly present the Pauli-Y and Pauli-Z gates and their transformations on a qubit. Section (d) showcases the Hadamard gate and its effect on states $|0\rangle$ and $|1\rangle$. Finally, Section (e) illustrates the controlled-NOT (CNOT) gate acting on three qubits, detailing its truth table-like behavior.

- **Rotation Gates:** Here, $R_x(\theta)$, $R_y(\theta)$, $R_z(\theta)$ rotate a qubit around X, Y, or Z axes by angle θ, used to introduce learnable parameters.

These sequences combine these gates to form quantum circuits, representing learnable QML models.

1) VARIATIONAL QUANTUM CIRCUITS (VQCs)

Variational Quantum Circuits (Parameterized Quantum Circuits or PQCs) are central to the design of trainable QML models [68]. They are used to approximate functions and are particularly well-suited to NISQ (Noisy-Intermediate-Scale Quantum) devices due to their shallow depth [69]. The components of a VQC are:

1) **Data Encoding Layer**: This layer maps classical input (e.g., pixel intensities from medical images) into quantum states via encoding strategies.
2) **Parameterized Quantum layers**: Gates with tunable parameters (e.g., $R_y(\theta)$) that evolve the quantum state.
3) **Entanglement layers**: Here, gates like CNOT are used for entangling qubits and enabling correlation-based learning.
4) **Measurement**: Here, qubits are collapsed to classical bits; measurements are typically made in the computational basis.
5) **Cost function**: The output probabilities from measurements are passed to the cost function for evaluating model performance.
6) **Classical optimizer**: Here, gradient-free (e.g., COBYLA) or gradient-based methods (e.g., parameter-shift rule) minimize the cost function and update parameters.

VQCs have the added advantage of their flexibility in architectural design and natural suitability for hybrid quantum-classical learning [70]. This could be trained for classification, regression, or even reconstruction of medical images.

Variational Quantum Circuits (VQCs) are inherently flexible and can be adapted to a wide range of learning tasks by modifying their measurement strategy, cost function, and classical post-processing pipeline. This adaptability makes VQCs suitable for classification, regression, and image reconstruction tasks in medical imaging. For classification tasks, VQCs are typically designed to output class probabilities by measuring one or more qubits in the computational basis. Expectation values of Pauli operators are mapped to class logits and optimized using classification loss functions such as cross-entropy or hinge loss. In medical imaging, this formulation has been applied to disease detection, tumor classification, and abnormality screening, where compact quantum feature representations can be learned from reduced-dimensional image inputs. In regression tasks, VQCs are adapted by interpreting measurement expectation values as continuous-valued outputs. Instead of discrete class labels, the circuit learns a smooth mapping between quantum-encoded inputs and real-valued targets, optimized using regression losses such as mean squared error. This formulation is particularly relevant for quantitative imaging applications, including tumor size estimation, tissue property prediction, and imaging-derived biomarker regression. For image reconstruction tasks, VQCs are employed as quantum-enhanced function approximators or optimizers within inverse problem formulations. In this setting, the VQC parameters are optimized to minimize a reconstruction loss that measures the discrepancy between observed measurements (e.g., undersampled k-space data in MRI or sparse CT projections) and reconstructed image outputs. Hybrid quantum–classical pipelines are commonly used, where classical components handle data consistency and spatial priors, while VQCs assist in learning compact latent representations or optimizing reconstruction parameters.

Across these tasks, the same underlying VQC architecture can be repurposed by altering the observable measurements and loss functions, highlighting the task-agnostic and modular nature of variational quantum learning.

2) QUANTUM NEURAL NETWORKS (QNNs)

Quantum neural networks aim to mimic classical neural networks using quantum principles. These use quantum gates and circuits for building network-like architectures capable of learning complex, non-linear mappings. The key

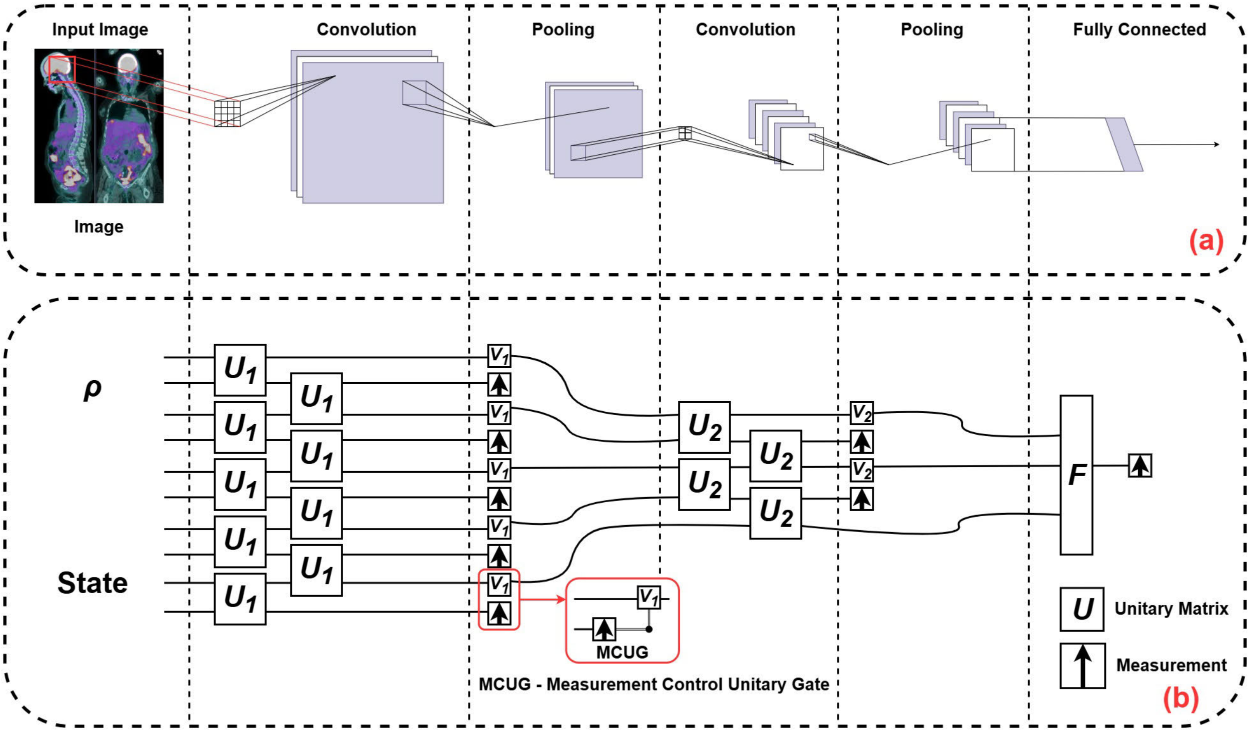


FIGURE 4. **The image illustrates a comparison between a classical Convolutional Neural Network (CNN) architecture (a) and a corresponding Quantum Convolutional Neural Network (QCNN) implementation (b). The CNN processes an input image through sequential layers of convolution, pooling, and fully connected layers to extract features and perform classification. The QCNN attempts to mimic this process using quantum circuits, employing unitary operations (U_1, U_2, F) and measurement-controlled unitary gates (MCUG) acting on a quantum state ρ. The measurements (V_1, V_2, A) in the QCNN influence subsequent quantum operations, aiming to achieve analogous feature extraction and classification capabilities in a quantum computing paradigm.**

characteristics include nodes, which are replaced by qubits, and weights are replaced by rotation angles in gates [71]. The activation functions are realised via interference patterns and measurement statistics [72]. For example, a 3-layer QNN uses a layer for input encoding, a hidden layer with parameterised entangled states, and an output layer measured and classically post-processed [73].

Quantum Convolutional Neural Networks (QCNNs) (see Figure 4) are inspired by classical CNNs but tailored to quantum systems. They are highly relevant for medical image analysis, especially for classification and segmentation. The architecture of QCNN is:

- Input layer where image data is encoded into quantum states using basis or angle encoding.
- Convolutional layer localised entangling operation simulating feature extraction.
- Pooling layer selectively measures or discards qubits, reducing dimensionality (quantum analog of max/average pooling).
- Fully connected layer entangles the remaining qubits and measures to produce the final output.

The advantages of this include efficient representation of hierarchical features, which requires fewer parameters than classical CNNs. This is also compatible with current quantum hardware due to low circuit depth.

TABLE 3. **Desirable properties of an encoding scheme.**

Property	Description
Fidelity Preservation	Retains critical patterns and relationships in data.
Scalability	Efficiently handles high-dimensional medical imaging datasets.
Feasibility	Can be implemented on current quantum hardware with limited qubit counts.
Entanglement-Friendly	Supports entanglement for capturing complex feature relationships.
Reversibility	Allows accurate retrieval or reconstruction, useful in image reconstruction tasks.

3) QUANTUM DATA ENCODING

One of the primary challenges in QML is converting classical data into quantum-readable formats, known as quantum data encoding or quantum feature mapping [74]. Since quantum algorithms operate on qubits in superposed and entangled states, data must be embedded into quantum states in a way that is faithful to the original data and computationally efficient on limited quantum hardware (especially NISQ devices). In medical image analysis, where data is often

TABLE 4. Detailed comparison of quantum data encoding strategies.

Criteria	Basic Encoding	Amplitude Encoding	Angle Encoding	QSample Encoding	Hamiltonian Encoding
Definition	Maps binary data to basis states	Encodes normalized classical data as amplitudes	Uses rotation gates to encode data	Encodes probability distributions	Encodes into Hamiltonian parameters
Mathematical Form	$x_i \rightarrow \|x_i\rangle$	$\|\psi\rangle = \sum x_i\|i\rangle, \sum \|x_i\|^2 = 1$	$R_y(x_i)\|0\rangle = \cos(x_i/2)\|0\rangle + \sin(x_i/2)\|1\rangle$	$\|\psi\rangle = \sum \sqrt{p_i}\|i\rangle$	$\|\psi(t)\rangle = e^{-iHt}\|\psi(0)\rangle$
Qubit Requirement	n qubits for n bits	$\log_2(n)$ qubits	n qubits	$\log_2(n)$ + ancilla	Varies
Circuit Depth	Very Low	High	Low–Medium	Medium–High	High
Data Type Suitability	Binary	Continuous, normalized	Continuous, real-valued	Probabilistic data	Time-series or differential
Scalability	Poor	Excellent	Moderate	Moderate	Limited
Noise Resilience	High	Low	High	Medium	Low
Entanglement Support	Requires entangling layers	Intrinsic via amplitudes	Integrated via entangling gates	Yes	Yes
Interpretability	High	Low	Moderate	Low	Very Low
Computational Complexity	Very Low	High	Low–Medium	Medium	High
Ease of Implementation	Easy	Complex	Easy–Moderate	Moderate–Complex	Difficult
Current Hardware Suitability (NISQ)	Excellent	Poor–Moderate	Excellent	Moderate	Poor
Use in Medical Imaging	Binary classification	High-res MRI	Cancer grading, segmentation	Radiomics modeling	fMRI signal modeling
Example QML Applications	Disease detection	MRI reconstruction	Histopathology classification	QGAN for synthetic imaging	Temporal encoding tasks

TABLE 5. Quantum machine learning algorithms and its use cases in medical imaging.

Classical Algorithm	Quantum Equivalent	Working Principle	Applications in Medical Imaging	Advantages	Limitations
Support Vector Machine (SVM)	Quantum SVM (QSVM)	Uses quantum-enhanced kernel estimation via inner product calculations in Hilbert space	Tumor classification (MRI); Lesion detection (CT/X-ray) [81]	Faster kernel evaluation; Handles high-dimensional data	Requires efficient kernel design; Noise sensitivity
Principal Component Analysis (PCA)	Quantum PCA (QPCA)	Uses quantum phase estimation to extract principal components from density matrices	Dimensionality reduction in histopathology; Preprocessing	Exponential speedup in feature extraction	Needs pure quantum states; Matrix formulation complexity
k-Nearest Neighbors (kNN)	Quantum kNN (QkNN)	Computes distances via quantum inner products; amplitude encoding for similarity	Disease pattern matching; Large dataset retrieval [82]	Reduced query complexity; Efficient similarity matching	Quantum memory requirements; Encoding challenges
Neural Networks (NNs)	Quantum Neural Networks (QNNs)	Uses parameterized quantum circuits to mimic activation and learning	Brain abnormality detection (fMRI); Cancer recognition [83]	Fewer parameters; Potential training advantage	Gradient vanishing; Limited scalability on NISQ
Convolutional Neural Networks (CNNs)	Quantum CNNs (QCNNs)	Employs entangled layers for convolution and pooling via quantum measurements	Organ segmentation; Texture recognition in tissues [84]	Spatial hierarchies with fewer gates; Input-size independent depth	Circuit design complexity; Hardware limitations
Generative Adversarial Networks (GANs)	Quantum GANs (QGANs)	Uses quantum circuits for generator and discriminator; hybrid training loops	Synthetic image generation; Data augmentation [85]	Richer generative distributions; Realistic samples	Instability in training; Slow convergence
Boltzmann Machines	Quantum Boltzmann Machines (QBMs)	Exploits quantum sampling for probabilistic modeling	Anomaly detection; Image distribution modeling	Faster sampling; Efficient probabilistic inference	Requires annealing; Deep circuit constraints
Reinforcement Learning (RL)	Quantum RL (QRL)	Learning policies using unitary transformations and quantum-encoded feedback	Surgical planning; Adaptive enhancement	Faster policy convergence potential	Complex simulation; Limited practical use
Autoencoders	Quantum Autoencoders (QAEs)	Compresses states by projecting redundant information	Feature extraction; Noise reduction in imaging [86]	Efficient data compression; Compact representation	Hard training; Noisy environments
Decision Trees / Random Forests	Quantum Decision Trees	Implements decisions via quantum-controlled gates or walks	Skin disease classification; Retinopathy detection [87]	Fast traversal; Lower depth complexity	Scalability issues; Experimental stage

high-dimensional, the data encoding strategy is crucial for effective learning and accurate inference [75].

An ideal quantum encoding strategy should satisfy the criteria mentioned in Table 3. The most common practical encoding strategies employed in QML are shown below.

Basic encoding where each bit of the binary string is mapped to the computational basis state of a qubit. A 4-bit binary 1010 would be encoded as

$$|1010\rangle = |1\rangle \bigotimes |0\rangle \bigotimes |1\rangle \bigotimes |0\rangle \tag{3}$$

This can be used in binary classification problems [76] or quantized grayscale images [77] in medical imaging. This will also be useful in early-stage cancer detection, where imaging is converted to binary presence/absence signals. This encoding is simple and hardware-efficient and directly maps to low circuit depth [78]. The limitations include its poor scalability, which requires one qubit per feature, making it infeasible for high-resolution images [79].

Amplitude encoding comes next, where the main concept lies in its data vector $\mathbf{x} = [x_0, x_1, \ldots, x_{2^n-1}]$ is encoded in the amplitudes of a normalized quantum state.

$$|\psi\rangle = \sum_{i=0}^{2^n-1} x_i|i\rangle \quad where \quad \sum |x_i|^2 = 1 \tag{4}$$

The efficiency of this encoding for compressed MRI, 3D CT Scans, or histopathological images builds its use case in medical imaging. This enables full vector encoding with fewer qubits (n qubits encode 2^n dimensions). This highly compact representation supports inner product computation efficiently, which is useful for quantum kernel methods [80]. But this is difficult to implement and requires complex quantum circuits and data normalisation. The circuit depth here can be large, which makes it unsuitable for NISQ devices.

Based on the comparative analysis in Table 4, Angle Encoding currently offers the optimal balance between accuracy and feasibility for NISQ-era medical applications. While Amplitude Encoding theoretically provides the highest data density (essential for high-resolution MRI/CT), its requirement for deep state-preparation circuits makes it prone to decoherence errors on current hardware. Consequently, practical implementations predominantly utilize Angle Encoding, typically preceded by classical dimensionality reduction (e.g., PCA or autoencoders) to map complex medical images into a qubit-compatible feature space without exceeding coherence times.

Thirdly, **Angle Encoding (Rotation Encoding/Parametric Encoding)** comes as a very important encoding technique where data values are encoded as rotation angles on single-qubit gates (e.g., R_x, R_y, R_z), as

$$R_y(x_i)|0\rangle = \cos\left(\frac{x_i}{2}\right)|0\rangle + \sin\left(\frac{x_i}{2}\right)|1\rangle \tag{5}$$

The data value x_i directly controls how the qubit is rotated. Tumor classification, organ segmentation [88], and diabetic retinopathy grading could be the best use case of this encoding technique. This is frequently used in VQCs and hybrid quantum-classical models [89], [90]. This is simple to implement on real devices [91], [92] and supports continuous-valued features like pixel intensities [93]. But, as a limitation, this requires one qubit per feature, limiting its scalability, and this requires entanglement layers for capturing interactions between features.

QSample Encoding (Quantum Sampling Encoding) encodes classical probability distributions into quantum states. It prepares the states like $|\psi\rangle = \sum_i \sqrt{p_i}|i\rangle$, where p_i is the probability of outcome i. Its best use case will be stochastic modelling of disease occurrence or Monte Carlo simulations in radiomics [94]. This can also be used in generative models like QGANs for synthetic image generation [95], [96]. This is good for modelling uncertainty and noise in medical data and enables probabilistic inference. Talking about limitations, this has a high overhead for state preparation and often needs ancillary qubits and deep circuits.

Lastly, **Hamiltonian encoding** maps data to parameters of a Hamiltonian, which evolves the quantum state via Schrödinger's equation. The encoding is kept implicit in the evolution of the system $|\psi(t)\rangle = e^{-iHt}|\psi(0)\rangle$. The theoretical usage is in differential imaging, especially in dynamic MRI or fMRI for modelling neural activity [97], which will be the best use case in medical imaging. This encodes rich temporal and structural dependencies and is highly expressive for time-series imaging. Talking about the limitations, this is not practical on NISQ devices and requires precise modelling and control. The detailed comparison of encoding strategies in QML, specifically for medical imaging analysis, is shown in Table 4.

Encoding high-dimensional medical images into quantum states presents several fundamental challenges. Medical imaging data, such as 3D MRI volumes, CT scans, and histopathological whole-slide images, are inherently high-dimensional and often contain millions of pixels or voxels. Directly mapping such data into quantum states would require an impractically large number of qubits or extremely deep quantum circuits, both of which exceed the capabilities of current Noisy Intermediate-Scale Quantum (NISQ) devices. The key challenges associated with quantum encoding of high-dimensional medical images include:

- **Qubit scalability**: Basis and angle encoding typically require one qubit per feature, making direct encoding infeasible for high-resolution images.
- **Circuit depth and state preparation cost**: Compact schemes such as amplitude encoding reduce qubit requirements but introduce deep and complex state preparation circuits, which are highly sensitive to noise.
- **Information loss and fidelity trade-offs**: Dimensionality reduction or patch-based encoding is often required prior to quantum processing, which can result in loss of global spatial context critical for clinical interpretation.
- **Noise and decoherence sensitivity**: High-dimensional encodings amplify the impact of gate errors and decoherence, degrading model reliability in medical applications where precision is essential.
- **Data normalization and precision constraints**: Quantum encoding often requires normalized inputs and limited numerical precision, which may distort subtle intensity variations important for disease characterization.

Due to these constraints, most practical QML approaches for medical imaging adopt hybrid quantum–classical architectures, where classical neural networks perform feature extraction or dimensionality reduction, and quantum circuits operate on compact, task-relevant representations.

Quantum computing can enhance or replicate several classical ML algorithms as shown in Table 5. Most QML algorithms are implemented as hybrid models, using classical preprocessing and post-processing with quantum core components. Medical imaging applications primarily benefit from QSVM [98], QNN, and QCNN [99] for their capability to deal with large image matrices and spatial features. The scalability and hardware constraints remain bottlenecks, but simulators and NISQ-era devices allow the implementations to be a proof of concept.

4) QUANTUM FEATURE MAPS AND KERNEL METHODS

While Variational Quantum Classifiers (VQC) optimize circuits explicitly, Quantum Kernel Methods leverage the "kernel trick" to map classical data $\vec{x}$ into a high-dimensional

Hilbert space via a Quantum Feature Map $\phi(\vec{x})$. The inner product (similarity) between two data points is then estimated as $K(\vec{x}_i, \vec{x}_j) = |\langle\phi(\vec{x}_i)|\phi(\vec{x}_j)\rangle|^2$. Common feature maps include the Z-Feature Map and ZZ-Feature Map, which encode data into the phases of qubits. In medical imaging, these methods are particularly powerful for classifying complex non-linear boundaries (e.g., tumor margins) that are inseparable in the original pixel space. By computing the kernel matrix on a quantum processor and feeding it into a classical Support Vector Machine (SVM), these hybrid "Quantum-SVMs" (QSVM) often show better convexity and convergence properties than fully variational approaches.

C. ADVANTAGES AND LIMITATIONS OF QML FOR IMAGING TASKS

QML presents a transformative opportunity in medical imaging by offering new computational paradigms beyond classical limitations. However, despite its advantages, it poses substantial technical and practical challenges.

1) ADVANTAGES

Quantum computers exploit *superposition* and *entanglement*, which allows them to evaluate multiple input states simultaneously. For high-dimensional medical imaging data, such as 3D MRI scans or histopathology slides, this parallelism can significantly help reduce the time and computational resources needed for training and inference. For example, a quantum circuit can theoretically perform feature extraction on multiple voxels of an MRI scan in parallel, unlike classical methods, which do so sequentially [100].

Driven by the principle of superposition, quantum systems naturally operate in Hilbert spaces of exponentially increasing dimensionality with respect to the number of qubits. This makes it possible to efficiently encode and represent complex and subtle patterns in high-dimensional medical images (e.g., microcalcifications in mammograms or tumor boundaries in MRIs) with fewer resources. Quantum states can encode richer, non-linear relationships, potentially increasing model expressiveness and leading to better generalization in clinical settings [101].

Many medical imaging tasks suffer from limited labelled datasets due to the cost of experts' annotations. Quantum models, particularly variational quantum circuits, can learn with fewer parameters and lower sample requirements than their classical counterparts in some instances. This makes QML uniquely advantageous for specific tasks such as rare disease diagnosis (e.g., pediatric brain tumors) or few-shot transfer learning, where classical deep learning models typically struggle with overfitting due to parameter bloat [102]. Quantum models, particularly variational quantum circuits (VQCs), exhibit higher expressivity with fewer trainable parameters, effectively acting as implicit regularization to prevent overfitting. Concrete research supports this advantage: studies by Matic et al. [102] and Tasnim et al. [45] demonstrated that hybrid QML architectures outperformed classical baselines in accuracy and generalization when training data was restricted (simulating rare disease scenarios). Furthermore, theoretical work by Schuld et al. [80] indicates that quantum circuits can capture complex data correlations with significantly lower model complexity, making QML particularly attractive for rare disease diagnosis or imaging modalities with sparse data (e.g., PET scans in specific neurological disorders).

Quantum systems can exhibit unique loss landscapes due to their high-dimensional and non-convex nature [103], [104]. In some cases, these landscapes may help escape local minima and achieve better convergence during training. Variational quantum algorithms (VQAs) often benefit from smoother or flatter minima, potentially leading to more stable learning dynamics [105]. Quantum principal component analysis and other encoding schemes can assist in reducing the dimensionality of large medical imaging datasets while preserving critical diagnostic information [106], [107]. This is particularly useful for compressing 3D CT or MRI data for downstream tasks like anomaly detection [108].

While quantum machine learning offers theoretical advantages in terms of computational speed, representational capacity, and learning efficiency, most of these benefits have so far been demonstrated under idealized assumptions or small-scale simulation environments. Current quantum processors operate in the Noisy Intermediate-Scale Quantum (NISQ) regime, characterized by limited qubit counts, short coherence times, non-negligible gate error rates, and restricted circuit depth. These constraints significantly limit the size and complexity of QML models that can be executed reliably on physical hardware.

2) LIMITATIONS

Current quantum hardware falls under Noisy Intermediate-Scale Quantum (NISQ) devices. These systems are characterized by the limited number of qubits, typically fewer than 100 usable qubits. The high gate error rates and short coherence times constrained the depth and complexity of quantum circuits. These hardware limitations restricted the practical use of QML to toy problems or small image patches rather than full-resolution medical scans. On the other hand, quantum systems are inherently fragile. The external environmental factors or imperfections in quantum gate operations lead to decoherence, an irreversible loss of quantum information. Even slight inaccuracies can lead to significant errors in medical imaging, where high precision is paramount (e.g., surgical planning) [109].

Encoding high-dimensional classical medical images into quantum states is a non-trivial task. The amplitude encoding can represent complex images efficiently, but it is computationally expensive [110] and challenging to implement on actual quantum hardware. The angle or basis encoding is more hardware-friendly but less expressive, which creates a trade-off between fidelity and feasibility. The scarcity of publicly available quantum-native medical imaging datasets tends to rely on classical datasets and perform simulations on classical hardware. The absence of standardized QML benchmark datasets hinders reproducibility and comparative evaluation across models [111].

III. MEDICAL IMAGING MODALITIES AND THEIR CHALLENGES

This section covers both anatomical and molecular medical imaging modalities, including MRI, CT, PET, SPECT, Ultrasound, X-ray radiography, and histopathological imaging, with emphasis placed on modalities where QML has demonstrated either practical relevance or strong future potential.

A. MAGNETIC RESONANCE IMAGING (MRI)

Magnetic Resonance Imaging (MRI) is a non-invasive imaging technique that utilizes strong magnetic fields and radiofrequency pulses to generate detailed anatomical and functional images of soft tissues in the human body. It operates on the principle of nuclear magnetic resonance (NMR), where the alignment and relaxation of hydrogen protons in tissues produce spatially encoded signals that are reconstructed into images [112]. MRI offers superior soft tissue contrast compared to other imaging modalities, making it indispensable in neuroimaging, musculoskeletal imaging, cardiovascular assessments, and oncological evaluations [113]. The ability to perform functional MRI (fMRI) and diffusion-weighted imaging (DWI) further enhances its role in assessing physiological processes, such as brain activity and tissue microstructure [114]. Despite its advantages, MRI faces several challenges that impact its clinical utility and make it a compelling candidate for enhancement through advanced computational approaches like Quantum Machine Learning (QML) [115]:

1) **High Dimensionality and Data Volume:** MRI data are inherently high-dimensional, with typical scans producing hundreds of slices across multiple sequences (T1-weighted, T2-weighted, FLAIR, etc.) [116]. Functional and diffusion imaging add further complexity with time-series or vector-valued data. This creates significant demands on storage, processing, and model scalability [117].
2) **Long Acquisition Time:** MRI scans typically take longer than other modalities (e.g., CT), leading to patient discomfort, motion artifacts, and limitations in emergency settings. Faster image reconstruction techniques, especially those involving undersampled k-space data, are areas where QML can contribute [118], [119].
3) **Noise and Artifacts:** MRI images often suffer from various artifacts, including motion artifacts [120], [121], susceptibility-induced distortions [122], Gibbs ringing [123], and inhomogeneity of the magnetic field [124], [125]. These artifacts complicate image interpretation and downstream analysis [126].
4) **Inter-Scanner and Inter-Subject Variability:** Variations in scanner hardware [127], [128], pulse sequence parameters, and patient anatomy introduce domain shifts that hinder the generalizability of machine learning models trained on MRI data. Domain adaptation and harmonisation remain ongoing challenges [129], [130].
5) **Computational Demands of Advanced Reconstructions:** Adopting techniques like Compressed Sensing [131] and Deep Learning [132] for MRI reconstruction has improved speed and quality. However, these methods are computationally intensive, making quantum-enhanced solutions appealing due to their potential parallelism and ability to handle high-dimensional spaces efficiently [133], [134].
6) **Labeling and Ground Truth Generation:** Annotating MRI data requires expert radiological input and is time-consuming. This creates a bottleneck for supervised learning approaches and highlights the need for semi-supervised or unsupervised techniques, where QML's ability to work with limited labeled data can be particularly advantageous.

Given these challenges, MRI is a fertile ground for applying Quantum Machine Learning. The ability of quantum models to represent complex data spaces, accelerate computations, and enhance feature extraction aligns well with the needs of MRI-based analysis. Future work will explore QML-based image reconstruction, segmentation, registration, and disease classification within the MRI domain.

B. COMPUTED TOMOGRAPHY (CT)

Computed Tomography (CT) is a cornerstone imaging modality in medical diagnostics, offering high-resolution, cross-sectional views of internal anatomy. Despite its effectiveness, CT imaging presents several challenges, including radiation exposure [135], [136], reconstruction artifacts [137], [138], and computational demands [139], [140], especially in low-dose imaging scenarios. Traditional CT relies on solving inverse problems through techniques like filtered back projection (FBP) or iterative reconstruction [141], [142]. These methods, though effective, are computationally intensive and often struggle with noise and artifacts, particularly in low-dose or sparse-view CT scans [143], [144]. Machine learning has made strides in addressing these challenges, but training and inference on high-dimensional CT data remain resource-heavy [145]. Quantum Machine Learning (QML) offers promising avenues to address these issues through enhanced data processing capabilities enabled by quantum computation [146].

Quantum algorithms have the potential to significantly accelerate CT image reconstruction. Variational Quantum Algorithms (VQAs), such as the Variational Quantum Eigensolver (VQE) and Quantum Approximate Optimisation Algorithm (QAOA) [147], [148], can be applied to solve optimisation problems in image reconstruction.

TABLE 6. Detailed comparison of medical imaging works done with Quantum-based approaches on MRI, CT, and X-Ray modality. Note: While standard datasets are listed, most QML implementations utilize downsampled or feature-extracted versions of this data due to current hardware constraints.

Reference	Algorithm used	Dataset	Application	Result	Modality
Wang et al. (2025) [156]	Hybrid quantum-classical convolutional network (HQNet), Data Augmentation	BT-large-2c, Cheng, BT-large-4c	Brain Tumor	Acc. 99%, 98.6%, 97.5%	MRI
Belay et al. (2024) [157]	Ensemble deep learning models with QSVM classifier, used pre-trained VGG16 and ResNet50	ADNI1+ADNI2	Alzheimer's Detection	Acc. 99.89, F1 98.37	MRI
Mazher et al. (2024) [158]	Combine classical network with quantum network, Convolutional Neural Network	ADNI, Kaggle Brain Tumor MRI dataset	Alzheimer's Detection	Acc. 89.56, 95.33	MRI
Jeon et al. (224) [159]	Variational Quantum Circuit	Combined dataset(IXI, CAU, In-house)	Brain Aging	Acc. 81.8, F1 83.7	MRI
Amin et al. (2023) [160]	Seven layer Javeria Quanvolutional neural network (J.Qnet)	BRATS-2020, locally acquired images	Brain Tumor	Acc. 98.0, 96.0	MRI
Dong et al.(2023) [161]	Hybrid quantum-classical convolutional neural network (HQC-CNN)	Kaggle Brain Tumor MRI	Brain Tumor	Acc. 97.8	MRI
Alsharabi et al. (2023) [162]	AlexNet-quantum transfer learning, quantum variational circuit (QVC)	MRI Image Dataset	Alzheimer's, Parkinson	Acc. 96.0, 97.0	MRI
Moradi et al. (2022) [163]	Quantum distance classifier(qDS), simplified quantum kernel SVM(sqKSVM)	Wisconsin Breast cancer dataset, Prediatric bone marrow transplant dataset, Heart failure dataset	classification, prediction	Acc. 91.0, 87.0	MRI
Amin et al. (2022) [164]	2-qubit classification-segmentation quantum model (javeria)	BraTS2018, BraTS2019, BraTS2020, BraTS2021	Classification, Segmentation	Acc. 97.0	MRI
Konimozhi et al. (2022) [165]	CNN-quantum hybrid transfer learning	Kaggle MRI image dataset (253 images)	Brain Tumor	Acc. 96.7	MRI
Schuld et al. (2021) [166]	Quantum Convolutional Neural Network (QCNN)	Custom synthetic MRI dataset	Brain tumor classification	QCNN showed competitive accuracy with fewer parameters than classical CNNs	MRI
Subbiyan et al. (2025) [?]	Quantum-enhanced Artificial Neural Network (QANN)	Kaggle MRI Dataset, COVID-CXNet chest x-ray, Kaggle Brain CT Dataset	Compression	MRI: 73.3, X-ray: 74.1, CT-Scan 71.8	CT, MRI, X-ray
Bilal et al. (2025) [167]	Quantum-Genetic Binary Grey wolf optimizer (Q-GBGWO) with hybrid Extreme Learning Machine (ELM) with FuNet transfer learning mode	LIDC Dataset, Brain Tumor Dataset	Classification	Breast cancer: 98.80, Brain Tumor: 92.30, Skin Cancer: 97.0, Lung Cancer: 96.08	CT, MRI
Dremel et al. (2025) [168]	Quadratic-unconstrained-binary-optimization for CT data reconstruction	Simulated and measured CT data	Image Reconstruction	Perform reasonably well in reconstruction of images	CT
Alamri et al. (2025) [169]	Innovative Deep Learning and Quantum Entropy Techniques for Brain Tumor Edge Detection and Classification (IDLQET-BTEDC)	Figshare Brain Tumor Dataset	Brain Tumor Classification	Acc. 98.0	MRI
Ohata et al. (2025) [170]	Quantum Iterative Reconstruction(QIR), Image quality evaluation on Task-based Transfer Function(TTF), Noise Power Spectrum (NPS), Contrast-to-Noise Ratio (CNR_{10})	CT images acquired using PCCT system (NAEOTOM Alpha, Japan)	Image Reconstruction	Acc. 67.0-80.0, Specificity 66.0-80.0, Sensitivity 80.0-100	CT
Zhao et al. (2024) [171]	Hybrid Quantum-Classical Convolutional Neural Network (HQCNN) on stocastic quantum circuit	CT image dataset	COVID-19 Classification	Acc. 97.91-99.39, Precision 98.52-99.19	CT
Singh et al. (2024) [172]	Hybrid Quantum-Classical Model	COVID-19 CT Scan Dataset (3975 samples)	COVID-19 Classification	95.31 ($28 * 28$), 96.82 ($32 * 32$), 92.04 ($64 * 64$)	CT
Jannapureddy et al. (2024) [173]	Hybrid Matrix Product State (MPS) and Variational Quantum Circuit (VQC)	CT Scan images (12446 samples)	Cyst, Tumor Classification	Acc. 99.49	CT
Martis et al. (2024) [174]	Hybrid Quantum architecture where pre-trained models used for feature extraction and quantum circits for classification	Chest X-ray8, LIDC-IDRI Dataset	Lung Cancer Detection, Classification	Acc.92.12, Sensitivity 94.0, Specificity 90.0, F1-score 93.0, Precision 92.0	CT, X-Ray
Sunkel et al. (2023) [175]	Hybrid quantum transfer learning with variational quantum circuit	COVID-CT-MD Dataset	COVID-19 Classification	Acc. 70.0-75.0	CT
Schuman et al. (2023) [176]	Quantum-Annealing (QA)-based Quantum Boltzmann machine, Hybrid quantum-classical machine learning	COVID-CT-MD Dataset	COVID-19 Classification	Acc. 70.0	CT
Kodipalli et al. (2023) [177]	Inverted Fuzzy c-means clustring, Deep quantum convolutional neural network	5437 CT images acquired from SDM Dharwad hospital	Ovarian Tumor Detection	84.4 (Benign), 77.03 (Malignant)	CT

Quantum-enhanced compressed sensing [149], for instance, enables faster reconstruction from fewer measurements by leveraging quantum parallelism. Recent studies have explored hybrid quantum-classical neural networks to reconstruct CT images from sparse or noisy data, demonstrating improvements in structural similarity and noise suppression. These models can be trained on near-term quantum hardware (NISQ devices) using quantum circuits as feature extractors.

Quantum convolutional neural networks (QCNNs) have shown promising results in denoising [150], [151], [152] and artifact correction tasks in CT imaging. By encoding CT slices into quantum states, QCNNs can process data in superposition, potentially reducing memory and computational requirements while preserving image quality [153], [154], [155]. These models can also be more robust against overfitting in small datasets, which is common in specialised medical imaging tasks [156].

TABLE 7. **Detailed comparison of medical imaging works done with Quantum-based approaches on X-Ray modality. Note: The performance metrics cited below are largely derived from proof-of-concept studies using downsampled or simulated data. Direct comparison with full-scale clinical baselines should be made with caution due to differing experimental constraints.**

Reference	Algorithm used	Dataset	Application	Result	Modality
Amin et al. (2022) [85]	Conditional Adversarial Network (CGAN) and Quantum Machine Learning	POF Hospital dataset, UCSD-AI4H dataset	COVID-19 Classification	Acc. 94.0, Recall 94.0, F1-score 94.0, Acc. 96.0, Recall 95.0, F1-score 96.0	CT
Zhao et al. (2022) [85]	Classical-quantum hybrid model using a variational quantum circuit	SARS-CoV-2 Dataset	COVID-19 Classification	Acc. 98.78, Precision 97.65, Recall 100.00, and F1-score 98.81	CT
Acar Erdi et al. (2021) [179]	Quantum machine learning to detect COVID-19 using IBM quantum real processor(IBMQx2, IBMQ-London, IBMQ-Rome)	Combined dataset(Radiopedia, SIRM, UCSD-AI4H, MEDSEG, RADASS, Kaggle)	CoVID-19 Detection	Acc. 90.9-97.7, Precision 92.6-97.4, Recall 89.0-98.4, F1 Score 90.8-97.6	CT
Gautam, A., Raman, B. (2021) [180]	Quantum machine learning based on Local Neighorhood Pattern(LNP) feature extractor	CT scan image dataset (900 images)	Brain stroke classification	Precision 79.16, Recall 79.11, F1 79.11	CT
Javaria et al. (2021) [181]	Conditional Generative Adversarial Network (C-GAN) to generate synthetic data for Quanvolutional Neural Network (QNN) training	POF hospital dataset, UCSD-AI4H dataset	COVID-19 Classification	Acc. 94.0-96.0, Recall 94.0-95.0	CT
Sengupta et al. (2021) [182]	QCNN model was used to train the pre-processed data by state preparation and normalization data techniques	COVID CT Scan	COVID-19 Classification	Acc 95.57	CT
Yousif et al. (2024) [183]	Quantum circuits of quantum convolutional neural network (CC-QCNN)	COVID-x CXR-3	Classification	Acc. 86.61	X-ray
Rao et al. (2024a) [184]	Custom convolutional neural network (CCNN)	COVID-19 Radiography Dataset (CRD)	Classification	Acc. 98.1	X-ray
Rao et al. (2024b) [185]	Quantum feature extractor and custom classifier (HQF-CC)	COVID-19 Radiography Dataset (CRD)	Classification	Acc. 98.8	X-ray
Li et al. (2024) [185]	Quantum diffusion model with spatio-temporal feature sharing to real time stenosis detection (STQD-Det)	233 XRA acquired from Peking Union Medical College Hospital China	Stenosis Detection	Precision 94.52, Sensitivity 90.46, F1-score 92.45	X-ray
Decoodt et al. (2023) [186]	Hybrid Classical-Quantum (CQ) transfer learning	2436 posteroanterior CXRs	Cardiomegaly Prediction	Acc. 87.0	X-ray
Kulkarni et al. (2023) [187]	Variational quantum circuit, CNN	X-ray dataset	Pneumonia Classification	Acc. 74.6, AUROC 83.6	X-ray
Ragab et al. (2022) [188]	Quantum seagull optimization algorithm with deep learning (QSGOA-DL) model	CXR image dataset	COVID-19 Classification	Acc. 99.83, F1-score 99.80, Precision 99.80	X-ray
Magallanes et al. (2022) [189]	Hybrid transfer learning paradigm to improvise pre-trained classical networks	Stenosis detection dataset	Stenosis detection	Acc. 91.80, Recall 94.91, F1-score 91.80	X-ray
Houssein et al. (2022) [190]	Hybrid quantum-classical convolutional neural network (HQ-CNN) model with random quantum circuits	Collection of 5445 chest X-ray images	COVID-19 Classification	Acc. 98.6, Recall 99.0	X-ray
Mogalapali et al. (2022) [191]	Classical-quantum transfer learning, Concatenation of pre-trained classical feature extractor with quantum circuit	1200 samples for Trash, 662 X-ray samples for TB classification, and concrete crack dataset	Classification	Acc. 94.5 (Trash), Acc. 89.55(TB), Acc. 91.2(Crack)	X-ray, other
Azevedo et al (2022) [192]	Quantum transfer learning	ImageNet, BCDR Dataset	Mammograms Classification	Acc. 81.0, F1-score 81.0, Recall 80.0	X-ray
Mathur et al. (2021a) [193]	Quantum Neural Network	PneumoniaMNIST, RetinaMNIST	Chest X-ray Classification	Acc. 98.0, Acc. 93.0	X-ray
Mathur et al. (2021b) [193]	Quantum Orthogonal Neural Network (qOrthNN)	PneumoniaMNIST, RetinaMNIST	Chest X-ray Classification	Acc. 96.0, Acc. 86.0	X-ray
Amin et al. (2022) [194]	4-qubit quantum model for segmentation & classification	Breast histopathology	Breast cancer detection	Acc. 95.0	Histopathological Imaging
Vashisth et al. (2021) [195]	Quantum Support Vector Machine (QSVM)	Wisconsin Breast Cancer Dataset (WBCD)	Tumor classification	Precision 92.0, Recall 96.0, F1-score 94.0	Histopathological Imaging
Majumdar et al. (2023) [196]	Classical CNN + Variational Quantum Circuit	Custom histopathology set (1000 images)	Cancer classification	Accuracy: 88.5, AUC: $\sim$93	Histopathological Imaging
Baral et al. (2023) [197]	QML robustness against adversarial attacks	Custom histopathology set (1000 images)	Robust cancer detection	Acc. 84.30	Histopathological Imaging
Ray et al. (2023) [198]	Hybrid Quantum-Classical GNN + VQC	Internal breast cancer subtype dataset	Tumor subtype classification	Precision 66.0, Recall 68.0, F1-score 67.0	Histopathological Imaging
Ahmed et al. (2023) [199]	Quantum Optimized AlexNet (QOA)	BreakHis-400x	Breast cancer classification	Accuracy: 93.67%	Histopathological Imaging
Lusnig et al. (2024) [200]	QML + Federated Learning	Liver histology (hepatic steatosis)	Liver disease classification	Accuracy: 97%, high privacy	Histopathological Imaging

1) **Nature of CT Data and Quantum Encoding Constraints**
CT imaging produces high-dimensional, volumetric datasets (e.g., $512 \times 512 \times N$ voxel volumes), which present a significant challenge for current quantum hardware [200]. Encoding such large datasets into quantum states requires a high number of qubits and efficient encoding schemes [201]. Existing methods like amplitude encoding and basis encoding have theoretical potential but are practically limited by the qubit and gate depth constraints on Noisy Intermediate-Scale Quantum (NISQ) devices.

2) **Quantum Hardware Limitations**
Current quantum processors lack the scale and noise resilience needed to handle the size and complexity of CT data [202], [203]. Medical imaging applications typically

involve real-valued, high-resolution data [204], [205], which must be preprocessed extensively before being compatible with quantum formats. Additionally, most existing quantum devices suffer from short coherence times [206], [207], gate errors, and limited connectivity [208], all of which reduce the reliability and scalability of QML models for CT image analysis [209].

3) **Preprocessing and Hybrid Model Overhead**
To apply QML to CT data, extensive preprocessing is often required, including dimensionality reduction (e.g., using PCA, downsampling, or patch extraction) to reduce the input size [210], [211]. This preprocessing introduces computational overhead on the classical side, potentially offsetting the speed gains expected from quantum processing [212], [213]. Moreover, most current QML implementations rely on hybrid quantum-classical architectures, which introduce latency due to data transfer between quantum and classical processors [214].

4) **Lack of Domain-Specific Quantum Algorithms**
While general-purpose quantum algorithms like Quantum Support Vector Machines (QSVMs) or Quantum Convolutional Neural Networks (QCNNs) exist, there is a lack of domain-specific quantum algorithms tailored for CT imaging tasks such as reconstruction [168], denoising [215], or segmentation. Classical deep learning methods have undergone years of domain adaptation; quantum counterparts have not yet reached similar levels of optimization [216].

5) **Limited Benchmarking and Validation**
There is a scarcity of standardized benchmarks for evaluating QML models in CT imaging. Most studies are proof-of-concept demonstrations on simulated or heavily downsampled data, with limited comparison to state-of-the-art classical methods. Without rigorous validation on clinically realistic datasets, it is difficult to assess the practical value of QML in this modality [217], [218].

6) **Ethical and Regulatory Considerations**
In medical imaging, especially with modalities like CT where radiation dose is a concern, any modification to the image acquisition or reconstruction process must be thoroughly validated. Quantum algorithms would need to demonstrate not only performance gains but also safety, reproducibility, and interpretability—areas where current QML methods are underdeveloped [219], [220] [221].

C. POSITRON EMISSION TOMOGRAPHY (PET) AND SINGLE-PHOTON EMISSION COMPUTED TOMOGRAPHY (SPECT)

Positron Emission Tomography (PET) and Single-Photon Emission Computed Tomography (SPECT) are molecular imaging modalities that provide functional and metabolic information at the cellular and biochemical levels. Unlike anatomical imaging techniques such as CT or MRI, PET and SPECT enable the visualization of physiological processes including glucose metabolism, receptor binding, and perfusion, making them indispensable in oncology, neurology, and cardiology.

PET and SPECT imaging pose significant computational challenges due to their inherently low spatial resolution, high noise levels, and reliance on complex inverse reconstruction problems. Image reconstruction, attenuation correction, and noise suppression are particularly demanding and have traditionally relied on iterative statistical methods. Recent advances in artificial intelligence have improved reconstruction quality and diagnostic accuracy; however, these methods remain computationally intensive and sensitive to limited training data.

From a Quantum Machine Learning perspective, PET and SPECT present promising—but largely unexplored—opportunities. Quantum-enhanced optimization, probabilistic modeling, and hybrid quantum–classical reconstruction frameworks may offer advantages in handling noisy, high-dimensional, and stochastic imaging data. Nevertheless, current QML applications in PET and SPECT remain largely conceptual or simulation-based, with practical deployment constrained by data encoding complexity and hardware limitations.

D. ULTRASOUND IMAGING (US)

Ultrasound (US) imaging is a widely used, real-time, and non-ionizing diagnostic modality, particularly valued for its portability, low cost, and safety. It plays a critical role in obstetrics, cardiology, musculoskeletal imaging, and image-guided interventions. However, ultrasound images are often affected by speckle noise, operator dependency, and limited field-of-view, which complicate automated image analysis.

Classical machine learning and deep learning approaches have been extensively applied to ultrasound image segmentation, motion tracking, and disease classification. In contrast, Quantum Machine Learning applications in ultrasound imaging are still in their infancy. The relatively lower dimensionality of ultrasound data, combined with real-time processing requirements, reduces the immediate feasibility of QML-based pipelines. Nonetheless, hybrid quantum–classical models may offer future potential in ultrasound signal processing, optimization-based beamforming, and uncertainty-aware diagnostic modeling.

E. X-RAY RADIOGRAPHY

X-ray radiography is one of the oldest and most widely used medical imaging modalities, providing rapid, low-cost visualization of internal anatomical structures [222], [223]. Despite its widespread use, the modality is inherently limited by its two-dimensional (2D) nature, overlapping anatomical structures, and lower contrast in soft tissues compared to modalities like CT or MRI [224], [225]. The integration of Quantum Machine Learning (QML) in radiographic image analysis presents intriguing possibilities but also faces significant practical and theoretical barriers [226].

1) **Low Data Dimensionality vs. Quantum Advantage**
Unlike CT or MRI, X-ray radiography produces 2D grayscale images with comparatively low data volume. This low dimensionality, while computationally efficient in classical systems, reduces the potential advantage of using QML, which typically excels in high-dimensional, complex feature spaces [227], [228], [229], [230]. The overhead of quantum data encoding and hybrid model orchestration may outweigh the benefits unless QML methods can extract non-obvious patterns in subtle diagnostic tasks (e.g., early-stage disease detection).
2) **Quantum Encoding Bottlenecks**
Even though radiographic images are smaller than CT volumes, quantum encoding remains non-trivial. Efficiently converting a 2D image (e.g., 256×256 pixels) into a quantum state still requires hundreds of qubits and deep quantum circuits, depending on the encoding strategy (e.g., amplitude or basis encoding) [201], [231], [232], [233]. Current Noisy Intermediate-Scale Quantum (NISQ) devices are limited in qubit count and coherence time, making real-time processing infeasible at present [234].
3) **Data Quality and Variability**
X-ray radiographs often suffer from variability in illumination, positioning [182], [235], and anatomical overlap [236]. QML models trained on such variable datasets may suffer from reduced generalization unless combined with robust classical preprocessing pipelines. Moreover, label noise in large public X-ray datasets (e.g., chest X-rays) further complicates the training of sensitive quantum classifiers [237], [238], [239].
4) **Limited Clinical Use Cases Identified**
While there is some early exploration of QML for image classification and anomaly detection in chest radiographs, the clinical utility of QML in X-ray analysis has not been clearly established [240]. Many tasks in X-ray diagnosis, such as fracture detection or pneumonia screening, already achieve high performance with classical deep learning [241], [242]. Demonstrating QML superiority or complementarity in these areas remains a major research gap [243].
5) **Sparse Literature and Lack of Benchmarks**
Compared to CT or MRI, the literature on applying QML to X-ray radiography is extremely sparse [102], [175], [244]. Most existing work consists of simulated proof-of-concept models with small, downsampled datasets [240]. There's a lack of comparative benchmarks between QML and classical models under identical conditions, which hinders a meaningful assessment of quantum advantage in this modality [245].
6) **Interpretability and Trust in Clinical Settings**
In medical radiography, explainability and trust are critical. QML models, especially those relying on complex entangled states or variational quantum circuits, lack the interpretability tools currently available for classical models (e.g., Grad-CAM, saliency maps) [246]. This impedes clinical adoption, particularly in high-stakes scenarios such as differential diagnosis or triage.

F. HISTOPATHOLOGICAL IMAGING

Histopathological imaging is the gold standard for diagnosing many cancers and other diseases at the cellular level [247], [248], [249]. Whole Slide Images (WSIs), produced by high-resolution scanners, enable detailed examination of tissue morphology [250]. The complexity and massive size of these images make them ideal candidates for machine learning–driven analysis [251], [252]. In theory, Quantum Machine Learning (QML) could offer new paradigms for feature extraction, classification, and segmentation. However, significant modality-specific limitations hinder the practical application of QML in histopathology [253].

1) **Ultra-High Resolution and Data Size**
Histopathological slides often exceed gigapixel resolution (e.g., 100,000 × 100,000 pixels) [254], [255]. Processing such images using QML is currently infeasible due to the extreme challenge of encoding this volume of data into quantum states [256]. Even patch-based approaches, where small image regions (e.g., 256×256 pixels) are extracted, still require extensive dimensionality reduction before they can be encoded for use in quantum circuits [257].
2) **Quantum Encoding Challenges for Texture and Color**
Unlike grayscale medical images such as X-rays, histopathology involves complex color patterns and fine-grained textural details [258], [259]. Encoding RGB or stain-normalized color channels into qubit states presents an additional layer of complexity [260]. Quantum data representations that preserve critical visual cues like nuclear atypia, mitotic figures, and tissue architecture are still underexplored [261], [262].
3) **Patch-Based Modeling and Loss of Context**
Due to hardware limitations, most potential QML approaches to histopathology rely on analyzing small, isolated patches rather than the full context of the tissue [263], [264], [265]. This can be problematic, as diagnostic accuracy often depends on spatial relationships across regions (e.g., tumor margin detection, grading) [266]. Classical deep learning models have mechanisms like attention and multi-instance learning to address this [267]; quantum equivalents are not yet well developed [268].
4) **Computational Cost of Hybrid QML Pipelines**
Applying QML to histopathology typically involves hybrid architectures where classical preprocessing is followed by quantum feature extraction or classification [269]. These systems often require significant classical resources for image preprocessing (e.g., stain normalisation, tiling, augmentation), which can negate

any speedup obtained via quantum inference, particularly given the I/O bottlenecks of current quantum systems.

5) **Lack of Annotated Datasets for Quantum Training**
Histopathology datasets are often large but sparsely labeled [270], [271], with annotations requiring expert pathologists [272], [273], [274], [275]. Training QML models with limited or weak supervision is an open challenge [276], [277], [278]. Furthermore, most QML research to date has focused on small toy datasets (e.g., MNIST, Fashion-MNIST), with minimal benchmarking on real-world digital pathology repositories like CAMELYON16, PANDA, or TCGA [279], [280], [281], [282].

6) **Explainability and Clinical Trust**
In pathology, interpretability is vital due to the high-stakes nature of diagnostic decisions. Tools like heatmaps and saliency maps allow classical AI models to provide visual explanations. QML models, in contrast, currently lack transparent interpretability mechanisms, posing a barrier to regulatory acceptance and clinical deployment [283], [284], [285], [286], [287], [288].

IV. PERSPECTIVE APPLICATIONS OF QML IN MEDICAL IMAGING

QML holds the potential for revolutionizing medical imaging tasks with quantum phenomena like superposition and entanglement, which provide exponential speedups in specific cases and better handling of high-dimensional image data. Here, we detailed the major application areas of QML in medical imaging, from basic classification tasks to advanced image reconstruction with an end-to-end landscape view.

A. IMAGE CLASSIFICATION

Image classification in medical imaging refers to automatically categorizing medical images into predefined disease or healthy classes. This is crucial for early diagnosis, treatment planning, and prognosis. QML introduced new possibilities with quantum properties like superposition and entanglement, which allow models to represent and process information in higher-dimensional spaces compared to classical approaches [289].

1) ROLE OF QML IN MEDICAL IMAGE CLASSIFICATION

The role of Quantum Machine Learning (QML) in medical image classification is transformative, introducing new capabilities that are not possible with traditional machine learning methods. Medical images are inherently high-dimensional and usually contain subtle, complex patterns that can be difficult for classical models to represent, such as MRI, CT images, and histopathology slides. Using principles of quantum mechanics such as superposition and entanglement, QML encodes and manipulates information in exponentially larger spaces [290]. As such, quantum models can encode and process more compactly and efficiently the richer feature relationships within medical images than their classical counterparts can.

The most crucial contribution of QML is enhancing feature extraction. Specifically, input features can be transformed into highly entangled quantum states through quantum circuits, especially with variational quantum circuits (VQCs) [291]. With these transformations, these correlations and patterns hidden from classical feature engineering or deep learning alone can be seen. This is particularly important since healthcare is a setting where subtle pathological tissue differences can make a big difference in diagnosis and approach to treatment.

QML also has good generalisation ability in a low-data regime. First, medical imaging datasets are typically small due to either privacy concerns, cost constraints, or the rarity of certain conditions. Quantum models are better suited to generalise from small datasets because they are more expressive and can learn in high dimensions compared to classical deep learning approaches, which are more susceptible to overfitting. Moreover, QML algorithms [292] naturally explore more complex hypothesis spaces and could find more complex decision boundaries with fewer parameters.

a: THE VOLUMETRIC DATA BARRIER

It is critical to note that while MRI and CT are inherently 3D modalities, the vast majority of QML applications reviewed here process data as a sequence of 2D slices. True 3D Quantum Convolutional Neural Networks (3D-QCNNs) require a qubit capacity that scales cubically with input size, which is currently beyond the reach of NISQ hardware. Therefore, current clinical applicability is limited to slice-based diagnosis rather than full volumetric analysis (e.g., 3D tumor volume estimation), representing a significant gap between theoretical potential and current practice.

2) WORKFLOW OF QML-BASED MEDICAL IMAGE CLASSIFICATION

The workflow of QML in medical image classification [293] involves several systematic stages that bridge traditional image processing with quantum computation. Each step here plays a crucial role in ensuring that medical images, which are large and complex, are efficiently processed within the current constraints of quantum hardware.

The first step is to preprocess the medical images to ensure they are consistent with quantum models. It is essential to be able to use quantum devices where images must currently be resized and normalized, since images now have a limited number of qubits and circuit depth of these devices in the NISQ era. For example, high-resolution MRI can be reduced to small patches or feature vectors. First, enumeration-encoded features are applied in some cases before dimensionality reduction techniques such as Principal Component Analysis (PCA).

After preprocessing, the data must be encoded into a quantum format called quantum data encoding [294]. Quantum encoding deals with the representation of the pixel

TABLE 8. Quantum encoding techniques.

Encoding Method	Description	Advantage	Challenge
Amplitude Encoding	Represents data amplitudes across quantum states	Compact representation of large vectors	Complex circuit preparation
Angle Encoding	Maps features to qubit rotation angles (e.g., R_x, R_y gates)	Simpler to implement, fewer qubits needed	May require many rotations for high-dimensional data

TABLE 9. Steps of the training phase.

Training Step	Task	Example
Forward Pass (Quantum)	Evaluate circuit, obtain measurement probabilities	Measurement indicates the predicted class
Loss Calculation	Compute how far predictions are from true labels	Cross-entropy loss used
Parameter Update (Classical)	Adjust gate parameters to reduce loss	Use classical optimizers like Adam

TABLE 10. Comparison of key quantum models used for medical image classification.

Quantum Model	Strength	Best for	Limitation
Quantum Support Vector Machine (QSVM) [295]	Natural high-dimensional mappings through quantum feature spaces	Small to medium-sized datasets where nonlinear separation is needed	Requires efficient quantum kernel evaluation, which may be costly for large datasets
Variational Quantum Classifier (VQC) [296]	High adaptability, suitable for hybrid quantum-classical workflows	Flexible modeling with small to moderately-sized medical image datasets	May suffer from barren plateaus (flat loss landscapes) during training
Quantum Convolutional Neural Networks (QCNNs) [216]	Hierarchical feature learning with reduced parameter complexity	Medical imaging tasks needing spatially aware feature extraction	Still theoretical for deep QCNNs on large images due to hardware limits
Hybrid Quantum-Classical Models [297]	Makes quantum approaches feasible with today's NISQ devices	High-dimensional medical images with limited quantum resources	Requires careful integration and tuning to balance classical and quantum parts

intensities or the extracted features in the form of quantum states, whereas classical data representation takes the pixel intensities or the extracted features as the inputs. Specifically, amplitude encoding, where the amplitudes of quantum states are retained by pixel intensity, and angle encoding, in which pixel values relate directly to rotation angles of qubits (see Table 8).

From there, the quantum model is built after encoding. Different quantum machine learning models can be used, depending on the complexity of the task and the amount of available quantum resources. Variational Quantum Classifiers (VQC) are common architectures where the quantum circuits are parameterized for the classification task, or Quantum Convolutional Neural Networks (QCNN), which resemble classical CNNs and have operations replaced by quantum equivalents. By exploiting quantum phenomena such as superposition, entanglement, or something even more exotic, these models aim to generate the best models of hidden relationships in the medical images.

In training quantum models, we adjust the circuit parameters (e.g., rotation angles of gates) to minimise a classification loss function. Quantum devices can compute loss and its gradient, but cannot perform optimization itself. Hence, a classical optimizer such as Adam, COBYLA, or SPSA is typically used. Because of the hybrid nature of the training (quantum forward pass, classical backward pass), it protects against noise and benefits from both quantum representations and classical powerful techniques (see Table 9).

Once the model is trained, it enters the inference phase. New unseen medical images are preprocessed and encoded into quantum states, passed through the trained quantum model, and the measurement outcomes are used for predicting class labels (e.g., malignant or benign). Because of quantum measurement's probabilistic nature, multiple runs (called shots) are usually performed, and the most frequent result is considered the final prediction.

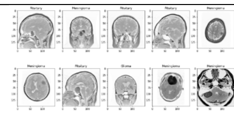
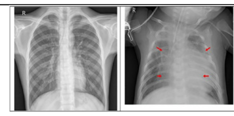
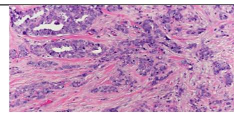
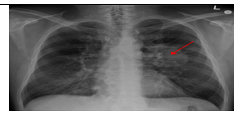
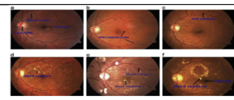
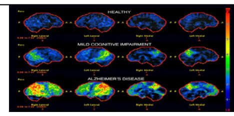
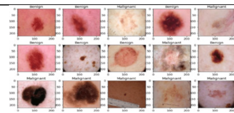
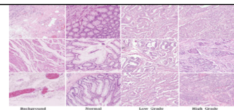
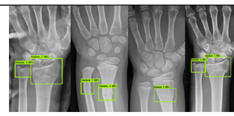
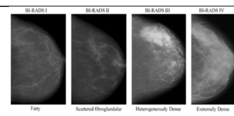
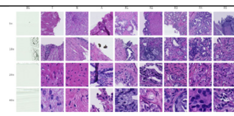
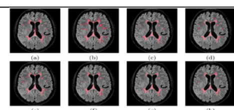
3) KEY QUANTUM MODELS USED

Quantum models for medical image classification aim to use the potential of unique properties of quantum computing, such as superposition, entanglement, and quantum interference, to achieve better feature learning, faster convergence, and improved generalization (see Table 10).

Quantum Support Vector Machine (QSVM) is a quantum extension of the classical support vector machine, designed for separating classes by finding an optimal hyperplane in high-dimensional quantum feature space. Instead of manually crafting complex kernels as in classical SVMs, QSVM utilized quantum kernels derived from quantum circuits. These quantum kernels can map data into feature spaces that are difficult or even impossible to simulate classically, which allows better classification boundaries, especially when dealing with complex medical images like MRI scans or histopathology slides. 1 **Variational Quantum Classifier (VQC)** is a highly flexible and adaptive model that uses parameterized quantum circuits (PQC) for learning tasks. In a typical VQC, input data is first encoded into quantum states, passed through a quantum circuit with tunable parameters, and finally measured to predict class labels. Training involves optimizing the circuit parameters using classical optimization algorithms (e.g., gradient descent). VQCs are particularly useful in medical image classification, where interpretability and adaptability are essential, as they can be fine-tuned based on dataset size and complexity.

QCNNs mimic the structure of classical CNNs but apply quantum operations for feature extraction and pooling. QCNNs perform quantum convolutions by applying quantum gates locally across a subset of qubits, followed by quantum pooling operations to reduce dimensionality. This architecture allows hierarchical feature extraction in quantum space, making QCNNs attractive for structured data like medical images (e.g., tumor localization, pneumonia detection).

TABLE 11. Clinical use cases of QML in medical image classification.

Application	Imaging Modality	Clinical Objective	QML Model best suited	Imaging Example
Brain Tumor Classification	MRI	Differentiate between glioma, meningioma, and pituitary tumors.	Hybrid Classical-CNN + Variational Quantum Classifier (VQC)	
Pneumonia Detection (including COVID-19)	Chest X-ray	Detect bacterial pneumonia, viral pneumonia, or COVID-19 infection.	Quantum Support Vector Machine (QSVM)	
Breast Cancer Histopathology Classification	Histopathological Images	Classify tissue samples into benign and malignant.	Quantum Neural Networks (QNN)	
Lung Cancer Nodule Classification	CT	Identify malignant vs benign lung nodules and stage progression.	Quantum Convolutional Neural Networks (QCNN)	
Diabetic Retinopathy Detection	Fundus Retinal Images	Early detection of diabetic-induced retinal damage.	VQC with Quantum Feature Maps	
Alzheimer's Disease Diagnosis	MRI (brain volumetric scans)	Classify between healthy aging, mild cognitive impairment (MCI), and Alzheimer's.	QSVM with Quantum Kernel Estimation	
Melanoma Skin Cancer Classification	Dermatoscopic Images	Detect and classify skin lesions into malignant melanoma or benign nevi.	Quantum-enhanced CNN (QCNN layers integrated)	
Colorectal Cancer Detection	Histopathological Images	Classify colon tissue samples into cancerous and non-cancerous.	VQC with hybrid layers	
Bone Fracture Detection	X-ray	Detect minor and complex bone fractures for orthopedic diagnosis.	QNN trained with reduced feature encodings	
Breast Density Classification	Mammograms	Classify breast images into different density categories (BI-RADS categories).	QSVM and Quantum Embedding Techniques	
Prostate Cancer Localization	MRI	Segment and classify localized prostate tumors.	Quantum U-Net Architectures (under research)	
Multiple Sclerosis Lesion Detection	MRI	Detect demyelinating lesions for MS progression tracking.	Quantum CNN + Hybrid Classical Processing	

Hybrid models combine the strengths of classical neural networks (especially for feature extraction) with quantum models for decision-making or fine-grained classification. Typically, a classical CNN (like ResNet or VGG) processes the raw medical image into feature embeddings, and then a quantum model (such as VQC or QSVM) takes over for the final classification. This approach helps bypass the limitation of the current quantum devices' small qubit counts while still gaining benefits from quantum computation in the most critical parts of the pipeline.

4) CLINICAL USE CASES

Recently, the clinical applications of medical image classification based on Quantum Machine Learning (QML) have been promising, as listed in Table 11. QML techniques have

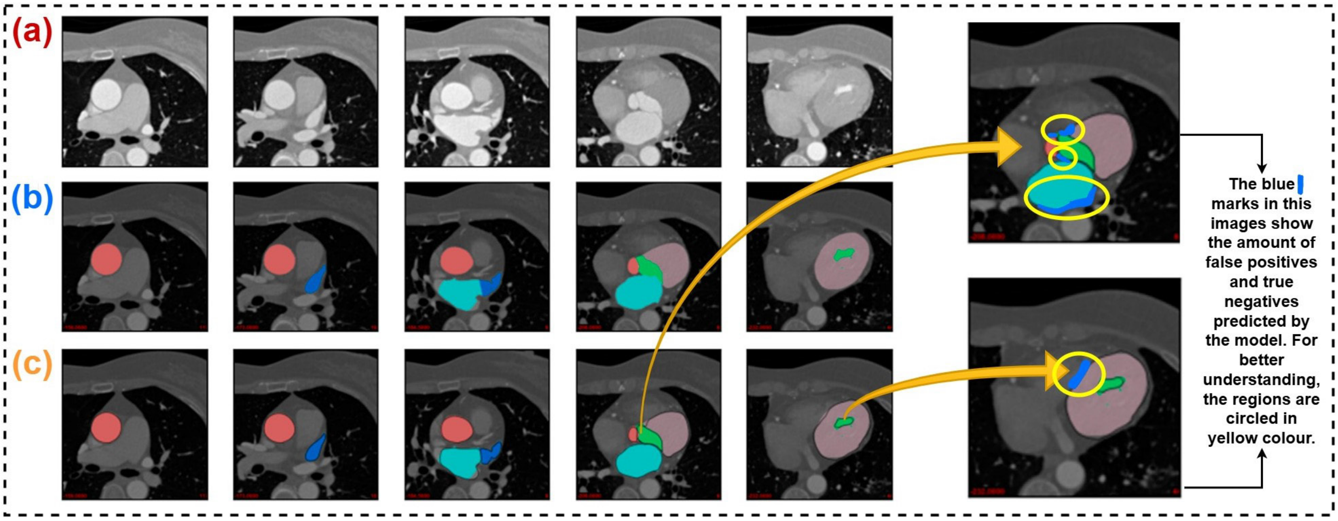


FIGURE 5. This is an image from the CCTA dataset for segmenting aorta, left ventricle, left atrium, left atrial appendage, and myocardium. (A) shows the original CT images from CCTA, (B) shows semi-automatic labeling of 2D slices, and (C) shows the prediction and labels plotted together by an advanced deep learning model [298]. The yellow circles on the left side shows the need of quantum algorithms in the scenario for better accuracy in segmentation results.

successfully solved critical diagnostic tasks in molecular biology, pathology, dermatology, histopathology, retinal fundus imaging, MRI, CT, and X-ray. In particular, Variational Quantum Classifiers (VQC) have been used to classify brain tumors from an MRI scan in a hybrid classical-quantum model. For the same, the Quantum Support Vector Machines (QSVM) have also taken the pneumonia and COVID-19 detection from chest X-rays to an unprecedented height. Quantum Neural Networks (QNN) and hybrid quantum architectures have enhanced the histopathological image analysis for breast and colorectal cancer with sensitivity and robustness, with limited data. Additionally, quantum-enhanced models accelerate and perform better than conventional models for detecting diseases like Alzheimer's, diabetic retinopathy, melanoma, and multiple sclerosis. QML also enables clinical objectives such as lesion segmentation and detection of malignancy, staging, and real-time surgery support. Clinical objectives cover a wide range, from lesion segmentation to malignancy detection, staging, and real-time surgery support. These clinical use cases suggest QML's potential to improve diagnostic accuracy, speed decision-making, and patient outcomes, especially in a scarce environment.

It is important to interpret these high-performance metrics with caution. As detailed in Table 6, while accuracies often approach 99%, these are frequently derived from experimental setups where feature dimensionality is heavily reduced (e.g., via PCA) to fit quantum circuits. This preprocessing step effectively hybridizes the result, making it difficult to isolate the specific contribution of the quantum component versus the classical dimensionality reduction. Future evaluations must rigorously decouple these effects to provide valid evidence of quantum utility.

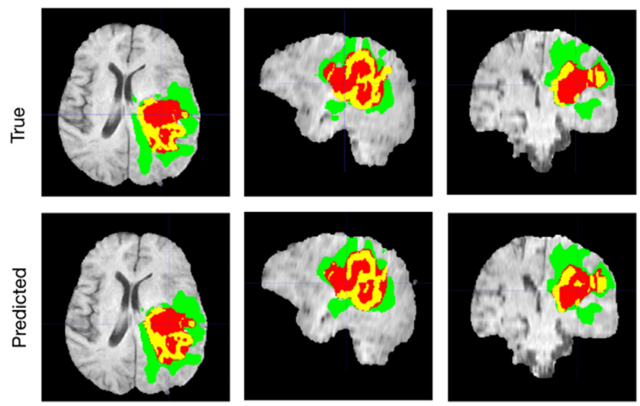


FIGURE 6. The whole tumor (WT) class is all visible in the tumor. However, red and yellow labels are a tumor core (TC) class union. It is yellow (a hyperactive tumor part), thus the advocating tumor core (ET) class. The predicted segmentation results are also quite similar to the ground truth. [299].

B. IMAGE SEGMENTATION

For accurate diagnosis and treatment planning, image segmentation involves partitioning medical images into meaningful regions, such as organs, tissues, lesions, or other structures. QML provides new opportunities to improve segmentation accuracy and efficiency by leveraging quantum computing to handle complex patterns in medical images, particularly in noisy or low-resolution data.

1) ORGAN AND TISSUE SEGMENTATION

The main use case is segmenting anatomical structures like the liver, heart, brain, and lungs from CT, MRI, and ultrasound images.

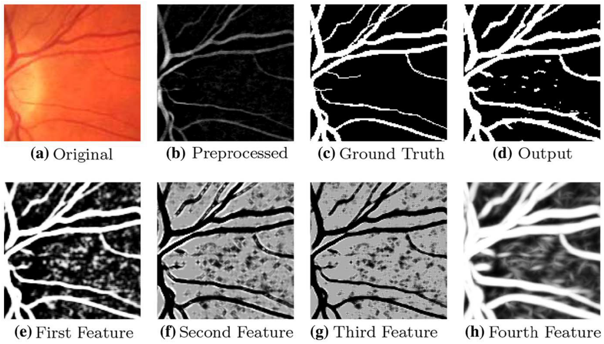


FIGURE 7. A small window of image 15 from the DRIVE database showing (a) the RGB image, (b) the background normalized image after preprocessing, (c) ground truth of the selected window, (d) the output of the selected window after applying all the steps of the algorithm. (e)–(h) The four generated features after normalization [301].

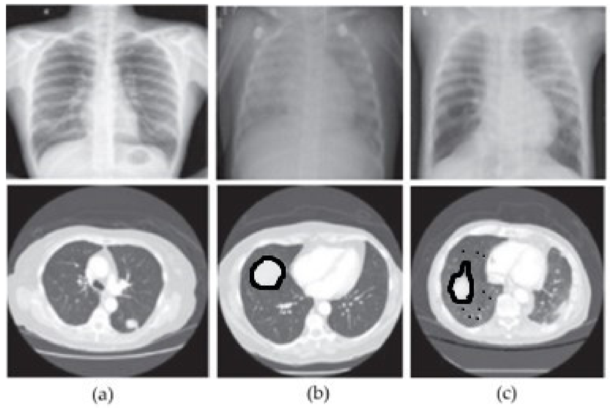


FIGURE 8. Lung cancer segmentation using framework of deep learning with quantum computing on chest radiographs and CT scan images (a) shows the normal one, (b) shows the benign one, and (c) shows the malignant one. The first row shows the CT scan images and the second row the chest radiographs [174].

Inspired by the classical U-Net architecture for segmentation, QML enhances it by incorporating quantum circuits in the encoder-decoder layers. The quantum layers captured high-dimensional relationships between the features, which are difficult for classical algorithms. QVCs are employed in the network bottleneck, helping the model learn more complex feature hierarchies by performing optimization across quantum states. Quantum layers often optimize loss functions, while classical components handle large preprocessing and post-processing.

Quantum U-Nets have shown improved accuracy in delineating organ boundaries, especially in cases where the data is noisy or the organs are adjacent and hard to differentiate. Quantum models help preserve subtle features important in early-stage disease detection. In the segmentation done between aorta, left ventricle, left atrium, left atrial appendage, and myocardium from the CCTA dataset shown in Figure 5, it can be seen that there are false positives in the segmentation results obtained, where the quantum algorithms are essential enough for accurate clinical implementation.

2) LESION AND TUMOR DELINEATION

Here, the main use case lies in segmenting cancerous lesions or tumors in radiological images (e.g., CT, MRI, X-Ray) to assist in diagnosis and treatment planning.

QCNNs have been used to capture spatial features more efficiently than classical CNNs. The quantum nature of QCNNs enables better feature extraction, particularly when tumors are located in heterogeneous tissue regions. On the other hand, quantum variational autoencoders help segment tumors from surrounding tissues, using latent space representations to refine tumor boundaries and improve delineation. Quantum models excel in cases where tumor boundaries are irregular, as quantum circuits can model more complex shapes and subtle textures that classical models might miss. They also offer robust performance in low-contrast images, where classical methods may struggle to separate lesions from background tissues. In MRI scans, quantum-enhanced

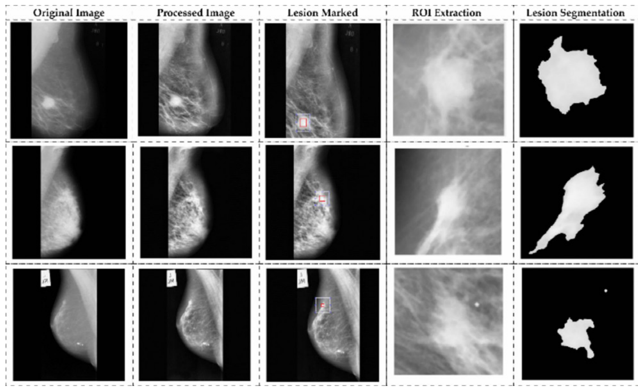


FIGURE 9. Breast cancer segmentation using Q-BGWO-SQSVM approach using improved quantum-inspired binary Grey Wolf Optimizer and combining it with SqueezeNet and Support Vector Machines [302].

segmentation methods like Quantum-Inspired Dragonfly Algorithm (QDA) [299] have been applied to delineate glioma and meningioma tumors accurately, which are often distinct in low-resolution or noisy images (see Figure 6).

3) VESSEL AND BLOOD FLOW SEGMENTATION

Here, the main use case is the segmentation of blood vessels, arteries, or veins from angiography images or MRI angiograms for vascular disease diagnosis.

Quantum models help improve edge detection for small, thin, and curvilinear structures like blood vessels by using quantum filters to enhance edge contrast. Quantum-enhanced graph-cut methods can also improve segmentation by better identifying vessel networks and reducing over-segmentation errors [300]. QML approaches have been shown to outperform classical graph-based methods in detecting small or fragmented vessels, particularly in noisy angiographic images, by capturing the intricate relationships between the image pixels in quantum feature space. Quantum methods have been used for high-accuracy segmentation of retinal

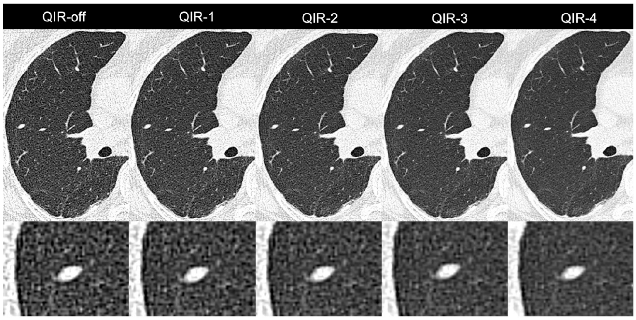


FIGURE 10. This is an image of a 58-year-old male patient with a solid 6mm pulmonary nodule in the lateral middle lobe. Here, the image was reconstructed using Quantum iterative reconstruction [303].

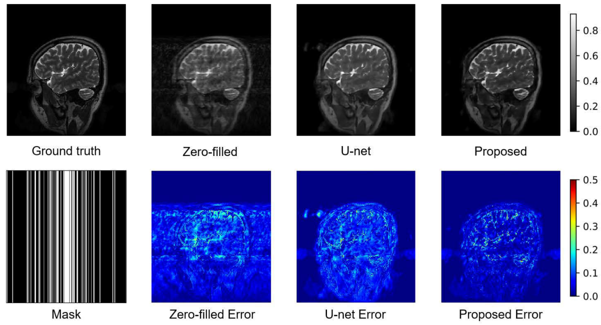


FIGURE 11. This image shows the reconstruction results with 4x acceleration. Includes the ground truth, mask, zero-filled image, U-net reconstruction result, quantum hybrid neural network reconstruction result, and their error map. [304].

blood vessels in OCT (Optical Coherence Tomography) and fundus images, which is crucial for diagnosing diabetic retinopathy and glaucoma (see Figure 7) [301].

4) TUMOR HETEROGENEITY AND MULTI-CLASS SEGMENTATION

Identifying and segmenting heterogeneous tumors that may consist of multiple subtypes or tissue types (e.g., necrotic, solid, and cystic) is very important nowadays. QML models can be trained to handle various tumor types or heterogeneous regions within a tumor by leveraging quantum circuits to model complex interactions between tumor subtypes. Attention mechanisms in quantum workflows allow the model to focus on different tumor subtypes within the same region, enabling multi-class segmentation from a single scan. These quantum-based models improve the segmentation precision by capturing complex intra-tumoral variations, which are essential for personalised treatment planning and assessing treatment response. For lung tumors in CT scans, quantum models can differentiate between normal, benign, and malignant tumor tissues, which helps in distinguishing active tumor growth from necrotic regions (see Figure 8) [174].

5) HISTOPATHOLOGICAL IMAGE SEGMENTATION

The main use case is segmenting cellular structures or tissue types in histopathology slides (e.g., identifying cancerous cells or tissue types in biopsies). This task involves applying quantum models to identify complex tissue patterns in histopathology images, such as glandular patterns, vascular structures, or inflammatory regions. Quantum clustering algorithms can identify subpopulations of cells or tissue regions with distinct features, aiding in cancer grading and prognosis [195]. Quantum segmentation algorithms can improve the detection of subtle features, such as small nuclei or tissue anomalies, which are critical for cancer diagnosis but challenging for classical methods to resolve. Quantum models are applied to histopathological slides for segmenting regions of interest (see Figure 9), such as tumor boundaries or cancerous cells in breast biopsies, improving the diagnostic accuracy compared to traditional image analysis methods [302].

C. IMAGE RECONSTRUCTION

Medical image reconstruction aims for the transformation of raw or incomplete acquisition data into clinically interpretable images. High-quality reconstruction is essential for accurate diagnostics, reducing patient risk (e.g., radiation exposure), and improving operational efficiency in healthcare settings. Quantum machine learning (QML) offers a new dimension to image reconstruction by exploiting quantum parallelism, faster optimization in high-dimensional spaces, and improved handling of noisy/incomplete data, all critical challenges in medical imaging.

1) LOW-DOSE CT RECONSTRUCTION

Lowering radiation dose in CT scans reduces patient risk but introduces noise and artifacts, degrading the image quality. A quantum generator produces high-quality CT images from noisy, low-dose inputs, while a discriminator evaluates the realism. Quantum algorithms reconstruct full CT images from undersampled projections, leveraging quantum speedups in solving inverse problems. The main impact lies in reducing patient radiation exposure and faster scan acquisition without compromising diagnostic value. Quantum-enhanced artifact removal in lung CTs aids in earlier and safer detection of lung cancer nodules, with quantum iterative reconstruction (QIR), for low-dose, ultra-high-resolution (UHR) photon-counting detector CT (PCD-CT) of the lung (see Figure 10) [303].

2) THE HHL ALGORITHM FOR RECONSTRUCTION

A fundamental challenge in MRI and CT reconstruction is solving large systems of linear equations ($Ax = b$). The Harrow-Hassidim-Lloyd (HHL) Algorithm theoretically offers an exponential speedup ($O(\log N)$) over classical conjugate gradient methods ($O(N)$) for this task. In the context of medical imaging, b represents the measured k-space data, and x is the reconstructed image. While HHL is the theoretical "gold standard" for quantum linear algebra, its

TABLE 12. Limitations of quantum machine learning across medical imaging tasks.

Imaging Task	Key Limitations	Practical Implications
Image Classification	Limited qubit count; shallow circuit depth; encoding overhead	Restricts input resolution and class complexity
Image Segmentation	Difficulty encoding spatial context; lack of quantum pooling maturity	Patch-based analysis leads to loss of global structure
Image Reconstruction	High circuit depth for inverse problems; noise sensitivity	Limited applicability to full-resolution MRI/CT reconstruction
Multi-modal Imaging	Incompatible encoding schemes across modalities	Hinders fusion of MRI–PET, CT–US, etc.
Real-time Clinical Use	Latency in hybrid quantum–classical loops	Unsuitable for time-critical procedures at present, such as real-time intraoperative surgical planning and navigation.
Generalization	Simulation-heavy evaluation; limited hardware validation	Unclear real-world robustness and scalability

TABLE 13. Future research prospects for QML-based medical image analysis.

Research Direction	Description	Expected Impact
Hybrid Quantum–Classical Architectures	Deeper integration of classical feature extractors with quantum cores	Improved scalability on NISQ devices
Advanced Encoding Strategies	Task-specific, compressive, and learnable encodings	Reduced qubit requirements and better data fidelity
Quantum-enhanced Optimization	Use of QAOA/VQE for reconstruction and segmentation	Faster convergence in inverse imaging problems
Noise-aware QML Models	Incorporation of hardware noise models during training	Increased robustness on real quantum hardware
Multi-modal Quantum Learning	Unified frameworks for MRI–PET–CT fusion	Enhanced diagnostic and prognostic accuracy
Explainable QML	Development of interpretability tools for quantum models	Increased clinical trust and regulatory acceptance
Quantum Federated Learning	Privacy-preserving distributed quantum learning	Secure collaboration across healthcare institutions

practical application is currently limited by the requirement for deep circuits and the difficulty of loading the vector b (the medical image data) into the quantum state efficiently (the "input problem").

3) ACCELERATED MRI RECONSTRUCTION

MRI is slow because it sequentially samples k-space (frequency domain). Faster scans are needed, especially in pediatric imaging or during cardiac monitoring. Using quantum autoencoders, compress the k-space data into lower-dimensional quantum representations and reconstruct full images with minimal information loss. Also, quantum-enhanced parallel imaging, multiple slices are reconstructed simultaneously via quantum entanglement-based multi-view learning. The real impact of this is that MRI scan times can be reduced by more than 50%, the patient's comfort is increased, and motion artifacts are minimized. Quantum model-based reconstruction of brain MRI enables real-time imaging during surgical interventions (see Figure 11) [304].

To provide a consolidated view of the challenges and opportunities discussed above, Tables 12 and 13 summarize the key limitations of current QML approaches in medical imaging and outline promising future research directions.

V. ARCHITECTURAL INNOVATIONS IN QML FOR IMAGING

QML for medical imaging necessitates unique architectural innovations to fully leverage the advantages of quantum computing while addressing the high-dimensional, complex nature of medical images. Here, we detailed the cutting-edge frameworks and algorithms designed to bridge quantum theory with practical imaging tasks.

A. QUANTUM NEURAL NETWORKS (QNNs) IN PRACTICE

QNNs represent a pioneering stride in the intersection of quantum computing and machine learning. As an analog to classical neural networks (CNNs, MLPs, RNNs, etc.), QNNs operate on quantum data structures and utilize quantum mechanical principles like superposition, entanglement, and interference to process and learn from data. In medical imaging, where data dimensionality is high, variability is significant, and precision is paramount, QNNs offer new opportunities to improve diagnostic accuracy, optimize data usage, and introduce scalable, intelligent systems.

QNNs are typically built upon Parameterized Quantum Circuits (PQCs), where learnable parameters control the quantum gates applied to qubits. These parameters are adjusted using classical optimization algorithms (e.g., gradient descent), making most QNNs part of a hybrid quantum-classical paradigm.

- **Quantum States and Qubits**: QNNs encode inputs as quantum states, where each qubit can represent multiple values simultaneously due to superposition.
- **Quantum Gates**: Rotational and entangling gates such as RX, RY, RZ, CNOT, and CZ form the building blocks of the network.
- **Circuit Depth and Width**: QNNs are defined by how many layers of quantum gates they contain (depth) and the number of qubits used (width), which affect expressivity, noise sensitivity, and the complexity of clinical interpretability.

In medical imaging, the architecture of QNNs must be customized to manage input complexity and ensure meaningful output for clinical interpretation.

1) BASIC FEEDFORWARD QNNs

These networks mimic dense classical neural networks, using quantum circuits to evolve an initial quantum state to a final state from which predictions are made via measurement. While the architecture of these networks was originally validated on generic datasets (e.g., MNIST or CIFAR) in the broader machine learning literature, their adaptation to medical imaging involves specific modifications to handle the high heterogeneity and noise profiles of biological data. A good example of this is a classification of 2D MRI slices as indicative of Alzheimer's or normal aging. This workflow starts with downsampling the image to a 1D vector, encoding it as a quantum state, processing it through layers of PQCs, measuring expectation values, and mapping it to a probability.

2) QUANTUM PERCEPTRON MODELS

Inspired by the McCulloch-Pitts model, the quantum perceptron applies unitary operators as activation functions in trainable PQC. This could be used in the classification of histopathological images into cancer subtypes, and quantum perceptrons can perform non-linear transformations inherently due to quantum state evolution.

3) QUANTUM GRAPH NEURAL NETWORKS

These are more advanced QNN variants that integrate graph representations, particularly useful in representing anatomical connectivity or tissue relationships. The best application could be brain connectivity analysis using fMRI data, with brain regions as nodes and functional links as edges.

Unlike classical neural networks, QNNs face unique challenges during training:

- The barren plateaus problems, where gradients can vanish exponentially with increasing qubit count or circuit depth, making the optimization difficult.
- Classical optimizers like COBYLA, SPSA, and Adam are commonly used with gradient-free or gradient-based updates.
- Cross-entropy and mean squared error are adapted to quantum outputs derived from measurement statistics.

a: THE HIDDEN COST OF PREPROCESSING

A methodological detail often omitted in the summary of QNN performance is the heavy reliance on classical preprocessing. Since current NISQ devices typically support fewer than 100 qubits, a standard 256×256 medical image (65,536 pixels) cannot be directly encoded. Consequently, studies achieving high accuracy (as seen in Tables 6-7) almost universally employ aggressive classical dimensionality reduction (e.g., PCA, LDA, or Autoencoders) to compress the image into a feature vector of size $N \leq 20$. This raises a critical interpretability issue: it is often unclear whether the high classification accuracy stems from the quantum circuit's entanglement capabilities or the feature extraction efficacy of the classical pre-processor.

Given the NISQ hardware limitations, noise-aware training is often employed here to simulate noise in the training pipeline, and hardware-specific noise profiles are also used to ensure robustness.

B. HYBRID QUANTUM-CLASSICAL PIPELINES FOR IMAGE TASKS

In the NISQ era, obtaining a fully quantum solution is impossible due to hardware constraints, including qubit limits, decoherence, and gate errors. To tackle this, Hybrid Quantum-Classical (HQC) architectures were developed as a practical middle ground, i.e., leveraging the best of classical approaches towards data preprocessing and optimization with the computational power of quantum models for feature extraction and learning. Several optimization techniques utilized in these hybrid pipelines, such as the Quantum Approximate Optimization Algorithm (QAOA), were initially developed for combinatorial problems in operations research and material science. In the context of this review, we focus strictly on their adaptation for medical tasks, such as optimizing the inverse problems in CT reconstruction or minimizing energy functions in image segmentation.

Hybrid pipelines are not a workaround: they are an innovation leveraging the synergistic combinatorics of the two paradigms. In medical imaging, we have succeeded in classification, segmentation, and reconstruction with these systems on MRI, CT, and histopathology modalities. The typical HQC pipeline for medical image analysis consists of three primary stages: classical processing layer, quantum layer, and classical postprocessing layer. The hybrid quantum-classical pipeline for medical image analysis leverages the complementary strengths of classical image preprocessing and quantum-enhanced learning capabilities. Initially, a raw medical image $I \in \mathbb{R}^{H \times W \times C}$ is converted into grayscale to reduce computational complexity and then resized and flattened into a vector $\mathbf{x} \in \mathbb{R}^n$. This vector undergoes normalisation to fit within a standardised input range, critical for quantum state encoding.

In the quantum state preparation phase, each element x_i of the input vector is encoded into a single qubit using *amplitude encoding*. Specifically, each qubit is initialized in the state $|\psi_i\rangle = \cos(\pi x_i)\,|0\rangle + \sin(\pi x_i)\,|1\rangle$, enabling the quantum system to represent the entire classical data vector in a highly compact form. These qubits are tensor-producted to form the global quantum state $|\Psi\rangle = \bigotimes_{i=1}^{n} |\psi_i\rangle$.

1) DOMAINS OF HYBRID SUPERIORITY

It is crucial to contextualize the performance of hybrid models. They do not universally outperform classical deep learning in standard, data-abundant tasks. Rather, literature indicates their specific superiority lies in (1) Data-Scarce Regimes: Hybrid models, particularly those using Variational Quantum Circuits (VQCs), have demonstrated higher validation accuracy than classical counterparts on small datasets (e.g., $<$ 500 samples) due to the superior expressivity and regularization properties of quantum circuits, making them

TABLE 14. Advantages of hybrid quantum-classical pipelines in medical image analysis.

Advantage Category	Specific Benefit	Explanation	Impact on Medical Imaging	Example Use Case
Computational Efficiency	Reduced Parameter Count	Quantum circuits require fewer trainable parameters due to expressive state spaces.	Helps avoid overfitting in data-limited medical settings.	Tumor classification on small MRI datasets using QNN layers.
	Dimensionality Reduction	Embedding in high-dimensional Hilbert space with minimal input overhead.	Enables better separation of complex patterns.	Quantum-enhanced texture feature extraction in dermoscopy.
Data Efficiency	Better Generalization	Quantum models generalize with fewer samples due to richer embeddings.	Crucial for rare disease or small cohort datasets.	Cancer subtype detection in histopathology with <1000 samples.
	Quantum Regularization	Quantum noise acts as implicit regularization.	Improves model robustness in real-world noisy environments.	Chest X-ray classification under noise and occlusion.
Integration Feasibility	Compatibility with Classical Preprocessing	Supports traditional steps like denoising, segmentation, or feature scaling.	Smooth integration into existing clinical pipelines.	CT preprocessing with classical methods followed by quantum anomaly detection.
	Hardware-Aware Deployment	Classical components on local devices, quantum parts on cloud or QPU.	Enables hybrid execution and future scalability.	Ultrasound preprocessing at edge and QNN inference on cloud.
Performance Enhancement	Improved Accuracy and Sensitivity	Quantum entanglement and interference uncover hidden correlations.	Useful for detecting subtle anomalies like microcalcifications.	Hybrid CNN-QNN improves AUC in mammogram classification.
	Reduced Inference Time (with QPUs)	Parallelism of quantum processing can reduce runtime.	Important for real-time diagnostics and surgical decisions.	Live brain scan analysis during neurosurgery planning.
Interpretability and Explainability	Quantum Kernel Mapping Visualization	Alternate perspectives of data separability via quantum embeddings.	Enhances trust and interpretability for clinical users.	Saliency maps for MRI tumor detection using QML.
	Layerwise Contribution Analysis	Hybrid architecture allows tracking of classical vs quantum contributions.	Useful for audits and regulatory approval processes.	Traceable decision explanation in diagnostic tools.
Scalability and Modularity	Layer-Level Flexibility	Quantum layers can be modularly inserted in architectures.	Adapts to segmentation, classification, and reconstruction tasks.	U-Net with quantum bottleneck for CT segmentation.
	Interoperability with Frameworks	Supported by platforms like Qiskit, PennyLane, TensorFlow Quantum.	Accelerates development and deployment.	Training hybrid QNNs using PyTorch + PennyLane.
Resilience and Robustness	Partial Noise Isolation	Limiting quantum operations to critical layers controls error propagation.	Increases model reliability in clinical settings.	Resilient inference on noisy PET scans.
	Task-Specific Quantum Involvement	Quantum can be toggled on/off depending on runtime or task needs.	Enhances operational flexibility.	QNN deactivation fallback in emergency diagnosis.

ideal for rare pathology classification. (2) Complex Kernel Evaluation: In tasks involving highly non-linear feature correlations (e.g., texture analysis in histopathology), hybrid models utilizing Quantum Kernels (QSVM) can identify decision boundaries that are computationally expensive or intractable for classical kernel methods.

The encoded quantum state is then passed through multiple layers of a *Variational Quantum Circuit (VQC)*. Each layer applies parameterized single-qubit rotation gates (e.g., $R_y(\theta_i)$) to introduce trainable parameters and two-qubit CNOT gates to entangle the qubits, thereby capturing complex correlations among features. The VQC's expressiveness is governed by the number of layers L and the parameterization depth, allowing the model to approximate complex decision boundaries.

After the quantum operations, qubit measurement is performed in the computational basis (Z-basis), and the expectation values $\langle\Psi|Z_i|\Psi\rangle$ are extracted. These measurement results form a vector $\mathbf{z} \in \mathbb{R}^n$, which acts as the bridge between the quantum and classical components of the pipeline.

In the classical postprocessing stage, the vector $\mathbf{z}$ is fed into a classical neural network composed of dense layers. A non-linear activation function σ, typically ReLU or tanh, is applied to introduce non-linearity, followed by a softmax layer that produces the final prediction $\hat{y}$. The entire pipeline is trained end-to-end using a hybrid optimization strategy, where classical optimizers such as Adam or RMSprop are used to update both the classical weights and quantum circuit parameters via a parameter-shift rule or gradient estimation techniques. To elaborate on the training mechanics, unlike classical layers where gradients are computed via standard backpropagation (differentiation), quantum circuit parameters are typically optimized using the Parameter-Shift Rule. This technique estimates the gradient of a quantum function with respect to its parameters by evaluating the circuit at two shifted configurations (typically $\theta + s$ and $\theta - s$). This provides an unbiased estimator of the gradient, allowing classical optimizers (like Adam) to update the quantum gates iteratively, effectively integrating the quantum circuit into the differentiable learning pipeline.

This architecture exemplifies a symbiotic integration where classical computation performs memory-efficient and well-understood tasks (like preprocessing and dense classification). In contrast, quantum computation focuses on encoding and learning rich, classically intractable feature representations. The design aligns to leverage *quantum advantage* in domains like medical imaging, where high-dimensional, noisy, and sensitive data can benefit from quantum-enhanced representations and processing.

The dominance of Hybrid Quantum-Classical (HQC) architectures is a direct consequence of NISQ limitations. Because current quantum processors cannot handle the sheer volume of data in a standard CT or MRI scan, the "heavy lifting" of feature extraction from high-resolution inputs must remain classical. The quantum component is restricted to processing highly compressed latent vectors (bottleneck features) where its superior representational power in high-dimensional Hilbert spaces can be leveraged without exceeding coherence limits.

To systematically understand the practical implications of hybrid quantum-classical frameworks in medical image analysis, we summarized the key advantages across multiple dimensions—from computational efficiency and data generalization to interpretability and system modularity. Table 14 outlines these benefits in detail, mapping each to its specific technical contribution, medical relevance, and real-world application scenarios. This tabular representation is a comprehensive reference for researchers aiming to design robust and clinically viable hybrid QML systems.

C. BENCHMARKING QUANTUM vs. CLASSICAL APPROACHES

Benchmarking quantum machine learning architectures against classical machine learning (CML) models is essential to assess the practicality, competitiveness, and scalability of QML for medical image analysis. With the novelty of QML and the rapid advancements in quantum hardware and software, a thorough comparison across multiple dimensions is necessary to understand where QML currently stands and where it holds future promise.

Benchmarking mainly aims to evaluate performance parity or advantage between QML and CML models. This identifies scenarios (e.g., small datasets, high-dimensional data) where QML may offer superiority. This helps understand the limitations in current quantum systems (hardware/software) and aids reproducibility and clinical translation by establishing standardized testbeds. The comparison between QML and classical models typically involves multi-criteria evaluation as shown in Table 15. For fair benchmarking, the selection of medical imaging datasets is essential. Using publicly available, widely accepted datasets (e.g., BraTS for brain tumors, ChestX-ray14, ISIC skin lesion datasets) is crucial in standardizing the methodology. For the size and resolution, datasets are often resized and downsampled to match quantum hardware limitations (e.g., using 4×4 or 8×8 patches). The intensity of the images is usually scaled to [0,1] or standardized for quantum amplitude encoding.

a: METHODOLOGICAL QUALITY AND STATISTICAL SIGNIFICANCE

A critical meta-analysis of the works summarized in Tables 6 and 7 reveals recurring methodological gaps. Many studies prioritize reporting "top-line" accuracy improvements (often margins of $< 2\%$) without reporting statistical significance (e.g., p-values) or confidence intervals. Given the stochastic nature of quantum measurement (shot noise) and the small size of quantum-ready datasets, there is a substantial risk that some reported gains are artifacts of overfitting or specific initializations rather than fundamental algorithmic superiority. Future benchmarking requires rigorous "fair" comparisons where classical baselines are restricted to comparable parameter counts to isolate the true quantum advantage.

b: CRITICAL ASSESSMENT OF CURRENT EVIDENCE

While the results summarized in Tables 6 and 7 indicate competitive performance—often exceeding 95% accuracy—a critical examination of the evidence reveals significant caveats. The majority of reviewed studies utilize relatively small, curated datasets (e.g., subsets of MNIST or downsampled MRI slices) to accommodate the limited qubit capacity of NISQ devices. Consequently, the reported "quantum advantage" often reflects the model's ability to overfit or generalize well in low-data regimes, rather than a superiority over state-of-the-art classical models trained on full-scale clinical datasets. Furthermore, true evidence-based comparisons are frequently absent; many studies compare QML models against basic classical CNNs rather than optimized architectures like ResNet-50 or Vision Transformers. Therefore, the current evidence base supports QML as a promising capability for data-efficient learning, but does not yet provide robust evidence of clinical superiority in standard, high-volume diagnostic workflows. A closer examination of the cited literature reveals significant disparities in experimental design.

Crucially, regarding the experimental verification of 'quantum advantage,' it must be stated that no study has yet demonstrated a definitive computational speedup or accuracy superiority of QML over state-of-the-art classical models on full-resolution medical imaging data using physical NISQ devices. Current 'advantages' are observed primarily in: (1) Data Efficiency, where quantum models generalize better from small datasets (as seen in Table 14), and (2) Hybrid Simulations, where quantum layers are simulated on classical hardware. The noise profile and limited connectivity of actual NISQ processors (as discussed in Section VI-A) currently prevent the experimental realization of theoretical quantum speedups (e.g., Grover's search or HHL) for standard medical imaging tasks.

- **Resolution and Data Size:** While studies frequently cite standard datasets (e.g., BraTS, CheXpert), the actual implementation often involves drastic downsampling (e.g., resizing 256×256 images to 32×32 or 64×64) to accommodate the limited number of qubits (typically < 20) available on NISQ simulators. This loss of resolution discards fine-grained texture details critical for tasks like micro-calcification detection, raising questions about clinical transferability.
- **Statistical Significance:** A major gap identified across the surveyed literature is the lack of rigorous statistical testing. Most QML studies report mean accuracy improvements without providing confidence intervals, p-values, or conducting hypothesis testing (e.g., t-tests) against classical baselines. Given the stochastic nature of quantum measurements (shot noise), this omission makes it difficult to ascertain whether reported marginal

TABLE 15. Detailed benchmarking parameters: core dimensions for QML vs. Classical ML in medical imaging.

Parameter	Classical ML (CML) Perspective	Quantum ML (QML) Perspective	Relevance in Medical Imaging
Accuracy	Uses standard metrics like precision, recall, F1-score, AUC-ROC; dependent on data size and features	Competitive on small datasets; limited scalability with large data due to qubit constraints	Reliability in diagnosis, though currently inflated in QML literature due to the use of simplified, balanced datasets; requires validation on clinically realistic, imbalanced data.
Data Efficiency	Needs large annotated datasets; performance drops on small or imbalanced data	Learns from fewer samples via superposition and entanglement-based patterns	Vital for rare diseases and expensive annotation scenarios
Model Complexity	Deep models with millions of parameters; risk of overfitting	Shallow quantum circuits with expressive quantum gate structures	Affects deployability and explainability in medical systems
Generalization	Requires augmentation, regularization, or transfer learning	May generalize better in low dimensions; limited by encoding scalability	Key to cross-modality or multi-hospital applicability
Computational Cost	GPU/TPU accelerated; energy-intensive for large networks	Smaller memory footprint; slower on simulators, potential for parallelism on QPUs	Important for edge devices or emergency settings
Training Convergence	Stable with SGD, Adam, and hyperparameter tuning	Uses parameter-shift rules; faces issues like barren plateaus	Impacts model readiness in clinical pipelines
Noise Robustness	Susceptible to corruption/adversarial attacks; mitigated via denoising	Sensitive to gate noise and decoherence; needs error mitigation	Essential under noisy or low-contrast clinical image acquisition
Scalability	Easily scaled with data parallelism and cloud training	Limited by circuit depth, qubit count, and noise resilience	Required for 3D imaging and full-resolution diagnostics
Interpretability	Achievable via Grad-CAM, SHAP, attention layers	Nascent field; efforts with Bloch vector visualizations, quantum gradients	Crucial for clinician trust and regulatory approval
Hardware Dependency	Mature classical infrastructure (CPUs/GPUs/TPUs) available	Dependent on QPUs or simulators (e.g., IBM Q, IonQ); varied performance	Determines institutional readiness for QML adoption
Memory Requirements	High memory demand for large images; managed by batching/dimensionality reduction	Compact quantum encoding but limited by current qubit capacities	Relevant for mobile/edge medical imaging systems
Latency (Inference Time)	Optimized engines yield low latency inference	Currently higher on simulators; QPUs expected to reduce this in future	Important for real-time use cases (e.g., surgery support)

TABLE 16. Detailed performance metrics for quantum and classical medical image analysis.

Metric	Formula / Definition	Significance in Medical Imaging	Applicable Task(s)
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$	Measures overall correctness of predictions. Effective for balanced datasets.	Classification
Precision (Positive Predictive Value)	$\frac{TP}{TP+FP}$	Ensures fewer false positives; vital for conditions with costly false alarms.	Classification
Recall (Sensitivity / TPR)	$\frac{TP}{TP+FN}$	Critical for identifying actual diseased cases. High recall reduces false negatives.	Classification
Specificity (TNR)	$\frac{TN}{TN+FP}$	Useful for ruling out healthy cases and balancing sensitivity.	Classification
F1-Score	$2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision}+\text{Recall}}$	Balances precision and recall; ideal for imbalanced datasets.	Classification
AUC-ROC	Area under ROC curve (TPR vs FPR)	Evaluates class separation ability and robustness to imbalance.	Classification
Confusion Matrix	Tabulation of TP, FP, TN, FN	Offers granular performance analysis across all prediction outcomes.	Classification
Dice Coefficient	$\frac{2 \cdot \lvert A \cap B \rvert}{\lvert A \rvert + \lvert B \rvert}$	Measures spatial overlap; key for segmentation tasks like tumor mapping.	Segmentation
IoU (Jaccard Index)	$\frac{\lvert A \cap B \rvert}{\lvert A \cup B \rvert}$	Evaluates overlap accuracy; slightly more penalizing than Dice.	Segmentation
Hausdorff Distance	$\max_{a \in A} \min_{b \in B} \lVert a - b \rVert$	Assesses worst-case boundary error; crucial for surgical planning.	Segmentation
Mean Absolute Error (MAE)	$\frac{1}{n} \sum \lvert y_i - \hat{y}_i \rvert$	Measures average prediction error; easy to interpret.	Regression, Reconstruction
Mean Squared Error (MSE)	$\frac{1}{n} \sum (y_i - \hat{y}_i)^2$	Penalizes large errors more than MAE. Suitable for enhancing image quality.	Regression
Root Mean Squared Error (RMSE)	$\sqrt{\text{MSE}}$	Same unit as target variable; interpretable for physical predictions.	Regression
R^2 Score (Coefficient of Determination)	$1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$	Reflects variance explained by model; assesses prediction accuracy.	Regression
Training Time	Time until convergence	Essential for evaluating real-time training feasibility and hardware load.	Efficiency
Inference Time	Time per prediction	Vital for real-time applications (e.g., intraoperative diagnosis).	Efficiency
Memory Footprint	RAM/VRAM used during inference/training	Evaluates deployability in edge or constrained environments.	Efficiency

gains are statistically significant or artifacts of specific initializations.

Consequently, the final decision on the accuracy factor and clinical reliability of a trained network is not based on a single scalar value. Instead, it is determined through a multi-dimensional evaluation using the metrics detailed in Table 16, where task-specific indicators (e.g., Sensitivity for disease detection or Dice Coefficient for tumor segmentation) are prioritized over raw accuracy to account for class imbalances typical in medical datasets.

A comprehensive set of performance metrics must be employed to systematically evaluate the efficacy of quantum machine learning (QML) models compared to classical machine learning (CML) approaches in medical image analysis. These metrics span classification (e.g., accuracy, precision, recall, F1-score, AUC-ROC), segmentation (e.g., Dice coefficient, IoU, Hausdorff distance), and regression (e.g., MAE, MSE, RMSE, R^2 score), along with hardware-aware efficiency indicators such as training time, inference time, memory footprint, and model-specific complexity measures like circuit depth for QML and FLOPs for CML. Moreover, QML-specific considerations such as noise resilience are increasingly relevant in the Noisy Intermediate-Scale Quantum (NISQ) era. Table 16 presents a detailed summary of these metrics, highlighting their mathematical formulations, significance in clinical imaging contexts, and applicable task domains. This unified benchmark provides a robust foundation for fair and meaningful comparison between classical and quantum paradigms in the medical imaging pipeline.

D. END-TO-END QUANTUM IMAGING PIPELINES: A VISION FOR THE FUTURE

As quantum computing technology continues to mature, a compelling frontier lies in building fully quantum imaging pipelines - systems where the entire process, from data ingestion to decision-making, is handled natively or predominantly on quantum hardware. End-to-end quantum pipelines are envisioned as holistic, quantum-native systems where each stage of a typical image analysis task - preprocessing, feature extraction, representation, classification, and decision support - is performed using quantum algorithms or quantum-enhanced modules. This vision mirrors end-to-end deep learning models in classical AI but replaces conventional layers and operations with quantum analogs, which creates a seamless flow of quantum data transformation without reverting to classical intermediaries at every step.

To counteract the multiple challenges mentioned above (in particular, quantum data encoding bottlenecks, NISQ scalability, cross-modal interpretability, and the clinical trust gap), a full-stack, end-to-end QML pipeline could be helpful in medical imaging and surgical decision support. In a hybrid classical-quantum setting, the algorithm will unify quantum native methods across all stages of the imaging pipeline from data ingestion, intermediate representation, quantum computing, to post hoc interpretability, while also keeping hybrid classical-quantum compatibility to current hardware constraints.

Preprocessing with Quantum Noise Signature Fingerprinting (QNSF) and Variational Quantum Normalization (VQN) is made to be resistant to data sparsity and noise, which may be spurred by qubit decoherence and fluctuations in medical data. To address the challenge of data encoding, Q-HealthNet proposes multi-level entanglement schemes, and specifically HYPER, encoding patient metadata relating to ancillary qubit and co-evolving with the imaging state to facilitate quantum-aware diagnostics. Scalabilities and resource eficiency can be achieved by the use of quantum residual blocks and multi-scale entanglement pooling with the number of gates and layers becoming significantly less compared to regular quantum CNNs. In contrast to the existing approaches, which differentiate between post-diagnosis and treatment planning processes, Q-HealthNet will merge these two functions by reinforcing a learning policy using quantum-generated 3D anatomical meshes, therefore, producing a holistic quantum clinical decision-making process. Besides, the model adds a Quantum Clinical Knowledge Graph Embedding (QCKGE) block to overcome the limitations of explainability and domain integration of existing QML frameworks. This allows statistically optimal and semantically congruent inferences. Lastly, the quantum entropy heatmaps and fidelity backtracking fill in the interpretability picture, making the results that reach the clinicians traceable and explainable based on quantum statistical physics.

1) ADVANTAGES OF FULL QUANTUM PIPELINES

Full quantum pipelines in medicine image analysis offer a revolutionary change in the image analysis paradigm as they offer many advantages in computational, clinical, and infrastructural domains. The key principle encompassing these benefits is quantum superposition, which allows quantum bits (qubits) to be in multiple states simultaneously, thus enabling exponential parallelism. By performing a quantum operation on a vast permutations of image data at once, quantum systems can significantly speed up tasks such as 3D MRI segmentation or multiscale image analysis. In addition, quantum entanglement allows for encoding richer inter-feature dependencies, which capture more complex diatomic relationships in medical images, critical for distinguishing very subtle distinctions between, for example, benign and malignant tumors. Moreover, quantum circuits are usually much more expressive — hence they use a lower complexity model — and are often orders of magnitude smaller than their classical deep learning counterparts, making them natural candidates for truly decentralized environments, such as those featuring edge computing and few hardware resources.

In addition, in fields that involve acquiring labeled datasets, quantum models also provide superior performance in low-data regimes, which is a highly valuable asset. Because they can generalize well with very little data, they are especially useful for detecting rare diseases or for groups not well represented in the data. However, quantum computing also excels in such tasks in solving optimization problems using algorithms such as Quantum Approximate Optimization Algorithm (QAOA) or Grover's algorithm, with which the convergence is faster and the optima are better than classical. In addition, quantum pipelines naturally provide the highest data privacy and security level. For example, techniques like quantum key distribution (QKD) and the no-cloning theorem ensure that sensitive medical images and patient data remain secure when transmitted and processed, which is critical for satisfying regulations like HIPAA and GDPR.

With quantum sensors set to enter imaging technologies from quantum-enhanced MRI or magnetoencephalography, a fully quantum native pipeline avoids adding latency and error from classical conversions taken in traditional HPC pipelines. As a result, this yields more accurate and real-time image analysis, which is especially important when working under a surgical procedure or during emergency diagnostics. The minimal circuit depth and parallel nature of operations in quantum inference allow for ultra-low latency decision making, which is essential for its use in fast, time-sensitive medical environments such as trauma centers or operating rooms. Meanwhile, while quantum AI is in its infancy in generating explainability, early tools that use quantum observables, fidelity metrics, and entanglement mapping are starting to shed light on the decision-making process. However, these progressions support compliance with clinical AI regs that require transparency and clinician trust.

Quantum pipelines are finally scalable for the long term. Quantum medical imaging solutions will grow financially viable as hardware technologies improve and become more affordable through cloud-based quantum platforms (IBM Q, IonQ, Xanadu, etc.). Full quantum pipelines are addressing current bottlenecks in computation and accuracy, ensuring future proofing of healthcare systems by ensuring alignment with the changing landscape of quantum computing. All these facets of these full quantum pipelines as a transformative force for precision medicine provide broad, dynamic advantages for full quantum pipelines, creating diagnostic power, security, and real-time decision support beyond the limits that classical systems can achieve.

VI. CURRENT LIMITATIONS AND CHALLENGES

Although Quantum Machine Learning (QML) is facing promising to revolutionize medical image analysis, the field is still in its infancy. There are several significant hurdles to applying it in the real world. They include challenges on hardware, algorithmic, data bottlenecks, and clinical integration. These obstacles must be addressed to transition QML from experimental setups to robust clinical tools.

A. QUANTUM HARDWARE CONSTRAINTS

Current quantum hardware falls under the Noisy Intermediate-Scale Quantum (NISQ) category, which imposes severe constraints on medical image analysis:

- **Qubit Count & Connectivity:** Modern processors typically offer 50-100 physical qubits, which is insufficient for representing high-resolution medical images (e.g., a 256×256 X-ray) without aggressive downsampling (e.g., to 32×32), resulting in significant information loss.
- **Coherence Times & Circuit Depth:** The short coherence times of superconducting qubits limit the number of sequential gate operations (circuit depth) that can be performed before the quantum state collapses due to decoherence. This prevents the deployment of deep quantum neural networks required for capturing complex anatomical features.
- **Shot Noise & Measurement:** Extracting a probability distribution from a quantum circuit requires repeated execution (shots). In medical imaging applications requiring high precision, the number of shots needed to overcome statistical noise can introduce latency that rivals or exceeds classical inference times.

B. NOISE AND ERROR CORRECTION IN QUANTUM CIRCUITS

As quantum systems are inherently fragile, any property that can be quantified tends to suffer from some form of decoherence, gate errors, and measurement inaccuracies. This is a serious issue in the medical domain where diagnostic precision and repeatability are critical. From the point of view of QEC, noise resilience would, in principle, be enabled by QEC, at the expense of substantial overhead in qubits. Although it is typically infeasible with current hardware, executing a single logical qubit through QEC often requires thousands of physical qubits. The lack of fault tolerance to QML output introduces a lack of reliability of QML outputs, thereby limiting the development of reliable models for tasks such as tumor classification or surgical planning, where even insignificant misclassification can have severe implications. In diagnostic settings, a wrong prediction can be reviewed; however, in real-time surgical planning or intraoperative navigation, reliability is non-negotiable. A lack of fault tolerance—where a single qubit error could distort a 3D tumor reconstruction—introduces unacceptable patient risk. Unlike classical systems where errors are often systematic, quantum errors can be stochastic and bursty. Therefore, concrete deployment strategies must include "Hybrid Assurance Layers," where a classical shadow model runs in parallel to validate quantum outputs in real-time, instantly overriding the quantum system if the deviation exceeds a safety threshold.

C. DATA ENCODING AND DIMENSIONALITY BOTTLENECKS

A significant challenge is efficiently encoding classical medical images into quantum states. Typical encoding schemes, for example, amplitude encoding or angle encoding, become more and more inefficient for increasing dimensionality of the input. For instance, a typical 512×512 grayscale medical image would be only 18 qubits to represent the image vector (forgetting the number of qubits for computation). It results in an exponential time increase and circuit complexity. In addition, the compression techniques that are common to reduce the input size tend to remove relevant spatial and context information necessary for differentiating subtle anomalies such as microcalcifications or early-stage lesions. QML suffers from the inability to capture and process full-resolution clinical data. This limits QML's effectiveness and restricts insight to only a small spectrum of medical problems. Future benchmarking efforts should prioritize direct experimental comparisons of these encoding strategies on identical medical datasets to quantify the precise trade-off between the information loss of Angle Encoding versus the noise susceptibility of Amplitude Encoding.

D. LIMITED BENCHMARKING AND STANDARDIZATION

Unfortunately, standardizing benchmarks for QML-based medical imaging is a significant barrier to progress. It is often the case that we perform comparisons between classical and quantum models under different conditions (e.g., with other datasets, various performance metrics, different preprocessing techniques, or with varying pipelines of evaluation) that make it difficult to establish whether there has been a quantum advantage. Furthermore, many studies take advantage of hybrid quantum-classical models, and the observed performance gains may primarily come from the classical component. It is difficult to assess whether quantum models outperform their classical counterparts or whether they are influenced by artifacts of the experiments or overfitting to the simulations.

Consequently, the field currently suffers from a ''reproducibility crisis'' where reported metrics cannot be easily validated against classical benchmarks, limiting the strength of the evidence base for clinical adoption.

E. SCALABILITY AND GENERALIZATION

Most current QML applications in medical imaging have been tested using limited, well-curated datasets. Still, these datasets do not represent the variability and complexity of the real-world clinical environment. The lack of diversity impairs the QML's generalization ability, which makes them prone to a decline in performance when the model is exposed to data from other patient populations, image devices, or institutions. Furthermore, scalability is an issue because quantum models trained on small-scale data may not generalize well to large, ubiquitous, multi-institutional datasets in healthcare. In this sense, the practical applicability of QML in the real world is uncertain without having comprehensive validation in different clinical contexts.

F. INTEGRATION WITH CLINICAL WORKFLOW AND STANDARDS

The transition of QML from lab to bedside faces the ''last mile'' problem of interoperability. Modern radiology workflows rely heavily on the DICOM standard and Picture Archiving and Communication Systems (PACS). Currently, no standardized protocol exists for ''Quantum-PACS'' integration, meaning QML models cannot yet ingest live hospital data streams or push results back to radiologist workstations without custom, fragile middleware. Furthermore, from a regulatory perspective, QML models fall under the ''Software as a Medical Device'' (SaMD) category. Regulatory bodies like the FDA and EMA require deterministic outputs for approval. The inherent probabilistic nature of quantum measurement (where the same input may yield slightly different outputs due to shot noise) poses a unique certification challenge, necessitating the development of strict ''variance bounds'' and ''deterministic fallback'' protocols before clinical certification is possible.

G. LACK OF QUANTUM-AWARE MEDICAL DATASETS

Furthermore, quantum-ready medical imaging datasets are missing, preventing further development of QML systems. All these datasets, such as BraTS, LIDC-IDRI, and TCIA, are constructed for classical machine learning and have high-dimensional images with many samples. These datasets are not best suited for quantum experimentation, for which small, annotated, and pre-encoded datasets are needed to test on real or simulated quantum hardware. This gap between the data format and the quantum requirement delays empirical validation one more time and decreases the reproducibility across independent research groups. Thus, many QML studies are limited by theoretical demonstration or simulations, rather than real clinical use cases.

H. EXPERIMENTAL AND STATISTICAL RIGOR

Unlike mature classical deep learning research, the QML landscape currently lacks standardized experimental protocols. Many studies evaluate models on ''toy'' subsets of real clinical data (e.g., binary classification of selected clear cases) rather than the full, noisy, and class-imbalanced datasets typical of clinical practice. Consequently, while quantitative studies comparing QML and classical DL exist (refer to Tables 6 and 7), they often lack parity in experimental design. Specifically, QML models are frequently tested on downsampled versions of datasets (e.g., MNIST-like reductions of X-rays) while classical baselines are capable of processing the original high-resolution inputs. Future quantitative studies must enforce strict 'identical dataset' benchmarks where both quantum and classical models process the same information content to allow for a fair assessment of quantum advantage. Furthermore, the absence of ablation studies—specifically separating the gains from classical pre-processing (e.g., PCA) vs. the actual quantum circuit—remains a prevalent issue. Future work must prioritize ''fair'' comparisons where classical baselines are restricted to similar parameter counts or computational budgets to accurately gauge the quantum advantage.

VII. FUTURE DIRECTIONS AND OPPORTUNITIES

Since QML is evolving, we can explore new frontiers to move medicine toward precision diagnostics and personalized treatment planning. Although there are real challenges in the current limitations, further research and technological developments promise a bright future. To this end, we describe below some of the main future directions and possibilities (See Figure 12) that could push QML much farther towards becoming a clinical mainstay.

A. ADVANCEMENTS IN FAULT-TOLERANT QUANTUM COMPUTING

Realisation of fault-tolerant quantum computing is one of the most anticipated milestones in the quantum ecosystem. Stable and reliable quantum systems can benefit from developing quantum error correction codes like the surface, cat, or practical qubit architectures. When fault-tolerant systems become available, QML models can utilize high-dimensional medical data for better accuracy and consistency. This could unlock full-resolution radiological and histopathological

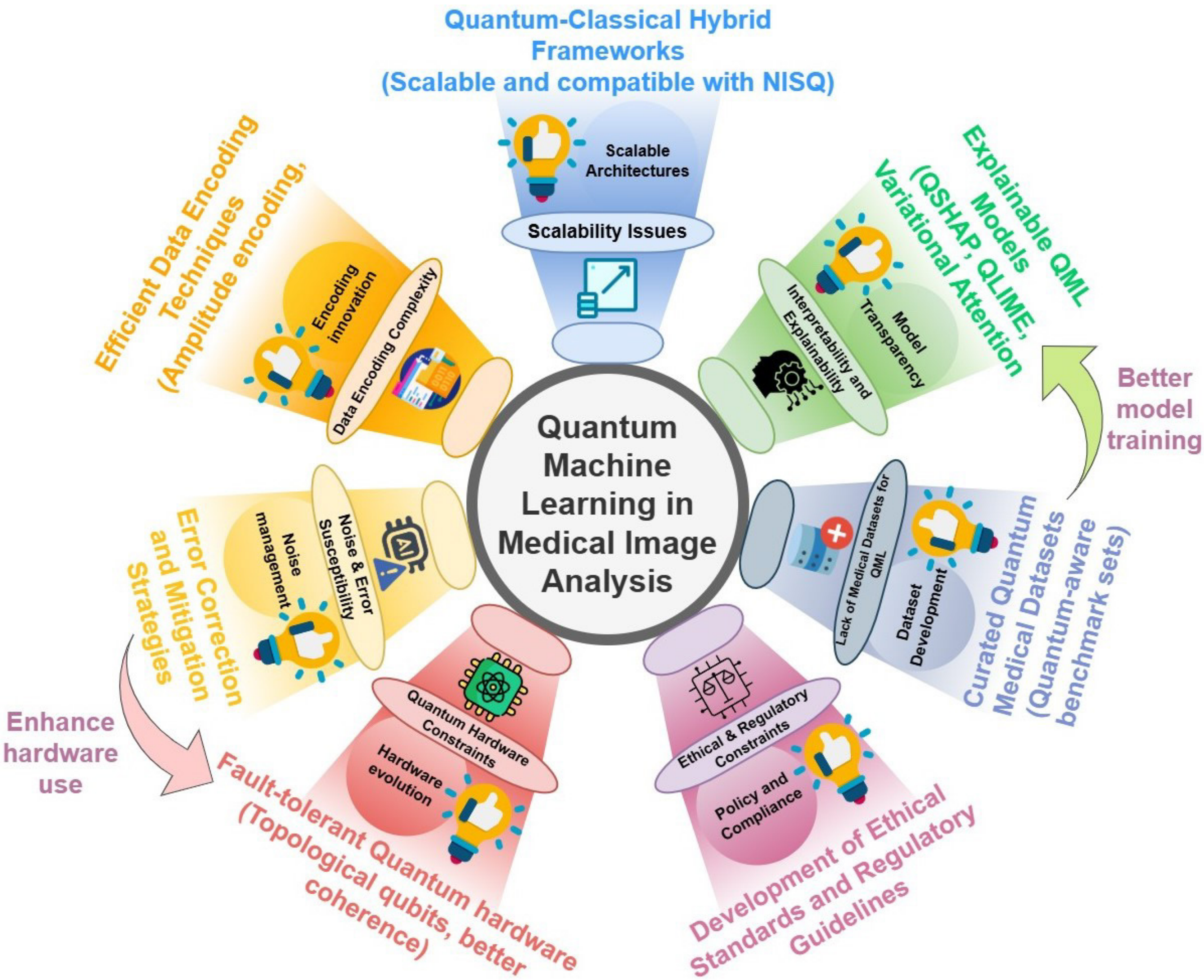


FIGURE 12. A conceptual infographic linking the current limitations and challenges of Quantum Machine Learning (QML) in medical image analysis with future directions and opportunities. Each node represents a core obstacle, such as hardware constraints, data encoding issues, and lack of interpretability, while the bulb icon illustrates an aligned solution or research avenue, including fault-tolerant quantum hardware, efficient data encoding methods, and explainable QML models. This depicts how advancements in specific areas can address existing challenges, while highlighting the interdependence among emerging solutions, reflecting a systemic approach toward the practical deployment of QML in healthcare.

images to use in QML, performing tasks such as multi-organ segmentation or multi-modality fusion at a clinical scale.

B. QUANTUM-INSPIRED ALGORITHMS FOR CLASSICAL HARDWARE

In the short term, quantum-inspired algorithms can utilize the benefits of quantum operations on conventional machines. Techniques such as tensor networks, quantum annealing emulation, and quantum kernel methods (i.e., quantum support vector machines) allow the approximation of quantum behaviour in a scalable way and within classical computing systems. Thus, these approaches can be applied to medical imaging problems, including anomaly detection, cancer classification, and prognosis modeling, to tap into some of the benefits of QML today, even without mature quantum infrastructure.

C. HYBRID QUANTUM-CLASSICAL ARCHITECTURES FOR REAL-WORLD APPLICATIONS

A promising way to undertake medical image analysis is by using hybrid models combining classical deep learning architectures with quantum circuits. Combining the strengths of the two paradigms is possible using these models: quantum subcircuits are utilized for feature extraction, while classical layers calculate decision making and optimization. For example, using convolutional neural networks, variational quantum circuits can be flexibly fine-tuned to perform tumor boundary segmentation or ischemic lesion detection tasks.

Thanks to the incremental nature of these hybrid systems, the smooth path from hybrid to full quantum implementation will accompany the increasing maturity of quantum hardware.

D. DEVELOPMENT OF QUANTUM-AWARE MEDICAL DATASETS

The immediate need is to engineer curated, quantum-ready medical datasets for QML experimentation. To address this, we propose the adoption of a Standardized Quantum-Medical Data Format (SQMDF). Such datasets must go beyond simple resizing; they should provide:

1) **Dual-Resolution Tiers:** Standardized inputs at 16×16, 32×32, and 64×64 pixels to benchmark models across varying qubit capacities (e.g., 8 to 12 qubits).
2) **Pre-Encoded State Vectors:** To eliminate preprocessing variability, datasets should include pre-calculated unitary rotation parameters (θ) for Angle Encoding and normalized amplitude vectors for Amplitude Encoding.
3) **Noise-Aware Annotations:** Metadata indicating the noise level or scanner type, allowing for the training of noise-resilient quantum circuits.

Establishing these standards will enable the direct comparison of QML architectures without the confounding variables of data preprocessing. Such repositories would create a means of reproducibility, facilitate benchmarking, and encourage everyone in the quantum health care field to work together at a faster pace.

E. INTERPRETABILITY AND EXPLAINABILITY IN QUANTUM MODELS

QML systems must be explainable and interpretable to be accepted in clinical environments. However, future work should be directed toward developing means of visualizing quantum decision boundaries, tracing model inferences, and justifying predictions in a human-interpretable way. These techniques are already transitioning from theory to application. Notable examples include the Quantum Gradient Class Activation Map (Q-Grad-CAM), which has been successfully applied to visualize decision 'hotspots' in medical scans by tracking gradient flow through variational circuits [251]. Similarly, Quantum SHAP (Q-SHAP) values have been employed to rank the importance of radiomic features, assisting clinicians in understanding why a QML model flagged a specific region as cancerous or abnormal. This will be essential in making QML part of the process that will drive regulatory requirements and decision-making.

While classical AI utilizes tools like Grad-CAM to highlight "hotspots" in an image, quantum explainability faces the "Measurement Collapse" problem. We cannot inspect the internal activations of a quantum neural network during processing without destroying the superposition state. Future research must therefore focus on "Quantum Non-Demolition" measurement techniques or proxy-based explainability, where a classical surrogate model approximates the quantum decision boundary to provide clinician-interpretable rationales (e.g., "This region was flagged due to texture irregularity"). Without these concrete audit trails, QML cannot meet the "Right to Explanation" requirements of GDPR or the trust requirements of oncologists.

F. DOMAIN-SPECIFIC QML APPLICATIONS

While current research often focuses on generic classification or segmentation tasks where classical baselines are already strong, the future of QML lies in domain-specific applications that hit classical computational ceilings. We prioritize areas like intraoperative imaging, radiomics-based survival prediction, and precision oncology because they require modeling high-order feature correlations and real-time processing of high-dimensional data—tasks where quantum entanglement and parallelism offer a distinct theoretical advantage over classical heuristics.

G. FEDERATED AND PRIVACY-PRESERVING QUANTUM LEARNING

Because it is so sensitive, QML will be a key research frontier for integrating privacy-preserving paradigms like federated learning and homomorphic encryption. Federated learning allows several hospitals or research centers to learn models, while never revealing patient data jointly; this way, no patient data is required to be disclosed, and such regulations as HIPAA or GDPR are preserved. Finally, the intrinsic properties of quantum systems, such as no cloning and measurement-induced collapse, can be used to build inherently secure data transmission and model training protocols.

H. CLINICAL VALIDATION AND REGULATORY FRAMEWORKS

There are also some future work directions, such as validating robust pipelines and regulatory guidelines targeted to QML in healthcare. It encompasses multi-site clinical trials with standard metrics for QML evaluation and certification protocols adapted to quantum technologies. Bridging the gap between academic researchers, hospitals, quantum hardware companies, and regulatory agencies will be paramount to building trust and safe deployment. With the due maturation of such frameworks, they will enable a move from lab-based proofs of concept to deployed clinical tools.

I. STANDARDIZED EVALUATION FRAMEWORKS

The current literature suffers from a lack of comparison standards. To move beyond proof-of-concept, the QML community must establish a "Medical Q-Model Zoo" and standardized benchmark datasets (analogous to ImageNet in classical vision) that fix the train/test splits, resolution, and classical preprocessing steps. Without such a framework, it remains impossible to objectively verify whether a QML model offers a statistically significant advantage over a tuned classical ResNet on the same medical task.

VIII. CONCLUSION

Quantum Machine Learning (QML) is at the cutting edge of a revolutionary technological epoch that combines the probabilistic nature of quantum mechanics with the pattern recognition prowess of machine learning. QML is a disruptive change in approaching computing in the domain of medical image analysis (a field characterized by high-dimensional data, complex structure, and critical decision-making needs). This review has described a summary of how QML is used and has future potential across various modalities such as MRI, CT, X-ray, and histopathology, constituting the basis for modern clinical diagnostics.

Further, we systematically explore how quantum-enhanced models are being applied to fundamental medical imaging tasks of classification of pathological structures, segmentation of anatomical regions, and reconstruction of corrupted or undersampled images. Although quantum approaches are still nascent compared to classical deep learning methods, they are already demonstrating competitive—and in some cases superior—performance, especially in problems where computational complexity or feature entanglement is one of the bottlenecks on classical algorithms. One of the distinguishing features of this new paradigm is the architectural diversity that QML brings in. Other models, like variational quantum circuits (VQCs), quantum convolutional neural networks (QCNNs), and hybrid quantum-classical frameworks, encode, process, and interpret the medical image data in novel ways. As such, these architectures come with not just algorithmic innovation but also the promise of exponential speedups in certain subroutines like kernel evaluation, optimization in high-dimensional Hilbert spaces. In addition, hybrid methods open a near-term pathway for implementation, allowing researchers to harness the benefits of quantum acceleration with the classical infrastructure of maturity. However, despite the promise, it would face several challenges in the deployment of QML in real-world healthcare environments. They include hardware limitations, e.g., low qubit count and high error rates, as well as insufficiently efficient and lossless data encoding, and a lack of accepted standardized medical image analysis benchmarks in quantum settings. In addition, there are still questions concerning interpretability, ethical use, as well as regulatory compliance. However, the gaps in these phenomena underscore how urgently multidisciplinary collaboration of physicists, computer scientists, clinicians, and policymakers is required.

What challenges there are, however, are also opportunities. We review these future directions, which may lead to the integration of QML into clinical practice. Specifically, they entail building fault-tolerant quantum processors, quantum-aware medical datasets, interpretable QML models, and quantum federated learning frameworks that are private. They also provide high-value targets for QML innovation in the domain-specific use cases such as intraoperative imaging, survival prediction, and personalized therapy planning. With the field progressing, the required focus also needs to be on regulatory standards and clinical trial frameworks for quantum systems. In essence, Quantum Machine Learning has the potential to completely re-tool the acquisition and processing of medical images as well as how they are being understood through the ages of faster, more accurate, and deeply personalized healthcare. Research to date points to a near-immediate transition from theoretical exploration to practical application of QML, which, like deep learning in 2010, would represent a paradigm shift. Persistence, cross-domain synergy, and ethical vigilance are required to make the trip ahead, but the rewards are enormous: early disease detection, real-time surgical support, and population-scale precision medicine.

Therefore, QML is not only a new computational approach but a central issue in future intelligent medicine. Our ability to continue to leverage this technology in saving lives, improving outcomes, and rewriting the possibilities in healthcare will evolve with the improvement of quantum technology.

REFERENCES

[1] G. Choy and A. Ryu, *Utilization Management in Radiology*. Cham, Switzerland: Springer, Dec. 2016, pp. 267–271, doi: 10.1007/978-3-319-34199-6_24.

[2] P. A. Yushkevich and G. Gerig, "ITK-SNAP: An intractive medical image segmentation tool to meet the need for expert-guided segmentation of complex medical images," *IEEE Pulse*, vol. 8, no. 4, pp. 54–57, Jul. 2017, doi: 10.1109/MPUL.2017.2701493.

[3] K. P. Andriole, *Medical Imaging Modalities and Digital Images*. New York, NY, USA: Springer, 2009, pp. 3–13, doi: 10.1007/978-1-4419-0485-0_1.

[4] H. Otsuka, "Clinical imaging technology and the diagnosis in patient-centered interdisciplinary care," *J. Med. Invest.*, vol. 66, no. 1.2, pp. 31–34, Feb. 2019, doi: 10.2152/jmi.66.31.

[5] R. Birjais, K. I.-K. Wang, and W. Abdulla, "Training deep neural networks with HSIC and backpropagation," in *Proc. Asia–Pacific Signal Inf. Process. Assoc. Annu. Summit Conf. (APSIPA ASC)*, Dec. 2024, pp. 1–5, doi: 10.1109/apsipaasc63619.2025.10848746.

[6] M. Mythili, R. Thangarajan, and N. Krishnamoorthy, *Classification of Signal Versus Background in High-Energy Physics Using Deep Neural Networks*. Cham, Switzerland: Springer, Nov. 2019, pp. 1096–1106, doi: 10.1007/978-3-030-32150-5_111.

[7] J. Lu, S. Young, I. Arel, and J. Holleman, "30.10 A 1tops/W analog deep machine-learning engine with floating-gate storage in CMOS," in *IEEE Int. Solid-State Circuits Conf. (ISSCC) Dig. Tech. Papers*, Feb. 2014, pp. 504–505, doi: 10.1109/ISSCC.2014.6757532.

[8] L. Xiao and J. Pennington, "Synergy and symmetry in deep learning: Interactions between the data, model, and inference algorithm," 2022, *arXiv:2207.04612*.

[9] J. D. Prusa and T. M. Khoshgoftaar, "Designing a better data representation for deep neural networks and text classification," in *Proc. IEEE 17th Int. Conf. Inf. Reuse Integr. (IRI)*, Jul. 2016, pp. 411–416, doi: 10.1109/IRI.2016.61.

[10] A. S. Chauhan, R. Singh, N. Priyadarshi, B. Twala, S. Suthar, and S. Swami, "Unleashing the power of advanced technologies for revolutionary medical imaging: Pioneering the healthcare frontier with artificial intelligence," *Discover Artif. Intell.*, vol. 4, no. 1, Aug. 2024, doi: 10.1007/s44163-024-00161-0.

[11] S. Bashyam, P. Supraja, and P. Rajalingam, "Interpretable ai: Shedding light on medical image analysis using machine learning techniques," in *Explainable Artificial Intelligence in the Healthcare Industry*. USA: Wiley, Mar. 2025, pp. 257–282, doi: 10.1002/9781394249312.ch12.

[12] G. Fiorentino, M. Veniero, and C. Romano, "Ai powered cancer prediction, diagnosis and treatment," in *Proc. Ital-IA*, 2023, pp. 177–182.

[13] H. Kondylakis et al., "Data infrastructures for AI in medical imaging: A report on the experiences of five EU projects," *Eur. Radiol. Experim.*, vol. 7, no. 1, May 2023, doi: 10.1186/s41747-023-00336-x.

[14] J. Viswanathan, N. Saranya, and A. Inbamani, *Deep Learning Applications in Medical Imaging: Introduction To Deep Learning-Based Intelligent Systems for Medical Applications*. Palmdale, PA, USA: IGI Global, 2021, pp. 156–177, doi: 10.4018/978-1-7998-5071-7.ch007.

[15] S. Piffer, L. Ubaldi, S. Tangaro, A. Retico, and C. Talamonti, "Tackling the small data problem in medical image classification with artificial intelligence: A systematic review," *Prog. Biomed. Eng.*, vol. 6, no. 3, Jun. 2024, Art. no. 032001, doi: 10.1088/2516-1091/ad525b.

[16] A. Chehri, I. Ahmed, and G. Jeon, "From deep learning to interpretable and explainable deep learning in medical image computing: Balancing innovation with ethics and responsibilities," *Proc. Comput. Sci.*, vol. 246, pp. 302–311, Jan. 2024, doi: 10.1016/j.procs.2024.09.409.

[17] M. Ennab and H. Mcheick, "Enhancing interpretability and accuracy of AI models in healthcare: A comprehensive review on challenges and future directions," *Frontiers Robot. AI*, vol. 11, Nov. 2024, doi: 10.3389/frobt.2024.1444763.

[18] A. Senokosov, A. Sedykh, A. Sagingalieva, B. Kyriacou, and A. Melnikov, "Quantum machine learning for image classification," *Mach. Learn., Sci. Technol.*, vol. 5, no. 1, Mar. 2024, Art. no. 015040, doi: 10.1088/2632-2153/ad2aef.

[19] H. Wang, J. Tan, Y. Huang, and W. Zheng, "Quantum image compression with autoencoders based on parameterized quantum circuits," *Quantum Inf. Process.*, vol. 23, no. 2, Jan. 2024, doi: 10.1007/s11128-023-04243-3.

[20] A. De Lorenzis, M. P. Casado, M. P. Estarellas, N. Lo Gullo, T. Lux, F. Plastina, A. Riera, and J. Settino, "Harnessing quantum extreme learning machines for image classification," *Phys. Rev. Appl.*, vol. 23, no. 4, Apr. 2025, doi: 10.1103/physrevapplied.23.044024.

[21] M. T. West, S.-L. Tsang, J. S. Low, C. D. Hill, C. Leckie, L. C. L. Hollenberg, S. M. Erfani, and M. Usman, "Towards quantum enhanced adversarial robustness in machine learning," *Nature Mach. Intell.*, vol. 5, no. 6, pp. 581–589, May 2023, doi: 10.1038/s42256-023-00661-1.

[22] R. V. Aswiga, S. Sridevi, and B. Indira, "Leveraging quantum kernel support vector machine for breast cancer diagnosis from digital breast tomosynthesis images," *Quantum Mach. Intell.*, vol. 6, no. 2, Jul. 2024, doi: 10.1007/s42484-024-00170-3.

[23] J. C. L. Chow, "Quantum computing and machine learning in medical decision-making: A comprehensive review," *Algorithms*, vol. 18, no. 3, p. 156, Mar. 2025, doi: 10.3390/a18030156.

[24] J. C. L. Chow, "Quantum computing in medicine," *Med. Sci.*, vol. 12, no. 4, p. 67, Nov. 2024, doi: 10.3390/medsci12040067.

[25] K. S. Valluru, B. K. Chinni, and N. A. Rao, "Photoacoustic imaging: Opening new frontiers in medical imaging," *J. Clin. Imag. Sci.*, vol. 1, p. 24, May 2011, doi: 10.4103/2156-7514.80522.

[26] D. Hussain, N. Abbas, and J. Khan, "Recent breakthroughs in PET-CT multimodality imaging: Innovations and clinical impact," *Bioengineering*, vol. 11, no. 12, p. 1213, Nov. 2024, doi: 10.3390/bioengineering11121213.

[27] T. T. Jidney, A. Biswas, N. M. Abdullah Al, I. Hossain, M. J. Alam, S. Talukder, M. Hossain, and M. A. Ullah, *Automl Systems for Medical Imaging*. Cham, Switzerland: Springer, 2023, pp. 91–106, doi: 10.1007/978-3-031-47772-0_5.

[28] S. P. Gururama, K. S. Kumar, and T. G. Kumar, "Efficient machine learning techniques for medical images," in *Computational Imaging and Analytics in Biomedical Engineering*. County Clare, IR, USA: Apple Academic Press, 2024, pp. 299–319.

[29] A. Vlontzos, C. Müller, and B. Kainz, *Causal Reasoning in Medical Imaging*. Amsterdam, The Netherlands: Elsevier, 2025, pp. 367–381, doi: 10.1016/b978-0-44-323761-4.00029-8.

[30] S. Yepuri and A. Marandi, "Classification of blood cell data using deep learning approach," in *Proc. Int. Conf. Intell. Innov. Technol. Comput., Electr. Electron. (IITCEE)*, Jan. 2023, pp. 9–17, doi: 10.1109/IITCEE57236.2023.10090986.

[31] M. Jha and Y. Hasija, "Artificial intelligence in field of medical imaging informatics," in *Proc. 3rd Int. Conf. Advance Comput. Innov. Technol. Eng. (ICACITE)*, vol. 2, May 2023, pp. 661–666, doi: 10.1109/ICACITE57410.2023.10182498.

[32] R. Mothkur and K. M. Poornima, "Machine learning will transfigure medical sector: A survey," in *Proc. Int. Conf. Current Trends towards Converging Technol. (ICCTCT)*, Mar. 2018, pp. 1–8, doi: 10.1109/ICCTCT.2018.8551134.

[33] T. Emre, M. Oghbaie, A. Chakravarty, A. Rivail, S. Riedl, J. Mai, H. P. N. Scholl, S. Sivaprasad, D. Rueckert, A. Lotery, U. Schmidt-Erfurth, and H. Bogunović, "Pretrained deep 2.5D models for efficient predictive modeling from retinal OCT: A PINNACLE study report," in *Ophthalmic Medical Image Analysis (OMIA 2023)*. Cham, Switzerland: Springer, 2023, pp. 132–141, doi: 10.1007/978-3-031-44013-7_14.

[34] J. Chenchen, C. Yongqing, and H. Mengzhi. (Feb. 2025). *Optimization of 3D Convolutional Forward Operators Based on Domestic Accelerators*. [Online]. Available: www.ecice06.com

[35] B. Xin, J. Huang, Y. Zhou, J. Lu, and X. Wang, "Interpretation on deep multimodal fusion for diagnostic classification," in *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, Jul. 2021, pp. 1–8, doi: 10.1109/ijcnn52387.2021.9534148.

[36] J. Duan, J. Xiong, Y. Li, and W. Ding, "Deep learning based multimodal biomedical data fusion: An overview and comparative review," *Inf. Fusion*, vol. 112, Dec. 2024, Art. no. 102536, doi: 10.1016/j.inffus.2024.102536.

[37] M. Cuong, "A strategy for training 3D object recognition models with limited training data using transfer learning," *Proc. SPIE*, vol. 49, p. 38, Aug. 2020, doi: 10.1117/12.2575923.

[38] S. Zhang, Z. Li, H.-Y. Zhou, J. Ma, and Y. Yu, "Advancing 3D medical image analysis with variable dimension transform based supervised 3D pre-training," *Neurocomputing*, vol. 529, pp. 11–22, Apr. 2023, doi: 10.1016/j.neucom.2023.01.012.

[39] N. Kanchepu, *Unveiling the Black Box: The Crucial Role of Interpretability in Machine Learning Models*. Ann Arbor, MI, USA: Bentham science, Mar. 2025, pp. 22–44, doi: 10.2174/9789815305548125010004.

[40] R. González-Alday, E. García-Cuesta, C. A. Kulikowski, and V. Maojo, "A scoping review on the progress, applicability, and future of explainable artificial intelligence in medicine," *Appl. Sci.*, vol. 13, no. 19, p. 10778, Sep. 2023, doi: 10.3390/app131910778.

[41] M. Bali, V. P. Mishra, A. Yenkikar, and D. Chikmurge, "QuantumNet: An enhanced diabetic retinopathy detection model using classical deep learning-quantum transfer learning," *MethodsX*, vol. 14, Jun. 2025, Art. no. 103185, doi: 10.1016/j.mex.2025.103185.

[42] B. Tantawi, H. K. Ahmed, M. Magdy, and G. I. Sayed, *Automatic Classification of Medical Image Modality Using Quantum Convolutional Neural Network*. Palmdale, PA, USA: IGI Global, Jun. 2023, pp. 87–111, doi: 10.4018/978-1-6684-8913-0.ch004.

[43] A. Singh, G. Gaba, and L. Kansal, "Design and performance evaluation of hybrid segmentation technique," *Int. J. Appl. Eng. Res.*, vol. 10, pp. 8417–8435, Jan. 2015.

[44] Z. Bian, J. Huang, J. Ma, H. Zhang, Z. Liang, and W. Chen, "Iterative image reconstruction for low-dose X-ray CT using a sinogram restoration induced edge-preserving prior," in *Proc. IEEE 11th Int. Symp. Biomed. Imag. (ISBI)*, Apr. 2014pp. 1160–1163, doi: 10.1109/ISBI.2014.6868081.

[45] T. Tasnim, M. Rahman, and F. Wu, "Comparison of CNN and QCNN performance in binary classification of breast cancer histopathological images," in *Proc. IEEE Int. Conf. Big Data (BigData)*, Dec. 2024, pp. 3780–3787, doi: 10.1109/BIGDATA62323.2024.10825102.

[46] S. K. Roy and B. Rudra, "Quantum-inspired hybrid algorithm for image classification and segmentation: Q-means++ max-cut method," *Int. J. Imag. Syst. Technol.*, vol. 34, no. 1, Jan. 2024, doi: 10.1002/ima.23015.

[47] B. Sriya, S. R. Warrier, and J. Dontabhaktuni, "Detection of brain cancer using quantum-classical CNN based method," *Proc. SPIE*, vol. 26, p. 7, Mar. 2023, doi: 10.1117/12.2650132.

[48] B. Baral, R. Majumdar, B. Bhalgamiya, and T. D. Roy, "Evaluating quantum machine learning approaches for histopathological cancer detection: Classical, hybrid simulation, and IBM quantum computing," in *Proc. IEEE Int. Conf. Quantum Comput. Eng. (QCE)*, Sep. 2023, pp. 238–239, doi: 10.1109/QCE57702.2023.10222.

[49] K. Saini, R. Gupta, and S. Pundhir, *Quantum Computing: An Introduction*. Amsterdam, The Netherlands: Elsevier, 2025, p. 149165, doi: 10.1016/bs.adcom.2025.02.008.

[50] G. Xu and W. S. Oates, "Can quantum computers solve linear algebra problems to advance engineering applications?" in *Mechanics and Behavior of Active Materials; Structural Health Monitoring; Bioinspired Smart Materials and Systems; Energy Harvesting; Emerging Technologies*. San Antonio, TX, USA: American Society of Mechanical Engineers, Sep. 2018, doi: 10.1115/smasis2018-8087.

[51] N. Jyothi Ahuja and S. Dutt, *Implications of Quantum Science on Industry 4.0: Challenges and Opportunities*. Cham, Switzerland: Springer, 2022, p. 183204, doi: 10.1007/978-3-031-04613-1_6.

[52] Xue, Zhang, Wu, L.-, and Tarn, "Quantum operation for one non-Markovian qubit via AC control," in *Proc. 30th Chin. Control Conf.*, 2011, pp. 5352–5357.
[53] M. Mannone and D. Rocchesso, *Sing and Measure: Sound As Voice As Quanta*. Cham, Switzerland: Springer, 2022, p. 297312, doi: 10.1007/978-3-031-13909-3_12.
[54] Y. Yu, "Advancements in applications of quantum entanglement," *J. Phys., Conf. Ser.*, vol. 2012, no. 1, Sep. 2021, Art. no. 012113, doi: 10.1088/1742-6596/2012/1/012113.
[55] X. Zhao, V. Geskin, and R. Stadler, "Destructive quantum interference in electron transport: A reconciliation of the molecular orbital and the atomic orbital perspective," *J. Chem. Phys.*, vol. 146, no. 9, Dec. 2016, doi: 10.1063/1.4972572.
[56] Y.-Y. Feng, Y. Li, J. Li, J. Zhou, and J.-J. Shi, "Variational shadow quantum circuits assisted quantum convolutional neural network," *Adv. Quantum Technol.*, vol. 8, no. 8, Jan. 2025, doi: 10.1002/qute.202400510.
[57] A. Ticku, V. Sangwan, S. Balani, S. Jha, S. Rawat, A. Rathee, and D. Yadav, "Advancing neuroimaging with quantum convolutional neural networks for brain tumor detection," *Int. J. Inf. Technol.*, vol. 17, no. 9, pp. 5759–5766, Jan. 2025, doi: 10.1007/s41870-025-02401-7.
[58] F. J. Gil Vidal and D. O. Theis, "Input redundancy for parameterized quantum circuits," *Frontiers Phys.*, vol. 8, Aug. 2020, doi: 10.3389/fphy.2020.00297.
[59] M. Wiedmann, M. Hölle, M. Periyasamy, N. Meyer, C. Ufrecht, D. D. Scherer, A. Plinge, and C. Mutschler, "An empirical comparison of optimizers for quantum machine learning with SPSA-based gradients," in *Proc. IEEE Int. Conf. Quantum Comput. Eng. (QCE)*, Sep. 2023, pp. 450–456, doi: 10.1109/QCE57702.2023.00058.
[60] P. Tiwari and M. Melucci, "Towards a quantum-inspired framework for binary classification," in *Proc. 27th ACM Int. Conf. Inf. Knowl. Manage.*, Oct. 2018, pp. 1815–1818, doi: 10.1145/3269206.3269304.
[61] M. Mafu and M. Senekane, "Design and implementation of efficient quantum support vector machine," in *Proc. Int. Conf. Electr., Comput. Energy Technol. (ICECET)*, Dec. 2021, pp. 1–4, doi: 10.1109/ICECET52533.2021.9698509.
[62] R. Sangle, T. Khare, P. V. Seshadri, and Y. Simmhan, "Comparing the orchestration of quantum applications on hybrid clouds," in *Proc. IEEE/ACM 23rd Int. Symp. Cluster, Cloud Internet Comput. Workshops (CCGridW)*, May 2023, pp. 313–315, doi: 10.1109/CCGRIDW59191.2023.00069.
[63] X. Wang, Z. Wang, and B. Ni, "Mapping structural topology optimization problems to quantum annealing," *Struct. Multidisciplinary Optim.*, vol. 67, no. 5, May 2024, doi: 10.1007/s00158-024-03791-1.
[64] V. Russo, A. Mari, N. Shammah, R. LaRose, and W. J. Zeng, "Testing platform-independent quantum error mitigation on noisy quantum computers," *IEEE Trans. Quantum Eng.*, vol. 4, pp. 1–18, 2023, doi: 10.1109/TQE.2023.3305232.
[65] K. M. Barnes, A. Buyskikh, N. Y. Chen, G. Gallardo, M. Ghibaudi, M. J. A. Ruszala, D. S. Underwood, A. Agarwal, D. Lall, I. Rungger, and N. Schoinas, "Optimising the quantum/classical interface for efficiency and portability with a multi-level hardware abstraction layer for quantum computers," *EPJ Quantum Technol.*, vol. 10, no. 1, Sep. 2023, doi: 10.1140/epjqt/s40507-023-00192-z.
[66] L. Chhangte and A. Chakrabarty, "Mapping quantum circuits in IBM q devices using progressive qubit assignment for global ordering," *New Gener. Comput.*, vol. 40, no. 1, pp. 311–338, Mar. 2022, doi: 10.1007/s00354-022-00163-5.
[67] T.-H. Zhao, M.-H. Wang, and B. Zhou, "Optimal quantum state transformations based on machine learning," *Quantum Inf. Process.*, vol. 20, no. 6, Jun. 2021, doi: 10.1007/s11128-021-03148-3.
[68] J. Liu, F. Tacchino, J. R. Glick, L. Jiang, and A. Mezzacapo, "Representation learning via quantum neural tangent kernels," *PRX Quantum*, vol. 3, no. 3, Aug. 2022, doi: 10.1103/prxquantum.3.030323.
[69] Y. Zhu, A. Bouridane, M. E. Celebi, D. Konar, P. Angelov, Q. Ni, and R. Jiang, "Quantum face recognition with multigate quantum convolutional neural network," *IEEE Trans. Artif. Intell.*, vol. 5, no. 12, pp. 6330–6341, Dec. 2024, doi: 10.1109/TAI.2024.3419077.
[70] R. Adithya, J. Dsa, S. A. Rag, and S. A. Bhyratae, "Hybrid quantum-classical neural networks and its hyperparameter optimization—A study," in *Proc. Int. Conf. Comput.*, Nov. 2024, pp. 88–96, doi: 10.1109/cosmic63293.2024.10871871.
[71] P. Subbiah, M. Kandan, N. Krishnaraj, and S. K. Theodore, *Quantum Neural Networks*. New York, NY, USA: Auerbach Publications, Mar. 2025, pp. 133–146, doi: 10.1201/9781003499459-8.
[72] F. Tacchino, S. Mangini, P. K. Barkoutsos, C. Macchiavello, D. Gerace, I. Tavernelli, and D. Bajoni, "Variational learning for quantum artificial neural networks," *IEEE Trans. Quantum Eng.*, vol. 2, pp. 1–10, 2021, doi: 10.1109/TQE.2021.3062494.
[73] M. Maronese, C. Destri, and E. Prati, "Quantum activation functions for quantum neural networks," *Quantum Inf. Process.*, vol. 21, no. 4, Mar. 2022, doi: 10.1007/s11128-022-03466-0.
[74] M. M. Hossain, M. S. Ali, R. A. Swarna, M. M. Hasan, N. Habib, M. W. Rahman, M. M. Azad, and M. M. Rahman, "Analyzing the effect of feature mapping techniques along with the circuit depth in quantum supervised learning by utilizing quantum support vector machine," in *Proc. 24th Int. Conf. Comput. Inf. Technol. (ICCIT)*, Dec. 2021, pp. 1–5, doi: 10.1109/iccit54785.2021.9689853.
[75] S. Liao, Y. Gao, A. Oto, and D. Shen, *Representation Learning: A Unified Deep Learning Framework for Automatic Prostate MR Segmentation*. Berlin, Germany: Springer, 2013, pp. 254–261, doi: 10.1007/978-3-642-40763-5_32.
[76] P. Yee Lau and S. Ozawa, "An image-based analysis for classifying multimodal brain images in the image-guided medical diagnosis model," in *Proc. 26th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, vol. 4, Sep. 2004, pp. 3400–3403.
[77] J. B. Rapesta, V. Sanchez, J. S. Sagrsitá, M. W. Marcellin, F. A. Llinás, and I. Blanes, "Lossless medical image compression through lightweight binary arithmetic coding," *Proc. SPIE*, vol. 10, p. 27, Sep. 2017, doi: 10.1117/12.2273725.
[78] A. Revathi and N. Mahendran, "Design of CODEC using VLSI architecture for efficient communication," in *Proc. IEEE Int. Conf. Electr., Instrum. Commun. Eng. (ICEICE)*, Apr. 2017, pp. 1–5, doi: 10.1109/ICEICE.2017.8191922.
[79] D. Yu and J. Beom, "Fine spatial scalability in wavelet based image coding," in *Proc. IEEE Int. Conf. Image Process.*, Sep. 2005, p. 862, doi: 10.1109/ICIP.2005.1530192.
[80] M. Schuld and N. Killoran, "Quantum machine learning in feature Hilbert spaces," *Phys. Rev. Lett.*, vol. 122, no. 4, Feb. 2019, doi: 10.1103/physrevlett.122.040504.
[81] W. E. Maouaki, T. Said, and M. Bennai, "Quantum support vector machine for prostate cancer detection: A performance analysis," 2024, *arXiv:2403.07856*.
[82] S. Sharma, "QEML (quantum enhanced machine learning): Using quantum computing to enhance ML classifiers and feature spaces," 2020, *arXiv:2002.10453*.
[83] M. A.-Z. Khan, A. A. O. Galib, N. Innan, and M. Bennai, "Brain tumor diagnosis using quantum convolutional neural networks," 2025, *arXiv:2401.15804*.
[84] G. N. Meedinti, K. S. Srirekha, and R. Delhibabu, "A quantum convolutional neural network approach for object detection and classification," 2023, *arXiv:2307.08204*.
[85] H. Zhao, X. Deng, Z. Patrick, Y. Jiang, and H. Shao, "Classical-quantum hybrid transfer learning for COVID-19 classification," *Res. Square Platform LLC*, vol. 10, pp. 1–12, Jul. 2022, doi: 10.21203/rs.3.rs-1807201/v1.
[86] H. Asaoka and K. Kudo, "Quantum autoencoders for image classification," *Quantum Mach. Intell.*, vol. 7, no. 2, Jul. 2025, doi: 10.1007/s42484-025-00297-x.
[87] Z. Li and K. Terashi, "Quantum decision trees with information entropy," 2025, *arXiv:2502.11412*.
[88] P. Mei and F. Zhang, "A framework for processing large-scale health data in medical higher-order correlation mining by quantum computing in smart healthcare," *Frontiers Digit. Health*, vol. 6, Nov. 2024, doi: 10.3389/fdgth.2024.1502745.
[89] W. Winci, L. Buffoni, H. Sadeghi, A. Khoshaman, E. Andriyash, and M. H. Amin, "A path towards quantum advantage in training deep generative models with quantum annealers," *Mach. Learn., Sci. Technol.*, vol. 1, no. 4, Nov. 2020, Art. no. 045028, doi: 10.1088/2632-2153/aba220.
[90] P. Gohel, A. Chakraborty, and J. V. K. Rao, "Organ classification using quantum convolution network," in *Proc. IEEE Int. Conf. Quantum Comput. Eng. (QCE)*, Sep. 2022, pp. 831–832, doi: 10.1109/QCE53715.2022.00134.
[91] R. Mashtura, J. Mahmud, S. A. Fattah, and M. Saquib, "A parallel quantum feature encoding scheme for effective classical data classification in quantum convolutional neural networks," in *Proc. IEEE Region 10 Conf. (TENCON)*, Oct. 2023, pp. 1–5, doi: 10.1109/TENCON58879.2023.10322543.

[92] T. Shirakawa, H. Ueda, and S. Yunoki, "Automatic quantum circuit encoding of a given arbitrary quantum state," *Phys. Rev. Res.*, vol. 6, no. 4, Oct. 2024, doi: 10.1103/physrevresearch.6.043008.

[93] Y. Dong, X. Ni, T. Sun, G. Wu, and C. Lin, "Research on image classification using quantum convolutional neural networks based on multiple approaches," *Phys. Scripta*, vol. 100, no. 4, Mar. 2025, Art. no. 045116, doi: 10.1088/1402-4896/adc20e.

[94] S. Lavi, C. Michal, W. Zeev, G. Ya'ara, and M. Edwin, *Epidemiological Models Lacking Process Noise Can Be Overconfident*. Amsterdam, The Netherlands: IOS Press, 2017, doi: 10.3233/978-1-61499-753-5-136.

[95] Q. Ma, C. Hao, N. Si, G. Chen, J. Zhang, and D. Qu, "Quantum adversarial generation of high-resolution images," *EPJ Quantum Technol.*, vol. 12, no. 1, Jan. 2025, doi: 10.1140/epjqt/s40507-024-00304-3.

[96] C. Chu, G. Skipper, M. Swany, and F. Chen, "IQGAN: Robust quantum generative adversarial network for image synthesis on NISQ devices," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, Jun. 2023, pp. 1–5, doi: 10.1109/ICASSP49357.2023.10096772.

[97] J. Choi, T. Hur, D. K. Park, N.-Y. Shin, S.-K. Lee, H. Lee, and S. Han, "Early-stage detection of cognitive impairment by hybrid quantum-classical algorithm using resting-state functional MRI time-series," *Knowl.-Based Syst.*, vol. 310, Feb. 2025, Art. no. 112922, doi: 10.1016/j.knosys.2024.112922.

[98] S. Prabhu, S. Gupta, G. M. Prabhu, A. V. Dhanuka, and K. V. Bhat, "QuCardio: Application of quantum machine learning for detection of cardiovascular diseases," *IEEE Access*, vol. 11, pp. 136122–136135, 2023, doi: 10.1109/ACCESS.2023.3338145.

[99] H. Kumar, P. Sharma, A. Ajina, N. M. Kannal, and U. Kumar, "A novel approach to derma quantum (skin disease detection and classification using ResNet50 and QCNN)," in *Proc. 2nd Int. Conf. Comput. Data Anal. (ICCDA)*, Nov. 2024, pp. 1–6, doi: 10.1109/iccda64887.2024.10867304.

[100] J. Zhang, X. Xue, and Y. Ruan, "Hybrid neural network based on parameterized quantum circuits for image classification," in *Proc. Cross Strait Radio Sci. Wireless Technol. Conf. (CSRSWTC)*, Nov. 2024, pp. 1–3, doi: 10.1109/csrswtc64338.2024.10811600.

[101] A.-N. University, A. S. Abdalrazzaq, A. B. Khudhair, N. R. Mahdi, N. H. Mahmood, S. Alsalame, and A.-T. University, "Quantum computing role in advancing medical physics research," *Radioelectronics. Nanosyst. Inf. Technol.*, vol. 16, no. 6, pp. 755–766, Sep. 2024, doi: 10.17725/j.rensit.2024.16.755.

[102] A. Matic, M. Monnet, J. Lorenz, B. Schachtner, and T. Messerer, "Quantum-classical convolutional neural networks in radiological image classification," in *Proc. IEEE Int. Conf. Quantum Comput. Eng. (QCE)*, Sep. 2022, pp. 56–66, doi: 10.1109/QCE53715.2022.00024.

[103] P. Sen, A. S. Bhatia, K. S. Bhangu, and A. Elbeltagi, "Variational quantum classifiers through the lens of the Hessian," *PLoS ONE*, vol. 17, no. 1, Jan. 2022, Art. no. e0262346, doi: 10.1371/journal.pone.0262346.

[104] A. Agirre, E. van Nieuwenburg, and M. M. Wauters, "A Monte Carlo tree search approach to QAOA: Finding a needle in the haystack," *New J. Phys.*, vol. 27, no. 4, Apr. 2025, Art. no. 043014, doi: 10.1088/1367-2630/adc765.

[105] K. E. Hamilton, E. Lynn, and R. C. Pooser, "Mode connectivity in the loss landscape of parameterized quantum circuits," *Quantum Mach. Intell.*, vol. 4, no. 1, May 2022, doi: 10.1007/s42484-021-00059-5.

[106] B. Soni and N. Khare, "Quantum principal component analysis based on the dynamic selection of eigenstates," *Europhys. Lett.*, vol. 139, no. 4, p. 48002, Aug. 2022, doi: 10.1209/0295-5075/ac5647.

[107] B. Soni and N. Khare, "Advancement of quantum methods in principal component analysis," in *Proc. 12th Int. Conf. Comput. Commun. Netw. Technol. (ICCCNT)*, Jul. 2021, pp. 1–7, doi: 10.1109/ICCCNT51525.2021.9579998.

[108] M. Basthikodi, M. Chaithrashree, B. M. Ahamed Shafeeq, and A. P. Gurpur, "Enhancing multiclass brain tumor diagnosis using SVM and innovative feature extraction techniques," *Sci. Rep.*, vol. 14, no. 1, Oct. 2024, doi: 10.1038/s41598-024-77243-7.

[109] J. P. G. van Dijk, E. Charbon, and F. Sebastiano, "The electronic interface for quantum processors," *Microprocessors Microsyst.*, vol. 66, pp. 90–101, Apr. 2019, doi: 10.1016/j.micpro.2019.02.004.

[110] N. Mitsuda, T. Ichimura, K. Nakaji, Y. Suzuki, T. Tanaka, R. Raymond, H. Tezuka, T. Onodera, and N. Yamamoto, "Approximate complex amplitude encoding algorithm and its application to data classification problems," *Phys. Rev. A, Gen. Phys.*, vol. 109, no. 5, May 2024, doi: 10.1103/physreva.109.052423.

[111] M.-H. Wang and L. Hu, "Variational data encoding and correlations in quantum-enhanced machine learning," *Chin. Phys. B*, vol. 33, no. 9, Aug. 2024, Art. no. 090307, doi: 10.1088/1674-1056/ad5c3b.

[112] J. Yuan and Y. Wáng, "T1rho MR imaging: Principle, technology, and application," *MRI, Phys. Image Reconstruction, Anal.*, pp. 565–592, Oct. 2017.

[113] D. W. McRobbie, E. A. Moore, M. J. Graves, and M. R. Prince, *MRI From Picture to Proton*. Cambridge, U.K.: Cambridge Univ. Press, Sep. 2006. [Online]. Available: https://www.cambridge.org/core/books/mri-from-picture-to-proton/3ADC814FF8FC6A78A54D37746F806D5A

[114] A. Romano, A. Bozzao, M. Bonamini, F. Fasoli, M. Ferrante, R. Floris, C. Colonnese, and L. M. Fantozzi, "Diffusion-weighted MR imaging: Clinical applications in neuroradiology," *La Radiologia Medica*, vol. 106, nos. 5–6, pp. 521–48, 2004.

[115] S. L. Meisler, E. Kubota, M. Grotheer, J. D. E. Gabrieli, and K. Grill-Spector, "A practical guide for combining functional regions of interest and white matter bundles," *Frontiers Neurosci.*, vol. 18, Aug. 2024, Art. no. 1385847.

[116] M. Hund, W. Sturm, T. Schreck, T. Ullrich, D. Keim, L. Majnaric, and A. Holzinger, *Analysis of Patient Groups and Immunization Results Based on Subspace Clustering*. Cham, Switzerland: Springer, 2015, pp. 358–368, doi: 10.1007/978-3-319-23344-4_35.

[117] C. Hofer, R. Kwitt, Y. Höller, E. Trinka, and A. Uhl, "Simple domain adaptation for cross-dataset analyses of brain MRI data," in *Proc. IEEE 14th Int. Symp. Biomed. Imag. (ISBI)*, Apr. 2017, pp. 441–445, doi: 10.1109/ISBI.2017.7950556.

[118] M. Lustig, D. Donoho, and J. M. Pauly, "Sparse MRI: The application of compressed sensing for rapid MR imaging," *Magn. Reson. Med.*, vol. 58, no. 6, pp. 1182–1195, Oct. 2007. [Online]. Available: https://onlinelibrary.wiley.com/doi/10.1002/mrm.21391

[119] J. Xun, Q. Liu, S. Huang, A. Chen, and W. Shengjun, "Image compression and reconstruction based on quantum network," in *Proc. IEEE Int. Parallel Distrib. Process. Symp. Workshops (IPDPSW)*, May 2024, pp. 1128–1135, doi: 10.1109/IPDPSW63119.2024.00184.

[120] R. B. van Heeswijk, G. Bonanno, S. Coppo, A. Coristine, T. Kober, and M. Stuber, "Motion compensation strategies in magnetic resonance imaging," *Crit. Rev. Biomed. Eng.*, vol. 40, no. 2, pp. 99–119, 2012, doi: 10.1615/critrevbiomedeng.v40.i2.20.

[121] D. Stucht, S. Yang, P. Schulze, A. Danishad, I. Kadashevich, J. Bernarding, J. Maclaren, M. Zaitsev, and O. Speck, *Improved Image Segmentation With Prospective Motion Correction in MRI*. Cham, Switzerland: Springer, 2012, p. 2732, doi: 10.1007/978-3-642-28502-8_7.

[122] J. Jao, M. Cheng, H. Lee, J. Ting, and P. Chen, "Geometric distortion evaluation using a multi-orientated water-phantom at 0.2 t MRI," *Bio-Medical Mater. Eng.*, vol. 26, pp. S1431–S1438, Feb. 2015.

[123] T. Lei and J. K. Udupa, "Gibbs ringing artifact and spatial correlation in MRI," *Proc. SPIE*, vol. 5030, p. 961, Jun. 2003, doi: 10.1117/12.480197.

[124] Y. Shang, G. L. Simegn, K. Gillen, H.-J. Yang, and H. Han, "Advancements in MR hardware systems and magnetic field control: B0 shimming, RF coils, and gradient techniques for enhancing magnetic resonance imaging and spectroscopy," *Psychoradiology*, vol. 4, Feb. 2024, doi: 10.1093/psyrad/kkae013.

[125] D. A. Yablonskiy, A. L. Sukstanskii, J. Luo, and X. Wang, "Voxel spread function method for correction of magnetic field inhomogeneity effects in quantitative gradient-echo-based MRI," *Magn. Reson. Med.*, vol. 70, no. 5, pp. 1283–1292, Dec. 2012, doi: 10.1002/mrm.24585.

[126] E. M. Haacke, *Magnetic Resonance Imaging: Physical Principles and Sequence Design*. Hoboken, NJ, USA: Wiley, 1999. [Online]. Available: https://cir.nii.ac.jp/crid/1130282271830135680

[127] P. Saat, N. Nogovitsyn, M. Y. Hassan, M. A. Ganaie, R. Souza, and H. Hemmati, "A domain adaptation benchmark for T1-weighted brain magnetic resonance image segmentation," *Frontiers Neuroinform.*, vol. 16, Sep. 2022, doi: 10.3389/fninf.2022.919779.

[128] D. Komandur, U. Gupta, T. Chattopadhyay, N. J. Dhinagar, S. I. Thomopoulos, J. Chen, D. Beavers, G. V. Steeg, and P. M. Thompson, "Unsupervised harmonization of brain MRI using 3D CycleGANs and its effect on brain age prediction," in *Proc. 19th Int. Symp. Med. Inf. Process. Anal. (SIPAIM)*, Nov. 2023, doi: 10.1109/sipaim56729.2023.10373501.

[129] S. S. Loaliyan and G. Ver Steeg, "Comparative analysis of generalization and harmonization methods for 3D brain fMRI images: A case study on OpenBHB dataset," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. Workshops (CVPRW)*, Jun. 2024, pp. 4915–4923, doi: 10.1109/CVPRW63382.2024.00496.

[130] J. Wu, B. Qin, X. Zhang, J. Zhu, Z. Qian, and Q. Zhu, "An unsupervised domain adaptation method for cross-modality spine MRI segmentation," in *Proc. 4th Int. Conf. Electr. Eng. Control Sci. (IC2ECS)*, Dec. 2024, pp. 775–780, doi: 10.1109/ic2ecs64405.2024.10928517.

[131] Y. Lian, Z. Liu, J. Wang, and S. Lu, "Spatial-frequency aware zero-centric residual unfolding network for MRI reconstruction," *Magn. Reson. Imag.*, vol. 117, Apr. 2025, Art. no. 110334, doi: 10.1016/j.mri.2025.110334.

[132] L. Sun, Z. Fan, X. Fu, Y. Huang, X. Ding, and J. Paisley, "A deep information sharing network for multi-contrast compressed sensing MRI reconstruction," *IEEE Trans. Image Process.*, vol. 28, no. 12, pp. 6141–6153, Dec. 2019, doi: 10.1109/TIP.2019.2925288.

[133] F. Knoll, K. Hammernik, C. Zhang, S. Moeller, T. Pock, D. K. Sodickson, and M. Akcakaya, "Deep-learning methods for parallel magnetic resonance imaging reconstruction: A survey of the current approaches, trends, and issues," *IEEE Signal Process. Mag.*, vol. 37, no. 1, pp. 128–140, Jan. 2020. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/8962951

[134] G. B. Reddy, G. A. Saju, Y. Liu, and Y. Chang, "Quantum computing for data calibration in parallel magnetic resonance imaging reconstruction," in *Proc. IEEE High Perform. Extreme Comput. Conf. (HPEC)*, Sep. 2024, pp. 1–6, doi: 10.1109/HPEC62836.2024.10938445.

[135] A. Clement David-Olawade, D. B. Olawade, L. Vanderbloemen, O. B. Rotifa, S. C. Fidelis, E. Egbon, A. O. Akpan, S. Adeleke, A. Ghose, and S. Boussios, "AI-driven advances in low-dose imaging and enhancement—A review," *Diagnostics*, vol. 15, no. 6, p. 689, Mar. 2025, doi: 10.3390/diagnostics15060689.

[136] V. Tsapaki and M. Rehani, "Dose management in CT facility," *Biomed. Imag. Intervent J.*, vol. 3, no. 2, Apr. 2007, doi: 10.2349/biij.3.2.e43.

[137] A. Cai, L. Li, Z. Zheng, L. Wang, and B. Yan, "Block-matching sparsity regularization-based image reconstruction for low-dose computed tomography," *Med. Phys.*, vol. 45, no. 6, pp. 2439–2452, Apr. 2018, doi: 10.1002/mp.12911.

[138] V. S. S. Kandarpa, A. Perelli, A. Bousse, and D. Visvikis, "LRR-CED: Low-resolution reconstruction-aware convolutional encoder–decoder network for direct sparse-view CT image reconstruction," *Phys. Med. Biol.*, vol. 67, no. 15, Jul. 2022, Art. no. 155007, doi: 10.1088/1361-6560/ac7bce.

[139] H. Rahman, A. R. Khan, T. Sadiq, A. H. Farooqi, I. U. Khan, and W. H. Lim, "A systematic literature review of 3D deep learning techniques in computed tomography reconstruction," *Tomography*, vol. 9, no. 6, pp. 2158–2189, Dec. 2023, doi: 10.3390/tomography9060169.

[140] Y. Wang, Y. Liao, Y. Zhang, J. He, S. Li, Z. Bian, H. Zhang, Y. Gao, D. Meng, W. Zuo, D. Zeng, and J. Ma, "Iterative quality enhancement via residual-artifact learning networks for low-dose CT," *Phys. Med. Biol.*, vol. 63, no. 21, Oct. 2018, Art. no. 215004, doi: 10.1088/1361-6560/aae511.

[141] J. A. Seibert, "Iterative reconstruction: How it works, how to apply it," *Pediatric Radiol.*, vol. 44, no. S3, pp. 431–439, Oct. 2014, doi: 10.1007/s00247-014-3102-1.

[142] S. Magkos, A. Kupsch, and G. Bruno, "Direct iterative reconstruction of computed tomography trajectories reconstruction from limited number of projections with DIRECTT," *Rev. Sci. Instrum.*, vol. 91, no. 10, Oct. 2020, doi: 10.1063/5.0013111.

[143] Y. J. Cho, U. J. Schoepf, J. R. Silverman, A. W. Krazinski, C. Canstein, Z. Deak, J. Grimm, and L. L. Geyer, "Iterative image reconstruction techniques: Cardiothoracic computed tomography applications," *J. Thoracic Imag.*, vol. 29, no. 4, pp. 198–208, Jul. 2014, doi: 10.1097/rti.0000000000000041.

[144] S. Lee and S.-M. Kim, "Performance comparison of projector-backprojector pairs for iterative tomographic reconstruction," *Proc. SPIE*, vol. 5203, p. 656, Nov. 2003, doi: 10.1117/12.505148.

[145] F. Zanini, N. Bonato, D. Pentucci, and S. Carmignato, "Investigating the effects of machine learning generalization for enhancing accuracy in fast X-ray computed tomography for industrial metrology," *CIRP Ann.*, vol. 74, no. 1, pp. 719–723, Apr. 2025, doi: 10.1016/j.cirp.2025.04.025.

[146] V. Jeure, "Quantum-powered insights: Unravelling the Nexus of quantum computing, machine learning, and quantum machine learning," *Grenze Int. J. Eng. Technol.*, vol. 10, no. 2, pp. 1902–1908, Jul. 2024.

[147] D. Winderl, N. Franco, and J. M. Lorenz, "A comparative study on solving optimization problems with exponentially fewer qubits," *IEEE Trans. Quantum Eng.*, vol. 5, pp. 1–10, 2024, doi: 10.1109/TQE.2024.3392834.

[148] B. Dhara, M. Agrawal, and S. Dutta Roy, "Beamforming optimization via quantum algorithms using variational quantum eigensolver and quantum approximate optimization algorithm," *IET Quantum Commun.*, vol. 6, no. 1, Jan. 2025, doi: 10.1049/qtc2.12120.

[149] V. Suganesh, J. F. G. Poovathy, and S. Radha, "Filtering of Gaussian filter based embedded enhancement technique for compressively sensed images," in *Proc. Int. Conf. Wireless Commun.*, vol. 53, Mar. 2016, pp. 2177–2181, doi: 10.1109/WISPNET.2016.7566528.

[150] M. P. Heinrich, M. Stille, and T. M. Buzug, "Residual U-Net convolutional neural network architecture for low-dose CT denoising," *Current Directions Biomed. Eng.*, vol. 4, no. 1, pp. 297–300, Sep. 2018, doi: 10.1515/cdbme-2018-0072.

[151] Z. Yungang, Y. Benshun, W. Chenyue, and. F. Yu, "Low-dose ct image denoising method based on convolutional neural network," *Acta Optica Sinica*, vol. 38, no. 4, 2018, Art. no. 0410003, doi: 10.3788/aos201838.0410003.

[152] S. Katta, P. Singh, D. Garg, and M. Diwakar, "An efficient Gaussian noise denoising in CT images with deep convolutional neural networks," *Biomed. Pharmacol. J.*, vol. 18, no. December Spl Edition, pp. 139–159, Jan. 2025, doi: 10.13005/bpj/3078.

[153] Y. Song, J. Li, Y. Wu, S. Qin, Q. Wen, and F. Gao, "A resource-efficient quantum convolutional neural network," *Frontiers Phys.*, vol. 12, Apr. 2024, doi: 10.3389/fphy.2024.1362690.

[154] C. Lee, I. F. Araujo, D. Kim, J. Lee, S. Park, J.-Y. Ryu, and D. K. Park, "Optimizing quantum convolutional neural network architectures for arbitrary data dimension," *Frontiers Phys.*, vol. 13, Mar. 2025, doi: 10.3389/fphy.2025.1529188.

[155] A. Pesah, M. Cerezo, S. Wang, T. Volkoff, A. T. Sornborger, and P. J. Coles, "Absence of barren Plateaus in quantum convolutional neural networks," *Phys. Rev. X*, vol. 11, no. 4, Oct. 2021, doi: 10.1103/physrevx.11.041011.

[156] A. Wang, D. Mao, X. Li, T. Li, and L. Li, "HQNet: A hybrid quantum network for multi-class MRI brain classification via quantum computing," *Expert Syst. Appl.*, vol. 261, Feb. 2025, Art. no. 125537, doi: 10.1016/j.eswa.2024.125537.

[157] A. Jenber Belay, Y. M. Walle, and M. B. Haile, "Deep ensemble learning and quantum machine learning approach for Alzheimer's disease detection," *Sci. Rep.*, vol. 14, no. 1, Jun. 2024, doi: 10.1038/s41598-024-61452-1.

[158] M. Mazher, A. Qayyum, M. K. A. A. Khan, S. Niederer, M. Mokayef, C. S. Hassan, and A. Ridzuan, "Hybrid classical and quantum deep learning models for medical image classification," in *Proc. Int. Conf. Artif. Life Robot.*, vol. 29, Feb. 2024, pp. 222–226, doi: 10.5954/icarob.2024.os7-4.

[159] Y.-J. Jeon, S.-E. Park, and H.-M. Baek, "Predicting brain age and gender from brain volume data using variational quantum circuits," *Brain Sci.*, vol. 14, no. 4, p. 401, Apr. 2024, doi: 10.3390/brainsci14040401.

[160] J. Amin, M. A. Anjum, N. Gul, and M. Sharif, "Detection of brain space-occupying lesions using quantum machine learning," *Neural Comput. Appl.*, vol. 35, no. 26, pp. 19279–19295, Jun. 2023, doi: 10.1007/s00521-023-08717-4.

[161] Y. Dong, Y. Fu, H. Liu, X. Che, L. Sun, and Y. Luo, "An improved hybrid quantum-classical convolutional neural network for multi-class brain tumor MRI classification," *J. Appl. Phys.*, vol. 133, no. 6, Feb. 2023, doi: 10.1063/5.0138021.

[162] N. Alsharabi, T. Shahwar, A. U. Rehman, and Y. Alharbi, "Implementing magnetic resonance imaging brain disorder classification via AlexNet–quantum learning," *Mathematics*, vol. 11, no. 2, p. 376, Jan. 2023, doi: 10.3390/math11020376.

[163] S. Moradi, C. Brandner, C. Spielvogel, D. Krajnc, S. Hillmich, R. Wille, W. Drexler, and L. Papp, "Clinical data classification with noisy intermediate scale quantum computers," *Sci. Rep.*, vol. 12, no. 1, Feb. 2022, doi: 10.1038/s41598-022-05971-9.

[164] J. Amin, M. A. Anjum, N. Gul, and M. Sharif, "A secure two-qubit quantum model for segmentation and classification of brain tumor using MRI images based on blockchain," *Neural Comput. Appl.*, vol. 34, no. 20, pp. 17315–17328, May 2022, doi: 10.1007/s00521-022-07388-x.

[165] T. Kanimozhi, S. Sridevi, T. S. Manikumar, T. Dheeraj, and A. Sumanth, "Brain tumor recognition based on classical to quantum transfer learning," in *Proc. Int. Conf. Innov. Trends Inf. Technol. (ICITIIT)*, Feb. 2022, pp. 1–5, doi: 10.1109/ICITIIT54346.2022.9744220.

[166] M. Schuld, A. Bocharov, K. M. Svore, and N. Wiebe, "Circuit-centric quantum classifiers," *Phys. Rev. A, Gen. Phys.*, vol. 101, no. 3, Mar. 2020, doi: 10.1103/physreva.101.032308.

[167] A. Bilal, M. Shafiq, W. J. Obidallah, Y. A. Alduraywish, and H. Long, "Quantum computational infusion in extreme learning machines for early multi-cancer detection," *J. Big Data*, vol. 12, no. 1, Feb. 2025, doi: 10.1186/s40537-024-01050-0.

[168] K. Dremel, D. Prjamkov, M. Firsching, M. Weule, T. Lang, A. Papadaki, S. Kasperl, M. Blaimer, and T. O. J. Fuchs, "Utilizing quantum annealing in computed tomography image reconstruction," *IEEE Trans. Quantum Eng.*, vol. 6, pp. 1–10, 2025, doi: 10.1109/TQE.2025.3549305.

[169] A. Alamri, S. Abdel-Khalek, A. A. Bahaddad, and A. M. Alghamdi, "Innovative deep learning and quantum entropy techniques for brain tumor MRI image edge detection and classification model," *Alexandria Eng. J.*, vol. 122, pp. 588–604, May 2025, doi: 10.1016/j.aej.2025.03.038.

[170] M. Ohata, R. Fukui, Y. Morimitsu, D. Kobayashi, T. Yamauchi, N. Akagi, M. Honda, A. Hayashi, K. Hasegawa, K. Kida, S. Goto, and T. Hiraki, "Investigating the effects of reconstruction conditions on image quality and radiomic analysis in photon-counting computed tomography," *J. Med. Phys.*, vol. 50, no. 1, pp. 100–107, Jan. 2025, doi: 10.4103/jmp.jmp_114_24.

[171] H. Zhao, X. Deng, H. Shao, and Y. Jiang, "COVID-19 diagnostic prediction on chest CT scan images using hybrid quantum-classical convolutional neural network," *J. Biomolecular Struct. Dyn.*, vol. 42, no. 7, pp. 3737–3746, Jun. 2023, doi: 10.1080/07391102.2023.2226215.

[172] P. Singh and S. R. Joshi, "Severity classification of COVID-19 from chest CT image using integrated quantum-classical framework," in *Proc. Int. Conf. Inventive Comput. Technol. (ICICT)*, Apr. 2024, pp. 252–259, doi: 10.1109/icict60155.2024.10544406.

[173] V. R. Jannapureddy, S. Yoo, and H.-H. Tseng, "Utilizing a hybrid matrix product state and variational quantum circuit architecture for the detection of kidney diseases," in *Proc. Int. Conf. Mach. Learn. Appl. (ICMLA)*, Dec. 2024, pp. 1821–1826, doi: 10.1109/icmla61862.2024.00281.

[174] J. E. Martis, M. S. Sannidhan, R. Balasubramani, A. M. Mutawa, and M. Murugappan, "Novel hybrid quantum architecture-based lung cancer detection using chest radiograph and computerized tomography images," *Bioengineering*, vol. 11, no. 8, p. 799, Aug. 2024, doi: 10.3390/bioengineering11080799.

[175] L. Sünkel, D. Martyniuk, J. Reichwald, A. Morariu, R. H. Seggoju, P. J. Altmann, C. Roch, and A. Paschke, "Hybrid quantum machine learning assisted classification of COVID-19 from computed tomography scans," in *Proc. IEEE Int. Conf. Quantum Comput. Eng. (QCE)*, Sep. 2023, pp. 356–366, doi: 10.1109/QCE57702.2023.00048.

[176] D. Schuman, L. Snkel, P. Altmann, J. Stein, C. Roch, T. Gabor, and C. Linnhoff-Popien, "Towards transfer learning for large-scale image classification using annealing-based quantum Boltzmann machines," in *Proc. IEEE Int. Conf. Quantum Comput. Eng. (QCE)*, Sep. 2023, p. 4247, doi: 10.1109/QCE57702.2023.10182.

[177] A. Kodipalli, S. L. Fernandes, S. K. Dasar, and T. Ismail, "Computational framework of inverted fuzzy C-means and quantum convolutional neural network towards accurate detection of ovarian tumors," *Int. J. E-Health Med. Commun.*, vol. 14, no. 1, pp. 1–16, Apr. 2023, doi: 10.4018/ijehmc.321149.

[178] E. Acar and. Yilmaz, "COVID-19 detection on IBM quantum computer with classical-quantum transfer learning," Cold Spring Harbor Lab. (CSHL), Cold Spring Harbor, NY, USA, Tech. Rep., Nov. 2020, doi: 10.1101/2020.11.07.20227306.

[179] A. Gautam and B. Raman, "Brain strokes classification by extracting quantum information from CT scans," *Multimedia Tools Appl.*, vol. 82, no. 11, pp. 15927–15943, Sep. 2021, doi: 10.1007/s11042-021-11342-9.

[180] J. Amin, M. Sharif, N. Gul, S. Kadry, and C. Chakraborty, "Quantum machine learning architecture for COVID-19 classification based on synthetic data generation using conditional adversarial neural network," *Cognit. Comput.*, vol. 14, no. 5, pp. 1677–1688, Aug. 2021, doi: 10.1007/s12559-021-09926-6.

[181] K. Sengupta and P. R. Srivastava, "Quantum algorithm for quicker clinical prognostic analysis: An application and experimental study using CT scan images of COVID-19 patients," *BMC Med. Informat. Decis. Making*, vol. 21, no. 1, Jul. 2021, doi: 10.1186/s12911-021-01588-6.

[182] M. Yousif, B. Al-Khateeb, and B. Garcia-Zapirain, "A new quantum circuits of quantum convolutional neural network for X-ray images classification," *IEEE Access*, vol. 12, pp. 65660–65671, 2024, doi: 10.1109/ACCESS.2024.3396411.

[183] G. V. E. Rao, R. B., P. N. Srinivasu, M. F. Ijaz, and M. Woźniak, "Hybrid framework for respiratory lung diseases detection based on classical CNN and quantum classifiers from chest X-rays," *Biomed. Signal Process. Control*, vol. 88, Feb. 2024, Art. no. 105567, doi: 10.1016/j.bspc.2023.105567.

[184] G. V. Eswara Rao and B. Rajitha, "HQF-CC: Hybrid framework for automated respiratory disease detection based on quantum feature extractor and custom classifier model using chest X-rays," *Int. J. Inf. Technol.*, vol. 16, no. 2, pp. 1145–1153, Jan. 2024, doi: 10.1007/s41870-023-01681-1.

[185] P. Decoodt, T. J. Liang, S. Bopardikar, H. Santhanam, A. Eyembe, B. Garcia-Zapirain, and D. Sierra-Sosa, "Hybrid classical–quantum transfer learning for cardiomegaly detection in chest X-rays," *J. Imag.*, vol. 9, no. 7, p. 128, Jun. 2023, doi: 10.3390/jimaging9070128.

[186] V. Kulkarni, S. Pawale, and A. Kharat, "A classical–quantum convolutional neural network for detecting pneumonia from chest radiographs," *Neural Comput. Appl.*, vol. 35, no. 21, pp. 15503–15510, Apr. 2023, doi: 10.1007/s00521-023-08566-1.

[187] M. Ragab, S. Alshehri, N. A. Alhakamy, W. Alsaggaf, H. A. Alhadrami, and J. Alyami, "Machine learning with quantum seagull optimization model for COVID-19 chest X-ray image classification," *J. Healthcare Eng.*, vol. 2022, pp. 1–13, Mar. 2022, doi: 10.1155/2022/6074538.

[188] E. Ovalle-Magallanes, J. G. Avina-Cervantes, I. Cruz-Aceves, and J. Ruiz-Pinales, "Hybrid classical–quantum convolutional neural network for stenosis detection in X-ray coronary angiography," *Expert Syst. Appl.*, vol. 189, Mar. 2022, Art. no. 116112, doi: 10.1016/j.eswa.2021.116112.

[189] E. H. Houssein, Z. Abohashima, M. Elhoseny, and W. M. Mohamed, "Hybrid quantum-classical convolutional neural network model for COVID-19 prediction using chest X-ray images," *J. Comput. Design Eng.*, vol. 9, no. 2, pp. 343–363, Feb. 2022, doi: 10.1093/jcde/qwac003.

[190] E. Ardeshir-Larijani and M. M. Nasiri Fatmehsari, "Hybrid classical-quantum transfer learning for text classification," *Quantum Mach. Intell.*, vol. 6, no. 1, Mar. 2024, doi: 10.1007/s42484-024-00147-2.

[191] V. Azevedo, C. Silva, and I. Dutra, "Quantum transfer learning for breast cancer detection," *Quantum Mach. Intell.*, vol. 4, no. 1, Feb. 2022, doi: 10.1007/s42484-022-00062-4.

[192] N. Mathur, J. Landman, Y. Y. Li, M. Strahm, S. Kazdaghli, A. Prakash, and I. Kerenidis, "Medical image classification via quantum neural networks," 2021, *arXiv:2109.01831*.

[193] J. Amin, M. Sharif, S. L. Fernandes, S.-H. Wang, T. Saba, and A. R. Khan, "Breast microscopic cancer segmentation and classification using unique 4-qubit-quantum model," *Microsc. Res. Techn.*, vol. 85, no. 5, pp. 1926–1936, Jan. 2022, doi: 10.1002/jemt.24054.

[194] S. Vashisth, I. Dhall, and G. Aggarwal, "Design and analysis of quantum powered support vector machines for malignant breast cancer diagnosis," *J. Intell. Syst.*, vol. 30, no. 1, pp. 998–1013, Sep. 2021, doi: 10.1515/jisys-2020-0089.

[195] R. Majumdar, B. Baral, B. Bhalgamiya, and T. D. Roy, "Histopathological cancer detection using hybrid quantum computing," 2023, *arXiv:2302.04633*.

[196] B. Baral, R. Majumdar, B. Bhalgamiya, and T. Dutta Roy, "Adversarial attacks on hybrid classical-quantum deep learning models for histopathological cancer detection," 2023, *arXiv:2309.06377*.

[197] A. Ray, D. Madan, S. Patil, M. Anna Rapsomaniki, and P. Pati, "Hybrid quantum-classical graph neural networks for tumor classification in digital pathology," 2023, *arXiv:2310.11353*.

[198] H. K. Ahmed, B. Tantawi, M. Magdy, and G. I. Sayed, *Quantum Optimized AlexNet for Histopathology Breast Image Diagnosis*. Cham, Switzerland: Springer, 2023, pp. 348–357, doi: 10.1007/978-3-031-43247-7_31.

[199] L. Lusnig, A. Sagingalieva, M. Surmach, T. Protasevich, O. Michiu, J. McLoughlin, C. Mansell, G. de' Petris, D. Bonazza, F. Zanconati, A. Melnikov, and F. Cavalli, "Hybrid quantum image classification and federated learning for hepatic steatosis diagnosis," *Diagnostics*, vol. 14, no. 5, p. 558, Mar. 2024, doi: 10.3390/diagnostics14050558.

[200] Y. Li, S.-Y. Huang, M. Wang, C. Tu, X.-L. Wang, Y. Li, and H.-T. Wang, "Two-measurement tomography of high-dimensional orbital angular momentum entanglement," *Phys. Rev. Lett.*, vol. 130, no. 5, Feb. 2023, doi: 10.1103/physrevlett.130.050805.

[201] A. Geng, A. Moghiseh, C. Redenbach, and K. Schladitz, "Improved FRQI on superconducting processors and its restrictions in the NISQ era," *Quantum Inf. Process.*, vol. 22, no. 2, Feb. 2023, doi: 10.1007/s11128-023-03838-0.

[202] A. Litteken, L. M. Seifert, J. D. Chadwick, N. Nottingham, T. Roy, Z. Li, D. Schuster, F. T. Chong, and J. M. Baker, "Dancing the quantum waltz: Compiling three-qubit gates on four level architectures," in *Proc. 50th Annu. Int. Symp. Comput. Archit.*, Jun. 2023, pp. 1–14, doi: 10.1145/3579371.3589106.

[203] X. Zhou, S. Li, and Y. Feng, "Quantum circuit transformation based on simulated annealing and heuristic search," *IEEE Trans. Comput.-Aided Design Integr. Circuits Syst.*, vol. 39, no. 12, pp. 4683–4694, Dec. 2020, doi: 10.1109/TCAD.2020.2969647.

[204] S. R. Majji, A. Chalumuri, and B. S. Manoj, "Quantum approach to image data encoding and compression," *IEEE Sensors Lett.*, vol. 7, no. 2, pp. 1–4, Feb. 2023, doi: 10.1109/LSENS.2023.3239749.

[205] A. Prasetiadi and M. Mambo, "Parity-based amplitude embedding for rational quantum dataset preprocessing," in *Proc. Int. Conf. Quantum Commun., Netw., Comput. (QCNC)*, Jul. 2024, pp. 96–100, doi: 10.1109/qcnc62729.2024.00024.

[206] S. Khadirsharbiyani, M. Sadeghi, M. Eghbali Zarch, and M. T. Kandemir, "Minimizing coherence errors via dynamic decoupling," in *Proc. 38th ACM Int. Conf. Supercomputing*, May 2024, pp. 164–175, doi: 10.1145/3650200.3656617.

[207] K. N. Smith, G. S. Ravi, P. Murali, J. M. Baker, N. Earnest, A. Javadi-Cabhari, and F. T. Chong, "TimeStitch: Exploiting slack to mitigate decoherence in quantum circuits," *ACM Trans. Quantum Comput.*, vol. 4, no. 1, pp. 1–27, Oct. 2022, doi: 10.1145/3548778.

[208] R. Finsterhoelzl and G. Burkard, "Benchmarking quantum error-correcting codes on quasi-linear and central-spin processors," *Quantum Sci. Technol.*, vol. 8, no. 1, Nov. 2022, Art. no. 015013, doi: 10.1088/2058-9565/aca21f.

[209] J. Preskill, "Quantum computing in the NISQ era and beyond," *Quantum*, vol. 2, p. 79, Aug. 2018, doi: 10.22331/q-2018-08-06-79.

[210] C.-H. Yu, F. Gao, S. Lin, and J. Wang, "Quantum data compression by principal component analysis," *Quantum Inf. Process.*, vol. 18, no. 8, Jul. 2019, doi: 10.1007/s11128-019-2364-9.

[211] K. Yu, S. Lin, and G.-D. Guo, "Quantum dimensionality reduction by linear discriminant analysis," *Phys. A, Stat. Mech. Appl.*, vol. 614, Mar. 2023, Art. no. 128554, doi: 10.1016/j.physa.2023.128554.

[212] F. Yang, F. Wang, X. Xu, P. Gao, T. Xin, S. Wei, and G. Long, "Quantum resonant dimensionality reduction," *Phys. Rev. Res.*, vol. 7, no. 1, Jan. 2025, doi: 10.1103/physrevresearch.7.013007.

[213] G. S. Priyanka and M. Venkatesan, "Hyperspectral image classification using quantum machine learning," in *Proc. 1st Int. Conf. Adv. Comput. Emerg. Technol. (ACET)*, Aug. 2024, pp. 1–7, doi: 10.1109/acet61898.2024.10730182.

[214] T. J. van Dam, N. M. P. Neumann, F. Phillipson, and H. van den Berg, "Hybrid Helmholtz machines: A gate-based quantum circuit implementation," *Quantum Inf. Process.*, vol. 19, no. 6, Apr. 2020, doi: 10.1007/s11128-020-02660-2.

[215] S. Bi, H. Chen, Y. Ke, S. Rao, and J. Liu, "Processing algorithms for quantum remote sensing image data," *Proc. SPIE*, vol. 22, p. 42, Sep. 2019, doi: 10.1117/12.2528307.

[216] I. Cong, S. Choi, and M. D. Lukin, "Quantum convolutional neural networks," *Nature Phys.*, vol. 15, no. 12, pp. 1273–1278, Aug. 2019, doi: 10.1038/s41567-019-0648-8.

[217] M. Monnet, N. Chaabani, T.-A. Drăfgan, B. Schachtner, and J. M. Lorenz, "Understanding the effects of data encoding on quantum-classical convolutional neural networks," in *Proc. IEEE Int. Conf. Quantum Comput. Eng. (QCE)*, Sep. 2024, pp. 1436–1446, doi: 10.1109/QCE60285.2024.0017.

[218] K. Phalak and S. Ghosh, "Shot optimization in quantum machine learning architectures to accelerate training," *IEEE Access*, vol. 11, pp. 41514–41523, 2023, doi: 10.1109/ACCESS.2023.3270419.

[219] X. Tian, J. M. Wilson, D. P. Frush, and E. Samei, "Prospective optimization of CT under tube current modulation: II. image quality," *Proc. SPIE*, vol. 9033, Mar. 2014, Art. no. 903323, doi: 10.1117/12.2044013.

[220] S. Edyvean, "CT equipment and performance issues: Radiation protection 162," *Radiat. Protection Dosimetry*, vol. 153, no. 2, pp. 190–196, Nov. 2012, doi: 10.1093/rpd/ncs285.

[221] J. M. Kofler, D. D. Cody, and R. L. Morin, "CT protocol review and optimization," *J. Amer. College Radiol.*, vol. 11, no. 3, pp. 267–270, Mar. 2014, doi: 10.1016/j.jacr.2013.10.013.

[222] N. Variankaval, *X-ray Methods*. Boca Raton, FL, USA: CRC Press, Nov. 2004, pp. 239–256, doi: 10.1201/9780849390395.ch8.

[223] R. M. Reilly, "Xray, ct, and mammography technology," in *Medical Imaging for Health Professionals: Technologies and Clinical Applications*. USA: Elsevier, Jan. 2019, p. 116, doi: 10.1002/9781119537397.ch2.

[224] N. Matondo-Mvula and K. Elleithy, "Advances in quantum medical image analysis using machine learning: Current status and future directions," in *Proc. IEEE Int. Conf. Quantum Comput. Eng. (QCE)*, Sep. 2023, pp. 367–377.

[225] L. Wei, H. Liu, J. Xu, L. Shi, Z. Shan, B. Zhao, and Y. Gao, "Quantum machine learning in medical image analysis: A survey," *Neurocomputing*, vol. 525, pp. 42–53, Mar. 2023, doi: 10.1016/j.neucom.2023.01.049.

[226] R. U. Shaik, A. Unni, and W. Zeng, "Quantum based pseudo-labelling for hyperspectral imagery: A simple and efficient semi-supervised learning method for machine learning classifiers," *Remote Sens.*, vol. 14, no. 22, p. 5774, Nov. 2022, doi: 10.3390/rs14225774.

[227] M. Schuld, I. Sinayskiy, and F. Petruccione, "An introduction to quantum machine learning," *Contemp. Phys.*, vol. 56, no. 2, pp. 172–185, Oct. 2014, doi: 10.1080/00107514.2014.964942.

[228] P. Date and W. Smith, "Quantum discriminator for binary classification," *Sci. Rep.*, vol. 14, no. 1, Jan. 2024, doi: 10.1038/s41598-023-46469-2.

[229] T. Hubregtsen, J. Pichlmeier, P. Stecher, and K. Bertels, "Evaluation of parameterized quantum circuits: On the relation between classification accuracy, expressibility, and entangling capability," *Quantum Mach. Intell.*, vol. 3, no. 1, Mar. 2021, doi: 10.1007/s42484-021-00038-w.

[230] T. Valtinos, A. Mandilara, and D. Syvridis, "The gell-mann feature map of qutrits and its applications in classification tasks," *Proc. SPIE*, vol. 23, p. 51, Mar. 2024, doi: 10.1117/12.3001127.

[231] X.-W. Yao, H. Wang, Z. Liao, M.-C. Chen, J. Pan, J. Li, K. Zhang, X. Lin, Z. Wang, Z. Luo, W. Zheng, J. Li, M. Zhao, X. Peng, and D. Suter, "Quantum image processing and its application to edge detection: Theory and experiment," *Phys. Rev. X*, vol. 7, no. 3, Sep. 2017, doi: 10.1103/physrevx.7.031041.

[232] M. E. Haque, M. Paul, A. Ulhaq, and T. Debnath, "A novel state connection strategy for quantum computing to represent and compress digital images," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, Jun. 2023, pp. 1–5, doi: 10.1109/ICASSP49357.2023.10094832.

[233] M. Sarkar, *Novel Design of Quantum Circuits for Representation of Grayscale Images*. Singapore: Springer, 2023, pp. 435–442, doi: 10.1007/978-981-19-8563-8_42.

[234] C. Ciliberto, M. Herbster, A. D. Ialongo, M. Pontil, A. Rocchetto, S. Severini, and L. Wossnig, "Quantum machine learning: A classical perspective," *Proc. Roy. Soc. A, Math., Phys. Eng. Sci.*, vol. 474, no. 2209, Jan. 2018, Art. no. 20170551, doi: 10.1098/rspa.2017.0551.

[235] M. Unberath, J.-N. Zaech, C. Gao, B. Bier, F. Goldmann, S. C. Lee, J. Fotouhi, R. Taylor, M. Armand, and N. Navab, "Enabling machine learning in X-ray-based procedures via realistic simulation of image formation," *Int. J. Comput. Assist. Radiol. Surg.*, vol. 14, no. 9, pp. 1517–1528, Jun. 2019, doi: 10.1007/s11548-019-02011-2.

[236] M. Nawaz, T. Nazir, J. Baili, M. A. Khan, Y. J. Kim, and J.-H. Cha, "CXray-EffDet: Chest disease detection and classification from X-ray images using the EfficientDet model," *Diagnostics*, vol. 13, no. 2, p. 248, Jan. 2023, doi: 10.3390/diagnostics13020248.

[237] J. Irvin, P. Rajpurkar, M. Ko, Y. Yu, S. Ciurea-Ilcus, C. Chute, H. Marklund, B. Haghgoo, R. Ball, K. Shpanskaya, J. Seekins, D. A. Mong, S. S. Halabi, J. K. Sandberg, R. Jones, D. B. Larson, C. P. Langlotz, B. N. Patel, M. P. Lungren, and A. Y. Ng, "CheXpert: A large chest radiograph dataset with uncertainty labels and expert comparison," in *Proc. AAAI Conf. Artif. Intell.*, Jul. 2019, doi: 10.1609/aaai.v33i01.3301590.

[238] A. Talasila, A. Karthikeyan, S. Alle, M. Maity, and U. D. Priyakumar, "Self-supervision and weak supervision for accurate and interpretable chest X-ray classification models," in *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, Jun. 2023, pp. 1–8, doi: 10.1109/ijcnn54540.2023.10191913.

[239] S.-J. Tu, W.-Y. Chen, and C.-T. Wu, "Uncertainty measurement of radiomics features against inherent quantum noise in computed tomography imaging," *Eur. Radiol.*, vol. 31, no. 10, pp. 7865–7875, Apr. 2021, doi: 10.1007/s00330-021-07943-5.

[240] S. Chan, P. Kulkarni, P. H. Yi, and V. S. Parekh, "Expanding the horizon: Enabling hybrid quantum transfer learning for long-tailed chest X-ray classification," in *Proc. IEEE Int. Conf. Quantum Comput. Eng. (QCE)*, Sep. 2024, pp. 572–582, doi: 10.1109/QCE60285.2024.00073.

[241] B. Baral and T. D. Roy, "Integrating quantum principles with classical transfer learning approaches for pneumonia detection from chest radiographs," in *Proc. 4th Int. Conf. Sustain. Expert Syst. (ICSES)*, Oct. 2024, pp. 1042–1049, doi: 10.1109/ICSES63445.2024.10763087.

[242] T. Shahwar, F. Mallek, A. Ur Rehman, M. T. Sadiq, and H. Hamam, "Classification of pneumonia via a hybrid ZFNet-quantum neural network using a chest X-ray dataset," *Current Med. Imag. Rev.*, vol. 20, Nov. 2024, doi: 10.2174/0115734056317489240808094924.

[243] A. Abbas, D. Sutter, C. Zoufal, A. Lucchi, A. Figalli, and S. Woerner, "The power of quantum neural networks," *Nature Comput. Sci.*, vol. 1, no. 6, pp. 403–409, Jun. 2021, doi: 10.1038/s43588-021-00084-1.

[244] D. A. L. Montiel, O. Montiel, M. Lopez-Montiel, and O. Castillo, "Weight adjustment of the quantum layer in a hybrid model for skin cancer image classification," *Proc. SPIE*, p. 16, Sep. 2024, doi: 10.1117/12.3027860.

[245] N. Abdullayev, L. Aliyeva, and J. Hasanov, "Comparative study of quantum to classical machine learning algorithms for breast cancer classification," in *Proc. IEEE 17th Int. Conf. Appl. Inf. Commun. Technol. (AICT)*, Oct. 2023, doi: 10.1109/AICT59525.2023.10313161.

[246] H.-Y. Lin, H.-H. Tseng, S. Y.-C. Chen, and S. Yoo, "Quantum gradient class activation map for model interpretability," in *Proc. IEEE Workshop Signal Process. Syst. (SiPS)*, Nov. 2024, pp. 165–170, doi: 10.1109/SIPS62058.2024.00037.

[247] N. Elazab, H. Soliman, S. El-Sappagh, S. M. R. Islam, and M. Elmogy, "Objective diagnosis for histopathological images based on machine learning techniques: Classical approaches and new trends," *Mathematics*, vol. 8, no. 11, p. 1863, Oct. 2020, doi: 10.3390/math8111863.

[248] N. Wang, C. Zhang, X. Wei, T. Yan, W. Zhou, J. Zhang, H. Kang, Z. Yuan, and X. Chen, "Harnessing the power of optical microscopy for visualization and analysis of histopathological images," *Biomed. Opt. Exp.*, vol. 14, no. 10, p. 5451, Sep. 2023, doi: 10.1364/boe.501893.

[249] S. D. Thepade and A. Bhushari, "Improved classification of histopathological images using the feature fusion of thepade sorted block truncation code and Niblack thresholding," *ELCVIA Electron. Lett. Comput. Vis. Image Anal.*, vol. 22, no. 1, pp. 15–34, Jun. 2023.

[250] H.-C. Hsu, H.-W. Tsai, M. Gabrani, P.-C. Chung, A. F. Rodriguez, and Y.-T. Wu, "Using stain decomposition for nucleus segmentation on multisource H&E slide images," in *Proc. IEEE Symp. Ser. Comput. Intell. (SSCI)*, Dec. 2021, pp. 01–07, doi: 10.1109/SSCI50451.2021.9659856.

[251] V. D. Gowda, H. Y. Patil, S. Abidin, R. A. Panda, and S. Suneetha, *Quantum Machine Learning for Biomedical Data Analysis*. Palmdale, PA, USA: IGI Global, Dec. 2023, p. 180205, doi: 10.4018/979-8-3693-1479-1.ch011.

[252] L. K. Singh, G. Ranjitham, P. K. Parida, L. Guganathan, and S. Sridhar, "Detection of lung cancer in histopathological images utilizing self-guided quantum generative adversarial network with cat hunting optimization," in *Proc. 4th Int. Conf. Sentiment Anal. Deep Learn. (ICSADL)*, Feb. 2025, pp. 693–699, doi: 10.1109/icsadl65848.2025.10933406.

[253] S. Mittal, K. Yeh, L. S. Leslie, S. Kenkel, A. Kajdacsy-Balla, and R. Bhargava, "Simultaneous cancer and tumor microenvironment subtyping using confocal infrared microscopy for all-digital molecular histopathology," in *Proc. Nat. Acad. Sci. USA*, Jun. 2018, vol. 115, no. 25, pp. E5651–E5660, doi: 10.1073/pnas.1719551115.

[254] D. Komura, M. Ochi, and S. Ishikawa, "Machine learning methods for histopathological image analysis: Updates in 2024," *Comput. Structural Biotechnol. J.*, vol. 27, pp. 383–400, Nov. 2025, doi: 10.1016/j.csbj.2024.12.033.

[255] S. Kosaraju, J. Park, H. Lee, J. W. Yang, and M. Kang, "Deep learning-based framework for slide-based histopathological image analysis," *Sci. Rep.*, vol. 12, no. 1, Nov. 2022, doi: 10.1038/s41598-022-23166-0.

[256] T. M. Khan and A. Robles-Kelly, "Machine learning: Quantum vs classical," *IEEE Access*, vol. 8, pp. 219275–219294, 2020, doi: 10.1109/ACCESS.2020.3041719.

[257] D. Komura and S. Ishikawa, "Machine learning methods for histopathological image analysis," *Comput. Structural Biotechnol. J.*, vol. 16, pp. 34–42, Mar. 2018, doi: 10.1016/j.csbj.2018.01.001.

[258] B. Sun, A. M. Iliyasu, F. Yan, F. Dong, and K. Hirota, "An RGB multi-channel representation for images on quantum computers," *J. Adv. Comput. Intell. Intell. Informat.*, vol. 17, no. 3, pp. 404–417, May 2013, doi: 10.20965/jaciii.2013.p0404.

[259] M. Abdolmaleky, M. Naseri, J. Batle, A. Farouk, and L.-H. Gong, "Red-green-blue multi-channel quantum representation of digital images," *Optik*, vol. 128, pp. 121–132, Jan. 2017, doi: 10.1016/j.ijleo.2016.09.123.

[260] S. Das and F. Caruso, "A hybrid-qudit representation of digital RGB images," *Sci. Rep.*, vol. 13, no. 1, Aug. 2023, doi: 10.1038/s41598-023-39906-9.

[261] G. V. S. Sudhamsh, R. Rashmi, and S. Girisha, *Enhancing Histopathological Image Analysis: A Study on Effect of Color Normalization and Activation Functions*. Cham, Switzerland: Springer, Sep. 2024, pp. 220–232, doi: 10.1007/978-3-031-71484-9_20.

[262] N. Ioannou, M. Stanisavljevic, A. Anghel, N. Papandreou, S. Andani, J. H. Rüschoff, P. Wild, M. Gabrani, and H. Pozidis, *Accelerated MLAssisted Tumor Detection in High-Resolution Histopathology Images*. Cham, Switzerland: Springer, 2019, pp. 406–414, doi: 10.1007/978-3-030-32239-7_45.

[263] W. Lu, Y. Lu, J. Li, A. Sigov, L. Ratkin, and L. A. Ivanov, "Quantum machine learning: Classifications, challenges, and solutions," *J. Ind. Inf. Integr.*, vol. 42, Nov. 2024, Art. no. 100736, doi: 10.1016/j.jii.2024.100736.

[264] B. Saju, M. K. Gopal, B. Nithya, V. Asha, and V. Kumar, "Analysis on role of quantum computing in machine learning," in *Proc. 4th Int. Conf. Cognit. Comput. Inf. Process. (CCIP)*, Dec. 2022, pp. 1–8, doi: 10.1109/ccip57447.2022.10058679.

[265] M. T. West, J. Heredge, M. Sevior, and M. Usman, "Provably trainable rotationally equivariant quantum machine learning," *PRX Quantum*, vol. 5, no. 3, Jul. 2024, doi: 10.1103/prxquantum.5.030320.

[266] M. Cerezo, G. Verdon, H.-Y. Huang, L. Cincio, and P. J. Coles, "Challenges and opportunities in quantum machine learning," *Nature Comput. Sci.*, vol. 2, no. 9, pp. 567–576, Sep. 2022, doi: 10.1038/s43588-022-00311-3.

[267] Y. Fan and H. Gong, *An Improved Tensor Network for Image Classification in Histopathology*. Cham, Switzerland: Springer, 2022, pp. 126–137, doi: 10.1007/978-3-031-18910-4_11.

[268] G. Campanella, M. G. Hanna, L. Geneslaw, A. Miraflor, V. Werneck Krauss Silva, K. J. Busam, E. Brogi, V. E. Reuter, D. S. Klimstra, and T. J. Fuchs, "Clinical-grade computational pathology using weakly supervised deep learning on whole slide images," *Nature Med.*, vol. 25, no. 8, pp. 1301–1309, Jul. 2019, doi: 10.1038/s41591-019-0508-1.

[269] T. Mahmood, T. Saba, and A. Rehman, "Breast cancer diagnosis with MFF-HistoNet: A multi-modal feature fusion network integrating CNNs and quantum tensor networks," *J. Big Data*, vol. 12, no. 1, Mar. 2025, doi: 10.1186/s40537-025-01114-9.

[270] B. Denham, E. M.-K. Lai, R. Sinha, and M. A. Naeem, "Witan: Unsupervised labelling function generation for assisted data programming," *Proc. VLDB Endowment*, vol. 15, no. 11, pp. 2334–2347, Jul. 2022, doi: 10.14778/3551793.3551797.

[271] Y. Ozen, S. Aksoy, K. Kösemehmetoglu, S. Önder, and A. Üner, "Self-supervised learning with graph neural networks for region of interest retrieval in histopathology," in *Proc. 25th Int. Conf. Pattern Recognit. (ICPR)*, Jan. 2021, pp. 6329–6334, doi: 10.1109/ICPR48806.2021.9412903.

[272] X. Wang, S. Yang, J. Zhang, M. Wang, J. Zhang, J. Huang, W. Yang, and X. Han, *TransPath: Transformer-Based Self-supervised Learning for Histopathological Image Classification*. Cham, Switzerland: Springer, 2021, pp. 186–195, doi: 10.1007/978-3-030-87237-3_18.

[273] J. Li, J. Zhang, L. Schmidt, and A. J. Ratner, "Characterizing the impacts of semi-supervised learning for weak supervision," in *Proc. Adv. Neural Inf. Process. Syst.*, vol. 36, 2023, pp. 4309–4330.

[274] F. Fooladgar, M. Nguyen Nhat to, G. Javadi, S. Sojoudi, W. Eshumani, S. Chang, P. Black, P. Mousavi, and P. Abolmaesumi, "Semi-supervised learning from coarse histopathology labels," *Comput. Methods Biomechanics Biomed. Eng., Imag. Visualizat.*, vol. 11, no. 4, pp. 1143–1150, Dec. 2022, doi: 10.1080/21681163.2022.2154275.

[275] X. Li, C. Li, M. M. Rahaman, H. Sun, X. Li, J. Wu, Y. Yao, and M. Grzegorzek, "A comprehensive review of computer-aided whole-slide image analysis: From datasets to feature extraction, segmentation, classification and detection approaches," *Artif. Intell. Rev.*, vol. 55, no. 6, pp. 4809–4878, Jan. 2022, doi: 10.1007/s10462-021-10121-0.

[276] B. Boecking, W. Neiswanger, E. Xing, and A. Dubrawski, "Interactive weak supervision: Learning useful heuristics for data labeling," 2020, *arXiv:2012.06046*.

[277] Z. Chen, Z. Chen, J. Liu, Q. Zheng, Y. Zhu, Y. Zuo, Z. Wang, X. Guan, Y. Wang, and Y. Li, "Weakly supervised histopathology image segmentation with sparse point annotations," *IEEE J. Biomed. Health Informat.*, vol. 25, no. 5, pp. 1673–1685, May 2021, doi: 10.1109/JBHI.2020.3024262.

[278] J. G. C. Presotto, L. P. Valem, N. G. de, D. C. G. Pedronette, and J. P. Papa, "Weakly supervised learning through rank-based contextual measures," in *Proc. 25th Int. Conf. Pattern Recognit. (ICPR)*, Jan. 2021, pp. 5752–5759, doi: 10.1109/ICPR48806.2021.9412596.

[279] S. Budd, E. C. Robinson, and B. Kainz, "A survey on active learning and human-in-the-loop deep learning for medical image analysis," *Med. Image Anal.*, vol. 71, Jul. 2021, Art. no. 102062, doi: 10.1016/j.media.2021.102062.

[280] S. Nagdeote and S. Prabhu, "A model to perform prediction based on feature extraction of histopathological images of the breast," *Multimedia Tools Appl.*, vol. 83, no. 6, pp. 18119–18146, Jul. 2023, doi: 10.1007/s11042-023-16245-5.

[281] L. Peyrin-Biroulet, S. Adsul, A. Stancati, J. Dehmeshki, and O. Kubassova, "An artificial intelligence-driven scoring system to measure histological disease activity in ulcerative colitis," *United Eur. Gastroenterology J.*, vol. 12, no. 8, pp. 1028–1033, Apr. 2024, doi: 10.1002/ueg2.12562.

[282] A. Ganapathi, U. Sharma, S. Gupta, A. Deshwal, S. Vijh, and S. Kumar, "Predictive analysis on histopathological images using metaheuristics and machine learning method," *Int. J. Bioinf. Res. Appl.*, vol. 20, no. 5, pp. 517–530, 2024, doi: 10.1504/ijbra.2024.141779.

[283] E. Tjoa and C. Guan, "A survey on explainable artificial intelligence (XAI): Toward medical XAI," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 32, no. 11, pp. 4793–4813, Nov. 2021, doi: 10.1109/TNNLS.2020.3027314.

[284] J. Bhattacharya, A. Gupta, M. N. Dretsch, T. S. Denney, and G. Deshpande, "A reliable clinical decision support system for posttraumatic stress disorder using functional magnetic resonance imaging data," *IEEE Trans. Artif. Intell.*, vol. 5, no. 11, pp. 5605–5615, Nov. 2024, doi: 10.1109/TAI.2024.3411596.

[285] Y. Brima and M. Atemkeng, "Saliency-driven explainable deep learning in medical imaging: Bridging visual explainability and statistical quantitative analysis," *BioData Mining*, vol. 17, no. 1, Jun. 2024, doi: 10.1186/s13040-024-00370-4.

[286] P. V. Rajaraman and S. Udhayakumar, "Explainable AI for medical imaging: Advancing transparency and trust in diagnostic decision-making," in *Proc. Innov. Power Adv. Comput. Technol. (i-PACT)*, Dec. 2023, pp. 1–6, doi: 10.1109/i-pact58649.2023.10434658.

[287] M. F. Fayyad and Mustakim, "Application of AlexNet, EfficientNetV2B0, and VGG19 with explainable AI for cataract and glaucoma image classification," in *Proc. Int. Electron. Symp. (IES)*, Aug. 2024, pp. 406–412, doi: 10.1109/ies63037.2024.10665856.

[288] M. F. Ahamed, M. R. Islam, M. Nahiduzzaman, M. J. Karim, M. A. Ayari, and A. Khandakar, "Automated detection of colorectal polyp utilizing deep learning methods with explainable AI," *IEEE Access*, vol. 12, pp. 78074–78100, 2024, doi: 10.1109/ACCESS.2024.3402818.

[289] Y. Dong, X. Che, Y. Fu, H. Liu, Y. Zhang, and Y. Tu, "Classification of knee osteoarthritis based on quantum-to-classical transfer learning," *Frontiers Phys.*, vol. 11, Jul. 2023, doi: 10.3389/fphy.2023.1212373.

[290] M. F. Shahriyar and G. Tanbhir, "Advancements and challenges in quantum machine learning for medical image classification: A comprehensive review," in *Proc. 3rd Int. Conf. Intell. Syst., Adv. Comput. Commun. (ISACC)*, Feb. 2025, pp. 1126–1133, doi: 10.1109/isacc65211.2025.10969166.

[291] Y. Liu, D. Wang, S. Xue, A. Huang, X. Fu, X. Qiang, P. Xu, H.-L. Huang, M. Deng, C. Guo, X. Yang, and J. Wu, "Variational quantum circuits for quantum state tomography," *Phys. Rev. A, Gen. Phys.*, vol. 101, no. 5, May 2020, doi: 10.1103/physreva.101.052316.

[292] P. Mishra, R. Lessard, and I. Roychoudhury, "Procedures for evaluating classical, quantum, and hybrid machine learning algorithms," in *Proc. IEEE Int. Conf. Quantum Comput. Eng. (QCE)*, Sep. 2024, pp. 606–607, doi: 10.1109/QCE60285.2024.10427.

[293] A. Dixit, A. Mani, and S. Gorbachev, "Hybrid framework for medical image classification: Integrating quantum DE and deep learning," in *Proc. IEEE Int. Conf. Intell. Signal Process. Effective Commun. Technol. (INSPECT)*, Dec. 2024, pp. 1–6, doi: 10.1109/INSPECT63485.2024.10896054.

[294] A. Sinha and M. A. Thornton, "Fault tolerance enhancements for quantum data encodings," in *Proc. IEEE 18th Dallas Circuits Syst. Conf. (DCAS)*, Apr. 2025, pp. 1–6, doi: 10.1109/DCAS65331.2025.11045458.

[295] M. Mahdian and Z. Mousavi, "Entanglement detection with quantum support vector machine(QSVM) on near-term quantum devices," 2025, *arXiv:2503.23443*.

[296] A. Jain, R. Gupta, and J. Singhal, "Diabetic retinopathy detection using quantum transfer learning," 2024, *arXiv:2405.01734*.

[297] S. Anwar, S. Das, M. Iqbal Hossain, and J. Mahmud, "Hybrid quantum-classical learning for multiclass image classification," 2025, *arXiv:2508.18161*.

[298] S. Cai, Y. Lu, B. Li, Q. Gao, L. Xu, X. Hu, and L. Zhang, "Segmentation of cardiac tissues and organs for CCTA images based on a deep learning model," *Frontiers Phys.*, vol. 11, Aug. 2023, doi: 10.3389/fphy.2023.1266500.

[299] S. M. Darwish, L. J. Abu Shaheen, and A. A. Elzoghabi, "A new medical analytical framework for automated detection of MRI brain tumor using evolutionary quantum inspired level set technique," *Bioengineering*, vol. 10, no. 7, p. 819, Jul. 2023, doi: 10.3390/bioengineering10070819.

[300] L. Tse, P. Mountney, P. Klein, and S. Severini, "Graph cut segmentation methods revisited with a quantum algorithm," 2018, *arXiv:1812.03050*.

[301] A. Youssry, A. El-Rafei, and S. Elramly, "A quantum mechanics-based algorithm for vessel segmentation in retinal images," *Quantum Inf. Process.*, vol. 15, no. 6, pp. 2303–2323, Mar. 2016, doi: 10.1007/s11128-016-1292-1.

[302] A. Bilal, A. Alkhathlan, F. A. Kateb, A. Tahir, M. Shafiq, and H. Long, "A quantum-optimized approach for breast cancer detection using SqueezeNet-SVM," *Sci. Rep.*, vol. 15, no. 1, Jan. 2025, doi: 10.1038/s41598-025-86671-y.

[303] T. Sartoretti, D. Racine, V. Mergen, L. Jungblut, P. Monnin, T. G. Flohr, K. Martini, T. Frauenfelder, H. Alkadhi, and A. Euler, "Quantum iterative reconstruction for low-dose ultra-high-resolution photon-counting detector CT of the lung," *Diagnostics*, vol. 12, no. 2, p. 522, Feb. 2022, doi: 10.3390/diagnostics12020522.

[304] S. Zhou, Y. Zhou, C. Liu, Y. Zhu, H. Zheng, D. Liang, and H. Wang, "Quantum neural network for accelerated magnetic resonance imaging," 2024, *arXiv:2410.09406*.

AYAN SAR (Student Member, IEEE) received the B.Tech. degree in computer science, specializing in big data, artificial intelligence, and machine learning, from the School of Computer Science, University of Petroleum and Energy Studies (UPES), Dehradun, where he is currently pursuing the Ph.D. degree.

His academic rigor is complemented by hands-on industry experience, including an internship at Microsoft India Research and Development Pvt. Ltd., where he contributed to optimizing database queries and developing spam detection models for Microsoft 365 Copilot. He has authored and co-authored several research papers published in prestigious venues, such as IEEE and Springer Nature, focusing on AI applications, computer vision, geospatial intelligence, and computational security. He has also authored first-author publications in *FnT Signal Processing*, *FnT Computer Graphics and Vision*, IEEE Access, *Discover Food*, *Engineering Applications of Artificial Intelligence*, and *NeuroComputing*, and co-authored in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing and many other peer-reviewed high-quality journals, along with Core B and A conferences. His research interests include computer vision, geoinformatics, cybersecurity, and applied AI solutions.

Mr. Sar is a National Record Holder in the India Book of Records (Academic Category) and a Gold Medalist in the International Mathematics Olympiad, underscoring his dedication to academic excellence and innovation.

ANKIT KUMAR received the B.Tech. degree in computer science and engineering from West Bengal Technical University, Kolkata, in 2010, and the M.Tech. and Ph.D. degrees in computer engineering from the National Institute of Technology, Kurukshetra, India, in 2014 and 2021, respectively.

He is currently an Associate Professor with Galgotias University, Greater Noida, India. Before this role, he was an Assistant Professor with the School of Computer Science, University of Petroleum and Energy Studies (UPES), Dehradun, India. With more than 12 years of academic and research experience, he has authored numerous articles in esteemed international journals. A seasoned academic, he has represented his work on global platforms and has frequently participated in international academic events and collaborations.

Dr. Kumar was honored with the prestigious Ignaz Kögler Senior Research Fellowship by AImotion Bavaria, Germany, from 2023 to 2024. As the Ignaz Kögler Senior Fellow for Language Technology, he actively contributed to the university's international outreach through his work with the Speech and Text Understanding Research Group, AImotion Bavaria, Ingolstadt.

SAMPURNA ROY (Student Member, IEEE) is currently pursuing the B.Tech. degree in computer science and engineering, specializing in artificial intelligence, machine learning, cybersecurity, and UI/UX design, with the University of Petroleum and Energy Studies (UPES), Dehradun.

She has a strong foundation in deep learning algorithms and natural language processing, with a keen interest in integrating AI-driven technologies and computer vision into practical, real-world applications. She has gained hands-on experience through internships at Quality AI and PortWol, where she worked on developing machine learning models and enhancing user interface designs. She has authored first-author publications in *FnT Signal Processing*, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, *FnT Computer Graphics and Vision*, IEEE Transactions on AgriFood Electronics, and *NeuroComputing*, and has co-authored many other peer-reviewed high-quality journals along with Core B and A conferences.

ANURAG KAUSHISH is currently pursuing the B.Tech. degree in computer science and engineering, specializing in full-stack development and artificial intelligence, with the School of Computer Science, University of Petroleum and Energy Studies (UPES), Dehradun.

He is currently with the Ministry of Electronics and Information Technology (MeitY), Government of India, on a real-time project focused on counterfeit currency note detection through AI-enabled systems. In addition, he is the Co-Founder of LitigateIQ, an AI-based legal-tech startup that has secured seed funding. The platform is designed to revolutionize dashboard management and extract actionable legal insights from litigation documents using advanced NLP and analytics tools. He has published papers on Optimized Spoken Query Cross-Lingual Document Retrieval Using BM25 and Neural Re-Ranking with AdamW, and Development of a GI Cancer Diagnostic Chatbot Based on RAG Model. His research interests include information retrieval, natural language processing, AI for healthcare, image processing, and applied machine learning.

TANUPRIYA CHOUDHURY (Senior Member, IEEE) received the B.Tech. degree in computer science and engineering from West Bengal University of Technology, Kolkata, India, in 2008, the M.Tech. degree in computer science and engineering from the Dr. M.G.R University, Chennai, India, in 2010, and the Ph.D. degree in computer science and engineering from Jagannath University, Jaipur, India, in 2016.

He is currently a Professor with the School of Computer Science, University of Petroleum and Energy Studies (UPES), Dehradun, India. He is also a Visiting Professor with Daffodil International University, Bangladesh, and a Technical Advisor to various companies, including Deetya Soft Pvt. Ltd., Noida, IVRGURU, and Mydigital360. Previously, he has held academic and leadership roles at Symbiosis International (Deemed University), Pune; Graphic Era Hill University, Dehradun; Amity University, Noida; and other reputed institutions, including Dronacharya College of Engineering, Gurgaon, and Lingaya's University, Faridabad. He has more than 15 years of teaching and research experience. He has authored numerous research papers, filed 25 patents, and obtained 16 software copyrights from the Ministry of Human Resource Development (MHRD), India. His research interests include human computing, soft computing, cloud computing, and data mining.

Dr. Choudhury is a Lifetime Member of the International Engineering and Technology Association (IETA); IET, U.K.; and other technical societies. He is an Honorary Secretary at IETA, India, and a Senior Advisor to the INDO-UK Confederation of Science, Technology and Research Ltd., London, U.K., and the International Association of Professional and Fellow Engineers, USA.

MINAKSHI (Senior Member, IEEE) received the bachelor's degree in computer engineering and the M.Tech. and Ph.D. degrees in computer science from Suresh Gyan Vihar University (SGVU), Jaipur.

She is currently a Faculty Member with the College of Computer Science, King Khalid University, Abha, Saudi Arabia, and a Visiting Professor with the Department of Computer Science and Engineering, Uttaranchal University, India. She has more than 16 years of teaching and research experience. She has served at several esteemed institutions, including NCCE Israna; the Apeejay College of Engineering, Gurgaon; the WCTM College, Gurgaon; the Dronacharya College of Engineering, Gurgaon; and the Tula's Institute, Dehradun. She has published research papers in Scopus- and Thomson Reuters-indexed journals, filed patents. She is actively involved in multiple research projects. Her research interests include machine learning, grid computing, intelligent systems, operating systems, compiler designs, and data structures.

Dr. Minakshi serves as the Convenor of IEEE SIGHT for the IEEE Uttar Pradesh Section. She also leads the IEEE Student Branch at Uttaranchal University.

SAAD SAEED ALQAHTANI (Member, IEEE) received the B.Sc. degree in pharmaceutical science from King Khalid University, Abha, Saudi Arabia, in 2010, and the M.S. and Ph.D. degrees in pharmaceutical economics and policy and the Graduate Certificate in regulatory affairs and health policy from MCPHS University, Boston, MA, USA, in 2014, 2017, and 2017, respectively.

He is currently a Consultant and an Associate Professor of pharmacoeconomics and health policy with the Department of Clinical Pharmacy, College of Pharmacy, King Khalid University, Abha, Saudi Arabia, where he is also the Vice Dean for Student Affairs. Prior to this, he was the Head of the Clinical Pharmacy Department and the Vice Dean of Clinical Affairs at Jazan University, Saudi Arabia. He has published extensively, authoring more than 115 research papers in leading international journals, including *Nature Scientific Reports, Frontiers in Public Health, Saudi Pharmaceutical Journal, Molecules, Vaccines, Healthcare, and Pharmaceutics*. His research interests include pharmacoeconomics, pharmaceutical policy, pharmacoepidemiology, and health outcomes research.

Dr. Alqahtani has been recognized with several awards, including the Best Transformative Research Idea Award, the Best Distinguished Research Award, and the Best Academic Advisor Award from Jazan University, in 2023, 2022, and 2022, respectively. He was also the Best Research Poster Award Finalist from the ISPOR 20th Annual International Meeting, Philadelphia, PA, USA. His research has been presented at prominent global conferences, such as the American Public Health Association (APHA), the American Pharmacists Association (APhA), and the International Society for Pharmacoeconomics and Outcomes Research (ISPOR).

AJITH ABRAHAM received the Ph.D. degree from Monash University, Australia. He is currently the Vice Chancellor with Sai University, Chennai, and a Distinguished Leader in artificial intelligence research and higher education. Prior to this role, he was the Vice Chancellor at other reputed institutions and founded the globally recognized with the Machine Intelligence Research Labs (MIR Labs), a non-profit scientific research network headquartered in Seattle, WA, USA. With more than 35 years of multidisciplinary research experience, he has executed projects worth more than U.S. \$110 million as a principal or co-investigator across USA, European Union, and several Asian and Pacific nations. He has authored or co-authored more than 1500 research publications, including highly-cited books and articles, with several works translated into Chinese, Russian, and Japanese. His Scholarly impact includes more than 70 000 citations and an H-index exceeding 125 on Google Scholar. He has collaborated with leading researchers at institutions, such as MIT, Harvard University, the University of Cambridge, and the University of Oxford. He has delivered more than 250 plenary talks and tutorials in more than 20 countries and has held key leadership roles with the IEEE. He is consistently ranked among the world's top 2% most cited scientists and is listed in the top 0.01% globally in engineering and computer science.