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REVIEW

Quantum Machine and Deep Learning for Medical Image Classification: A Systematic Review of Trends, Methodologies, and Future Directions

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ABSTRACT

Quantum Learning (QL) has emerged as a promising approach to medical image classification, leveraging the principles of quantum mechanics to improve the performance and efficiency of machine learning algorithms. This systematic review provides a comprehensive critical assessment of the current status of QL techniques developed for medical image classification, with a specific focus on trends, methodologies, and future directions in this rapidly evolving field. A thorough literature search was conducted across five major databases, resulting in a total of 28 relevant studies published between 2018 and 2024. The studies were analyzed and classified based on the type of quantum algorithm, the medical image modality, and the performance metrics used. The analysis revealed a diverse range of QL techniques, including Quantum Support Vector Machines (QSVM), Quantum Convolutional Neural Networks (QCNN), and various hybrid quantum-classical approaches. These techniques have been applied to diverse medical image classification tasks, such as brain tumor classification, skin lesion classification, and COVID-19 detection, demonstrating promising results in terms of accuracy, sensitivity, and specificity. However, several challenges were identified, including the preprocessing and encoding of medical images for quantum processing, the limited scalability of current quantum hardware, and the need for interpretable and explainable QL models. This review underscores the immense potential of QL to revolutionize medical image classification, while also emphasizing the necessity of multidisciplinary collaborations and further research to overcome existing challenges and facilitate the integration of QL techniques into clinical practice.

Keywords: Quantum learning, Medical image classification, Quantum machine learning, Quantum deep learning, Systematic review

1. Introduction

The rapid development of quantum computing is quickly providing new ways to solve high-level scale issues in many fields, including machine learning and medical image analysis. Quantum Learning (QL) is a recent interdisciplinary scientific field that uses basic quantum mechanical principles of superposition and entanglement to enhance traditional machine learning by increasing performance and efficiency in executing machine learning algorithms [1]. QL, through the non-classical properties of quantum systems, will revolutionize the way in which high-dimensional and complex data, such as medical images, are processed, analyzed, and classified [2].

Medical image processing has been well established as a requisite ingredient in the diagnosis and treatment of different health anomalies, from the detection of cancer to neurological disorders [3]. However, the volume and increasing complexity of medical imaging data present a challenge for classic machine-learning approaches, which suffer from

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difficulties in capturing subtle patterns and variations in the images [4]. It is in this space where QL becomes relevant and offers a novel paradigm that will allow us to potentially go further than classical methods have been able to, via the expressive power residing in quantum systems for discriminative feature extraction and robust classification models [5].

Recently, with the rise of quantum computing capabilities, several algorithms and QL architectures have been designed to leverage certain quantum advantages [6], e.g., the Quantum Support Vector Machines (QSVM), which have outperformed their classical counterparts in terms of accuracy and efficiency in the classification of medical images [7]. Similarly, Quantum Convolutional Neural Networks (QCNN) have shown their competence in forming hierarchical features from medical images for more accurate and reliable diagnosis [8].

One of the crucial issues that arise in applying QL to medical image analysis is the high dimensionality of the data [9], which often exceeds the capabilities of current quantum devices. Researchers have therefore explored various techniques to compress and encode medical images in quantum-compatible forms, such as amplitude encoding and angle encoding. These encoding schemes enable large-scale image data to be processed on quantum computers effectively and thereby open the path to practical QL applications in medical diagnosis [10]. Hybrid models offer significant potential because quantum computing and classical computing can be combined to leverage their respective strengths, thereby overcoming the limitations that a purely quantum or purely classical approach imposes [11, 12].

Although the results are very encouraging and promising, several challenges remain for QL in the domain of medical image analysis [13]. In particular, the preprocessing and encoding of medical images for quantum processing must be carefully designed to obtain data in the right format, resolution, and dimensionality. Additionally, current quantum hardware limitations—including the small number of available qubits and issues with noise and decoherence—do not yet allow for the practical implementation and scalability of QL algorithms [14, 15]. Realizing the full potential of QL for medical image analysis would involve integrating expertise from three disciplines: quantum physics, computer science, and medical imaging. This insight motivates active research into new quantum algorithms, hybrid architectures, and error mitigation techniques that promise to overcome the current limitations of QL performance [16].

This systematic review aims to critically and comprehensively assess the state of the art of QL techniques applied to medical image classification. It examines key methodological advances and highlights the most promising applications and results to provide valuable insights into the current landscape and future directions of this rapidly evolving field.

This review will synthesize knowledge and progress in QL for medical image classification in a timely and informative manner. The contribution should have great value for researchers, practitioners, and policymakers in the healthcare and quantum computing communities. We hope that the insights gained through this review will guide further research efforts, support the development of more precise and efficient diagnostic tools, and eventually lead to improved patient care and outcomes.

In this review, we examine recent developments and potential solutions for the classification of medical images using various quantum processing techniques and QL models. This paper provides an overview of this emerging field, reviews the progress made recently, and addresses unanswered questions from previous surveys. Notably, previous reviews, despite their importance, have not focused exclusively on the classification of medical images. For instance, the review by Wang et al. [17] offers a comprehensive look at quantum image processing techniques in general but does not specifically focus on medical applications. Similarly, the review by Maheshwari et al. [18] covers QL applications in the biomedical field but does not provide in-depth coverage of image classification. In contrast, the review by Zeguendry et al. [19] covers various case studies on QL applications but does not give sufficient attention to the classification of medical images. The review by Ur Rasool et al. [20] provides a general view of quantum computing's potential in improving healthcare, with limited coverage of image classification applications. The review by Kharsa et al. [21] focused on image classification using QL techniques but did not dedicate specific attention to medical images. In Wei et al. [22], the use of QL in medical image analysis is explored, but it does not delve deeply into image classification. Finally, Ullah and Garcia-Zapirain [1] address quantum applications in healthcare in general, with limited references to image classification. Thus, there is a clear need for a systematic review focused exclusively on the classification of medical images using QL techniques, providing a detailed analysis of current challenges and proposed solutions. This review aims to fill an important gap in the existing literature and offers new insights that could contribute to the development of more efficient and accurate techniques in the future. This study offers several key contributions that enhance the understanding and application of QL in medical image classification:

1. This review exclusively targets the application of QL techniques to medical image classification, a focus absent in prior reviews. It addresses a critical gap by presenting a dedicated analysis of quantum models tailored to this domain.
2. The paper categorizes and evaluates QL models into pure quantum, hybrid quantum-classical, and quantum deep learning approaches. It provides detailed insights into their encoding techniques, preprocessing methods, quantum circuit architectures, and performance metrics.
3. This review systematically identifies and analyzes the technical hurdles faced by QL, including quantum hardware limitations, noise, encoding complexities, and the scalability of quantum algorithms.
4. By highlighting actionable strategies and showcasing successful applications, the study emphasizes the potential of QL in enhancing diagnostic workflows and supporting the development of precise, efficient diagnostic tools.

The rest of the paper is organized as follows: Section 2 presents the adopted methodology, including search strategies, inclusion and exclusion criteria, and analysis techniques. Section 3 discusses automated medical image classification and the shift towards quantum learning. Section 4 reviews the fundamental principles of quantum computing and its practical applications in medical image analysis, including the qubit structure, common quantum gates, encoding techniques, and preprocessing methods. Section 5 examines the different quantum learning models used, focusing on quantum machine learning, quantum deep learning, and hybrid approaches. Section 6 addresses the technical challenges and limitations of applying quantum learning techniques to medical image classification. Section 7 discusses the challenges and future trends in quantum learning for medical image classification. Finally, Section 8 concludes the paper by summarizing the key findings and providing actionable recommendations for future research in this field.

2. Materials and methods

2.1. Databases & query string

The initial step involves the collection of all relevant articles from the period spanning 2018 to 2024. The timeframe was selected due to the emergence and expansion of quantum devices, alongside the proliferation of Noisy Intermediate-Scale Quantum (NISQ) computers [2]. To undertake this process, the state of the art was explored through various scholarly databases, including Web of Science, Scopus, IEEE Xplore, Science Direct, and PubMed, as depicted in Fig. 1. The literature search for this systematic review was conducted using the following query:

((“QML” OR “quantum computing” OR “quantum machine learning”) AND (“medical” OR “images” OR “imaging”) AND (“classification”))

This Boolean search strategy was applied to the titles and abstracts of published studies to identify relevant research on the application of QL techniques in medical image classification.

The search was conducted on February 24, 2024, where researchers utilized a set of keywords and Boolean operations, focusing on titles and abstracts, to ensure the identification of studies that align with the objectives of the scientific review. The systematic and precisely defined approach facilitated the comprehensive collection of study data for the subsequent phases of eligibility assessment and data extraction. The search strategy and access date are reported to enhance the transparency and reproducibility of the review’s methodology.

2.2. Inclusion and exclusion criteria

This review focused on publications with the following characteristics:

Inclusion Criteria:

- Academic papers published in English.
- Peer-reviewed journal articles.
- Conference proceedings.
- Studies involving quantum machine learning (QML), or Quantum deep learning (QDL) techniques based on medical image datasets.

Exclusion Criteria:

- Preprints.
- Studies not involving QML or QDL techniques.
- Studies use text or signal datasets instead of medical images.
- Studies without implementation or simulation in quantum devices.
- Studies conducted on animals, plants, or in vitro.
- Studies evaluating QL applications outside the medical field.
- Exploratory articles without QML/QDL performance details.

The rationale for these criteria was to focus the review on high-quality, peer-reviewed research specifically addressing the application of QML and QDL techniques to medical imaging problems that could be practically implemented. By excluding certain study designs and domains, the aim was to synthesize a cohesive body of evidence relevant to the research objectives.

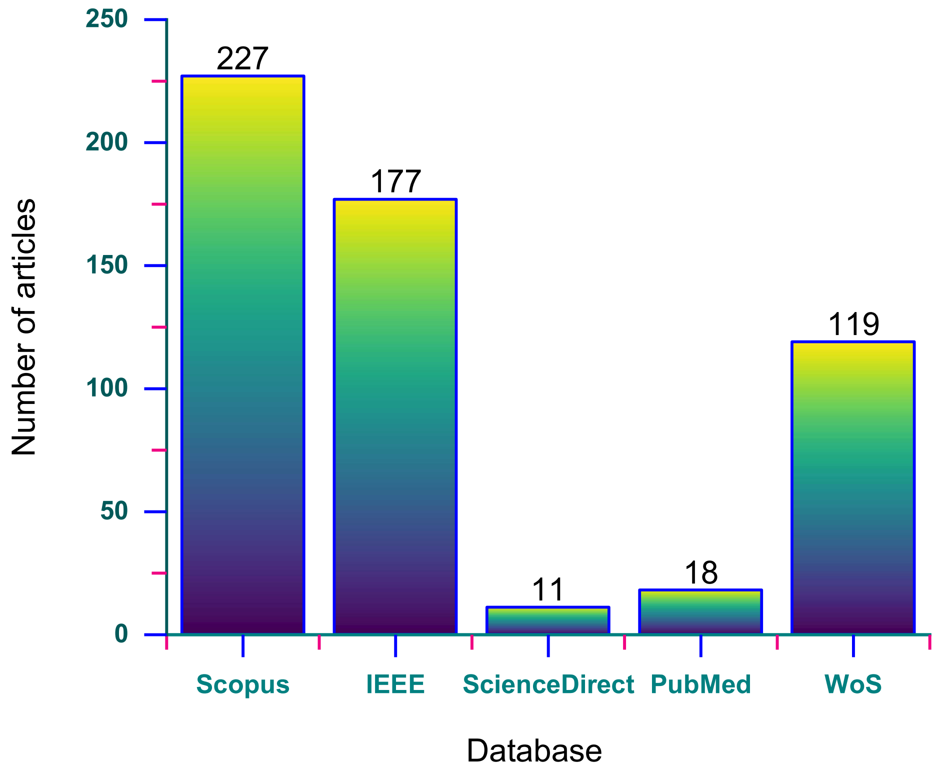


Fig. 1. Number of articles sourced from key databases on quantum machine learning in medical image classification.

2.3. Eligibility screening process

Two independent reviewers conducted the initial screening and selection of studies for inclusion in this review. The screening process consisted of the following steps:

Title and Abstract Screening: The titles and abstracts of all identified publications were screened by the three reviewers to assess their potential relevance. When the initial assessment of the reviewers differed, a consensus was reached through discussion.

Full-Text Screening: The full-text articles of the publications selected in the previous step were obtained and independently assessed by the two reviewers. The reviewers evaluated the articles against the pre-defined inclusion and exclusion criteria, as well as the overall study objectives. In cases where the initial assessments of the reviewers diverged, a final decision was made through consensus.

From the initial pool of 552 records identified across five open-source databases, 204 articles were removed as they were likely duplicates. This resulted in 348 unique papers. During the title and abstract screening stage, an additional 236 papers were excluded as they did not meet the specific requirements of the review. This included articles that utilized classical machine learning instead of quantum machine learning, or that used text datasets or signal datasets rather than medical image datasets. Of the remaining 112 records, 65 were further excluded based on the full-text screening process, where each study was carefully examined to ascertain its relevance. In conclusion, 47 studies that closely aligned with the goals of our proposed project were initially selected for analysis, as shown in Fig. 2. This selection followed a methodical and stringent review procedure, ensuring that each included study met the predefined quality and relevance criteria. However, to focus on the highest quality peer-reviewed journal articles, 19 conference papers were subsequently excluded from the final analysis. As a result, the final review includes 28 studies that fully met the established criteria and objectives.

2.4. Comprehensive analysis of quantum learning data for medical imaging

The purpose of this paper is to present a detailed analysis and classification of the contents of 28 eligible research articles addressing the application of QL techniques to medical image classification. The analysis was conducted using three different approaches with the aim of providing a comprehensive overview of the current state of research in this growing field.

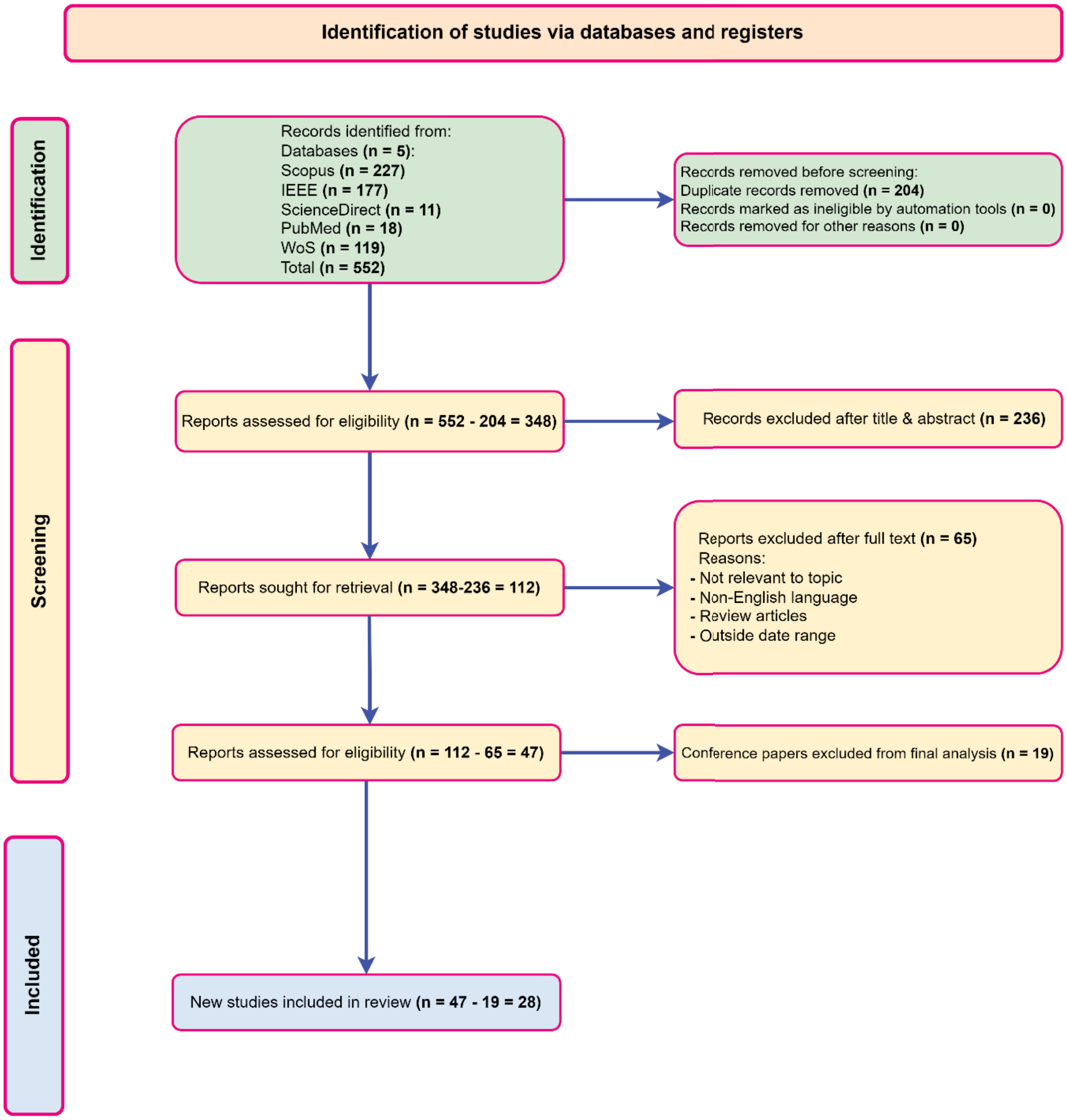


Fig. 2. PRISMA flowchart illustrating the publication selection process for studies on quantum machine learning in medical imaging.

2.4.1. Temporal trends in QL research

Based on the publication year, review of selected papers indicated that the QL-based classification of medical images is a field of increased scholarly interest and contributions. Fig. 3 depicts a progressive increase since 2018, with a peak of 24 publications in 2023. This signals an increasing number of researchers who are focusing on QL and its applications in medical imaging. The increase in QL research output over recent years reflects the medical imaging community's recognition of QL techniques for addressing the complexity of classification problems. This increased interest aligns with the general progress of quantum computing and growing awareness of the benefits that quantum methods could have in extracting useful information from medical image data.

2.4.2. Geographical distribution of QL research

The analysis of the selected papers by country, as shown in Fig. 4, offered additional insights into the geographical spread of research in this field. India was identified as the leading contributor, with 11 publications, while Saudi Arabia was the second highest with 7 articles. This assessment considered only articles published in journals.

2.4.3. Publication channels for QL research

The publication type of the chosen articles in this analysis is presented in Fig. 5. From the 47 relevant

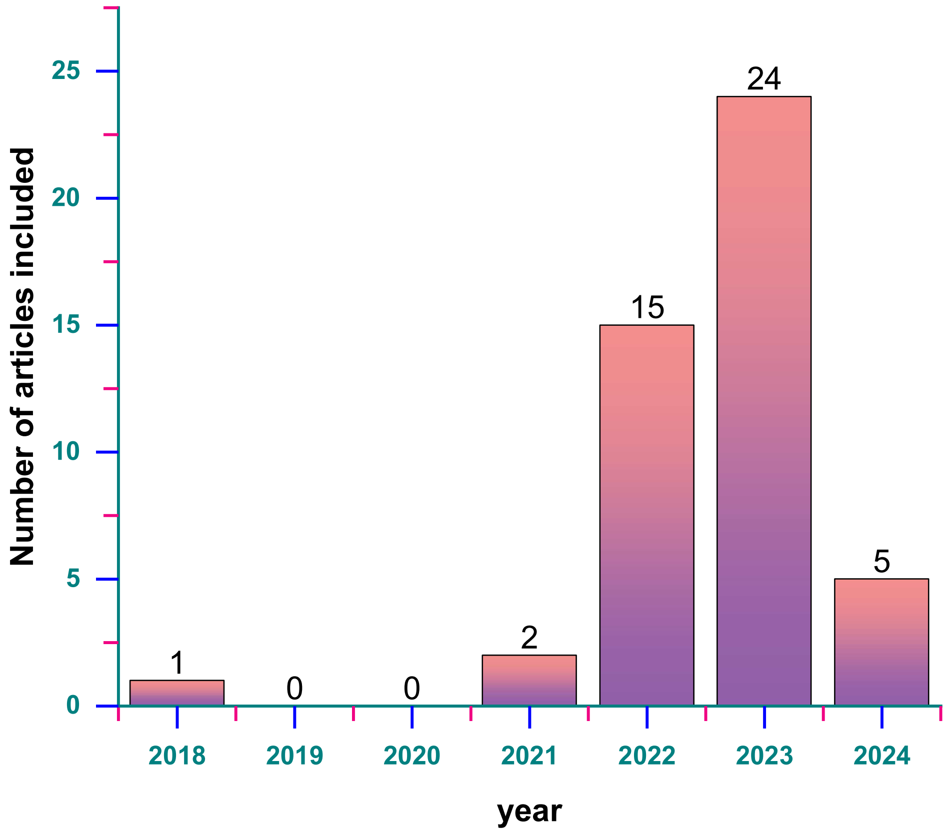


Fig. 3. Annual distribution of articles on quantum learning applications in medical image classification from 2018 to 2024.

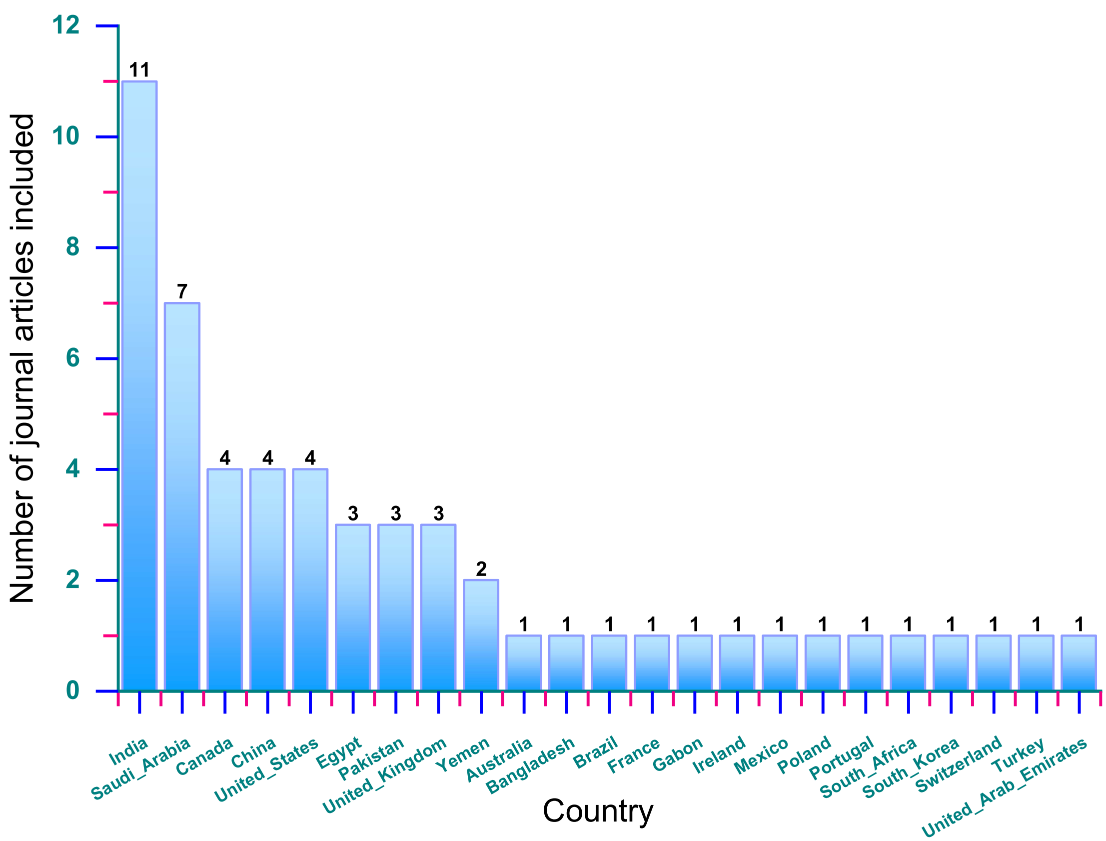


Fig. 4. Geographic distribution of journal publications by country.

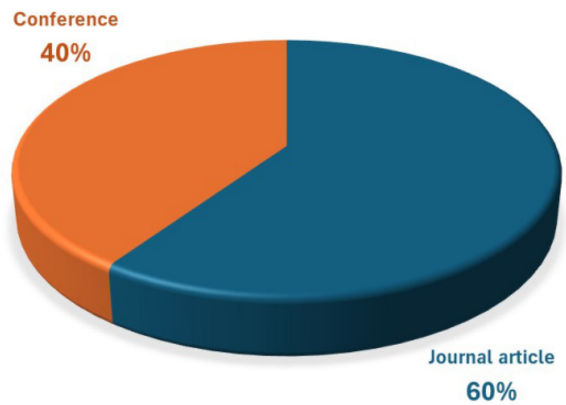


Fig. 5. Breakdown of selected publications by type, showing the proportion of journal articles and conference papers.

papers identified, 28 articles were published in international peer-reviewed journals, accounting for approximately 60%. As journal articles typically contribute to raising the level of rigor and reliability in a systematic review, the final sample was limited to journal articles only, while the remaining 40% comprised 19 conference papers. This selection approach justifies the scholarly importance and impact of the research on applying QL techniques to the classification of medical images. Journal articles are usually of higher quality and better at ensuring originality and methodological soundness due to their more rigorous review process. Focusing the analysis on higher quality peer-reviewed research provides this review with an elevated level of authority and trustworthiness for readers in determining the current state of the art for quantum solutions in medical imaging applications.

2.5. Research questions

This systematic review provides a detailed examination of the latest research on employing QL techniques for classifying medical images. The study focuses on several critical research questions:

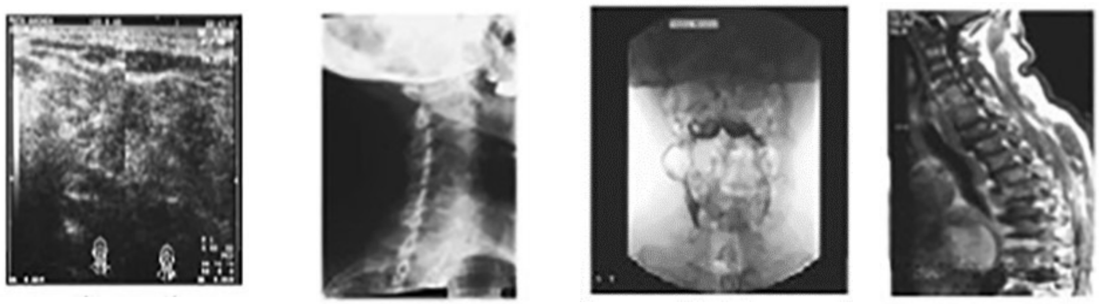
1. What quantum algorithms have been utilized in medical image classification tasks?
2. Which specific applications of medical imaging have QL been implemented in?
3. What medical image datasets are commonly used in QL modeling research?
4. What metrics are used to assess the effectiveness of QL solutions, and what values have been reported for these metrics?
5. What image preprocessing and encoding methods have been utilized in the reviewed studies?
6. What are the key challenges and hurdles when classifying images with QML and QDL?

This systematic review contributes comprehensive insight into the current trends, methodologies, and performance related to QL techniques applied within the field of medical image classification. The findings will inform future research directions and guide innovative quantum-based solution development in advanced medical imaging applications.

3. Automated medical image classification: The shift towards quantum learning

Medical image classification has become a fundamental part of modern medical systems, aiming to automatically classify images based on their visual content into predefined categories [23, 24]. This field plays a crucial role in supporting medical diagnosis, treatment planning, and contributing to medical research [25]. Various techniques, from traditional machine learning to deep learning, find their applications in medical image classification tasks. As medical imaging technologies continue to improve, these models are growing increasingly accurate and much faster [26, 27]. The most striking deep learning concept of Convolutional Neural Networks (CNNs) has transformed medical image classification in recent years [28]. These models automatically extract features from raw data, which may be very complicated, and hence allow for very accurate image classification [9]. These models require huge and diverse well-annotated datasets, which remains a challenge in the medical field [29, 30].

While classical machine learning and deep learning have seen much progress in image classification, traditional computing still puts some limits on the extent to which huge datasets can be leveraged [31]. This is where QL, based on the principles of quantum mechanics, aims to overcome such challenges. QL models enable data processing much faster and more accurately, allowing doctors and researchers to improve medical diagnosis and develop better treatment plans [22]. Today, large and complex datasets cover various medical domains, making them ideal for QL applications [32]. Among these fields, neurological disorders stand out, with datasets such as the Alzheimer's Disease Neuroimaging Initiative (ADNI) and the Parkinson's Progression Markers Initiative (PPMI) offering detailed insights into the neurological changes that occur over time. These datasets contribute to the early detection of diseases and the development of innovative treatments [33]. Ophthalmic conditions have also benefited from advanced classification techniques, where datasets such as APTOS 2019 and Retina-MNIST supported detailed analyses of minute changes in the retina. Such tools



Ultrasound X-ray Axial CT MRI

Fig. 6. Examples of medical imaging modalities, including ultrasound, X-ray, axial CT, and MRI, highlighting differences in contrast and quality across datasets [39].

help in early detection of diseases related to diabetic retinopathy and macular degeneration. QL techniques help identify subtle changes that traditional models may miss or overlook [34]. Another very important area in which medical imaging has helped significantly in recent times is the COVID-19 pandemic. Datasets such as the COVID-19 Radiography Database have contributed to developing models capable of identifying whether a person has COVID-19 or pneumonia from their chest Computed Tomography (CT) scans and X-rays. QL models accelerated the diagnostic processes, relieving pressure on healthcare systems during critically distressed periods [35]. Musculoskeletal diseases and cancers have also benefited from advancements in medical image classification. For example, datasets like the Osteoarthritis Initiative (OAI) [36] and the Mammographic Image Analysis Society (MIAS) [37] have contributed to the development of diagnostic models that assess joint health and detect early-stage cancers, improving diagnostic accuracy and personalized treatment plans [5].

The integration of QL with massive medical datasets has opened new horizons for improving medical image classification. These models not only accelerate diagnostic processes but also offer high accuracy, which can lead to significant improvements in patient outcomes and customized treatment plans [38]. Fig. 6 shows sample datasets for medical diagnostics, illustrating the differentiation of contrast and quality among several different imaging modalities.

4. Quantum learning

4.1. Quantum computing

The rapid development of quantum computing is quickly providing new ways to solve high-level scale issues in many fields, including machine learning and medical image analysis. Quantum Learning (QL) is a recent interdisciplinary scientific field that uses basic quantum mechanical principles to enhance traditional machine learning by increasing performance and efficiency in executing machine learning algorithms [20].

Unlike classical computers that rely on binary information, quantum computing processes utilize quantum bits or qubits that can exist in more than one state simultaneously through the principle of superposition. This property, along with quantum phenomena such as entanglement and quantum parallelism, enables quantum computing to process information exponentially faster and offer tremendous potential for analyzing complex medical images [40, 41].

In the field of medical imaging, these capabilities can lead to significant improvements in the efficiency and speed of image classification, supporting early and accurate diagnosis of various medical conditions [42].

4.2. Quantum learning in practice

Quantum Learning (QL) merges the laws of quantum mechanics with prevailing methods of conventional machine learning, extending the limits of computing speed and power. In practice, quantum learning systems can be categorized into four main classes based on the nature of the data and models used [4]:

- Classical Data with Classical Models (CC): Traditional machine learning systems.
- Classical Data with Quantum Models (CQ): Using quantum computing to process traditional data, which is the most commonly used approach in medical image analysis.
- Quantum Data with Classical Models (QC): Processing intrinsic quantum data using classical computational models.

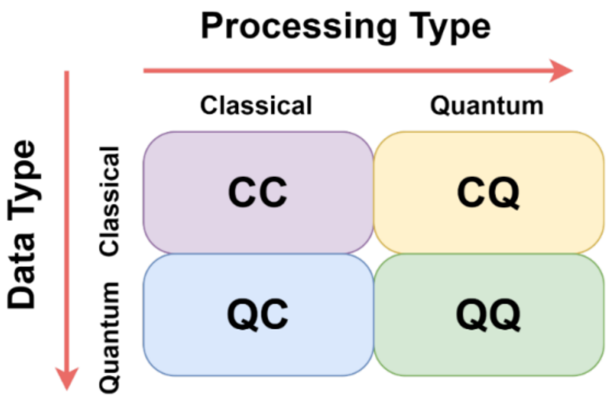


Fig. 7. Categorization of classical and quantum data and models in quantum learning: Classical-classical (CC), classical-quantum (CQ), Quantum-classical (QC), and quantum-quantum (QQ).

- Quantum Data with Quantum Models (QQ): A full quantum strategy.

In the medical imaging domain, the CQ approach is most prevalent, where quantum techniques are used to enhance the processing and classification of traditional medical images [1], as illustrated in Fig. 7.

4.2.1. Encoding techniques and preprocessing in quantum learning for medical images

Data encoding and preparation for quantum processing represent significant challenges in applying quantum learning algorithms to medical images. Several main encoding methods exist [7]:

- Basis Encoding: Suitable for simple arithmetic operations within a quantum context, but limited by quantum bit (qubit) availability [19].
- Amplitude Encoding: Translates classical data vectors into the amplitudes of quantum state vectors, offering greater efficiency in qubit usage and suitable for high-dimensional medical image data [43].
- Angle Encoding: Uses rotational quantum gates for embedding information, helping to capture complex nonlinear relationships in medical images [44].

In the context of medical images, preprocessing includes techniques such as background intensity normalization, noise reduction, and feature extraction [45]. Different normalization methods, such as min-max scaling and z-score normalization, work to make the intensity of medical images uniform for easier encoding into quantum states [22].

4.2.2. Variational quantum circuits: A core component of quantum learning

Variational Quantum Circuits (VQCs) are a central component in quantum learning and especially in medical imaging [22]. They are highly adaptable and utilize parameterized quantum gates that are optimized based on task-dependent cost functions such as image classification or segmentation [46].

Gates in quantum computation are fundamental building blocks that control states of qubits in a manner similar to classical gates in classical computation with the ability to harness quantum properties [47]. These circuits rely on a repertoire of diverse gates (such as rotation gates that control qubit states on different axes and entangling gates that create quantum correlations between qubits) that control qubits to process medical image data in ways that would be computationally costly in classical systems [17]. These circuits have been used successfully in a variety of medical applications to analyze images for skin lesion detection, brain tumor segmentation, and chest X-ray pneumonia diagnosis. With their abilities, QL algorithms can learn high-dimensional medical imagery with intricate patterns better than with classical machine learning methods [48], as presented in Fig. 8.

5. Quantum learning models

Quantum Learning is revolutionizing medical image analysis through a concerted effort and successful collaboration between quantum computation and classical advanced learning approaches. We group QL algorithms into three types: Quantum Machine Learning (QML), Quantum Deep Learning (QDL), and Hybrid Approach. QML is a design with a focus on maximum acceleration in computation and QDL with a focus on maximum improvement in pattern recognition. The hybrid approach is a fusion of both machine learning and deep learning with quantum approaches.

5.1. Quantum machine learning

5.1.1. Quantum support vector machine

Quantum Support Vector Machines (QSVMs) combine quantum computation with Support Vector Machine (SVM) theory in order to facilitate more sophisticated classification on medical images. QSVMs utilize quantum phenomena such as entanglement and superposition in order to enhance computation and classification performance [50].

While classical SVMs determine optimal hyperplanes in feature spaces to separate classes of data,

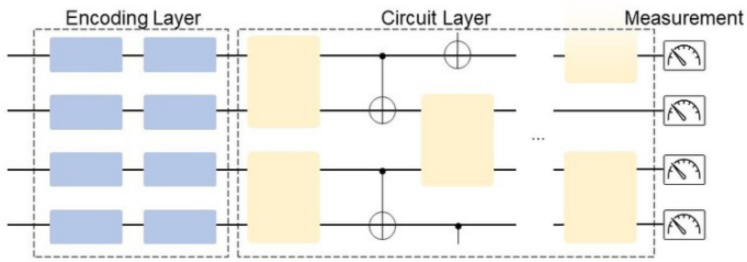


Fig. 8. Structure of a variational quantum classifier, illustrating the encoding layer, circuit layer, and measurement stage [49].

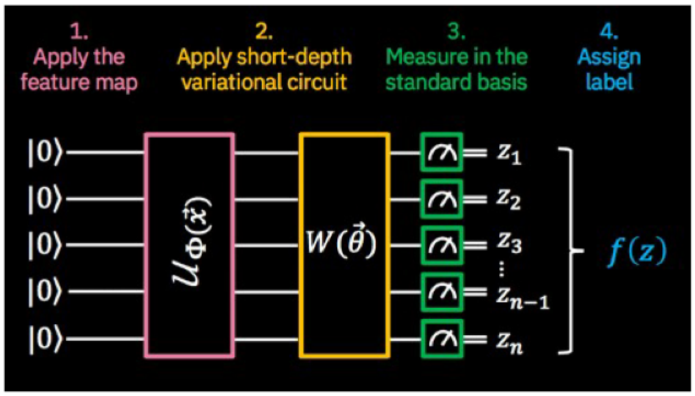


Fig. 9. Basic structure of a quantum support vector machine (QSVM), illustrating the feature map, variational circuit, measurement, and label assignment [55].

QSVMs generalize this to quantum feature spaces through the use of quantum kernels. These kernels express data point similarity in higher-dimensional quantum spaces and potentially uncover relations not attainable with classical methods [51]. QSVMs employs such kernels by means of quantum circuits that prepare states of data, process information with quantum gates, and make measurements in order to obtain results. With quantum computation, these models are superior in dealing with complex medical image data compared to classical approaches when dealing with large numbers of features common in medical imaging [52]. QSVMs have been reported to be promising in medical imaging. A study employed quantum annealing with SVM to classify between pneumonia from chest X-ray and reported enhanced efficiency in classification [53]. Another study employed QSVMs for thermal hand image classification in rheumatoid arthritis cases and reported enhanced classification accuracy by transforming classical features into quantum space [54]. The basic structure of a QSVMs is given in Fig. 9.

5.1.2. Quantum fuzzy C-means

The Quantum Fuzzy C-Means technique is a fuzzy clustering technique that is a combination of fuzzy and quantum and possesses enhanced medical image classification performance. Compared to classical fuzzy C-means that classify points based on their degree of membership, QFCM incorporates quantum-inspired optimization approaches in optimizing feature selection and increasing clustering efficiency and accuracy [56].

Such a study employed the Quantum Grasshopper Optimization Algorithm (QGH) with FCM for classifying Pap smear test images of cervical cancer. Such integration verified that combining quantum computation methods like QGH with fuzzy methods greatly enhances performance in medical image classification schemes. The introduced hybrid model not only achieved better accuracy but also feature space reduction [57]. So, a combination of fuzzy and quantum computing methods is a viable solution for accuracy and efficiency improvement in medical image analysis with intricate data like medical imaging.

5.2. Quantum deep learning

5.2.1. Quantum neural network

Quantum Neural Networks (QNNs) combine quantum mechanical rules with the structure of classical neural networks, creating potentially powerful paradigms for machine learning. QNNs extend classical neural networks by introducing quantum circuits, which perform operations on qubits to effect the

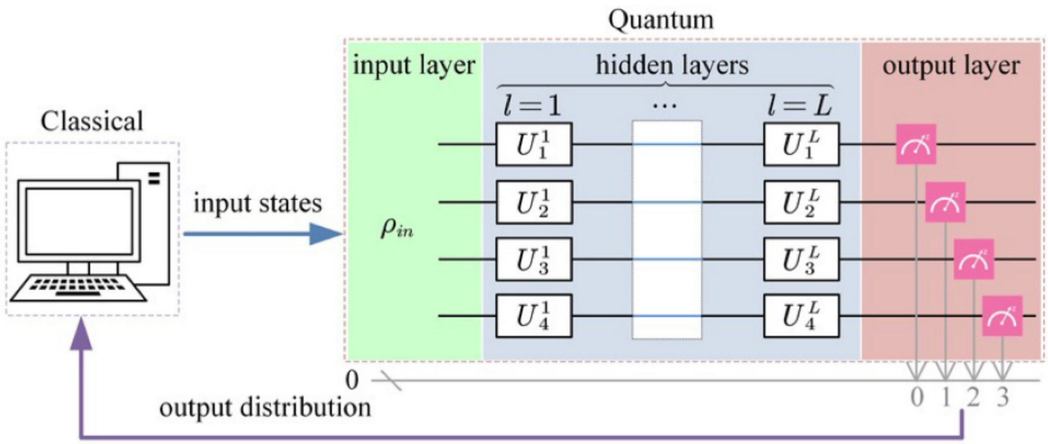


Fig. 10. General structure of a quantum neural network (QNN), depicting input, hidden, and output layers, with quantum operations applied in the hidden layers [60].

encoding of data, its processing, and the training of the network, thus realizing fundamentally different computational principles compared to classical systems [14].

The primary advantage of QNNs is their capability to perform matrix multiplications efficiently during the training process. This is made possible through quantum parallelism, which accelerates learning. More specifically, quantum-assisted neural networks, a subset of QNNs, use quantum computers for calculating inner products during the training and inference phases to reduce processing time and increase computational efficiency. Another variant is the Quantum Orthogonal Neural Network (QONN), in which the weight matrix remains orthogonal during training. Orthogonality is a property of unitary matrices used in quantum operations. Maintaining orthogonality during training stabilizes the learning process and reduces problems like vanishing or exploding gradients [58].

The advantages of using QNNs in medical imaging include the compact representation of high-dimensional data, allowing for more intricate feature extraction in medical images and potentially increasing accuracy in tumor detection or tissue segmentation. Furthermore, quantum algorithms are inherently robust to noise and effective in processing large datasets, both of which are important for medical image analysis [59]. Fig. 10 shows the main architectures of QNNs.

In the integration of quantum computing with classical neural networks, a study on COVID-19 CT scan classification used a shallow quantum circuit with 4 qubits. Hadamard gates initialized quantum states, while rotation gates (RY, RX, RZ) encoded image data, and Controlled-NOT (CNOT) gates enabled quantum entanglement, allowing high-dimensional processing [61]. Another study applied quantum-assisted neural networks on Pneumonia-MNIST and Retina-MNIST datasets, using Principal Component Analysis (PCA) for dimension reduction and quantum circuits on IBM's NISQ devices for inner product estimation. This approach demonstrated quantum methods' capability to match classical accuracy in binary classification [58]. In malaria detection, a Variational Quantum Circuit (VQC) was employed with a 4-qubit quantum circuit and a ZZ feature map for encoding. This setup improved diagnostic accuracy, though it faced challenges with quantum circuit complexity and reliance on simulations [62]. For respiratory disease detection, a hybrid quantum-classical framework (HQF-CC) used 4 qubits with Hadamard and rotational gates within a quantum circuit of 4-6 layers, showcasing superior accuracy over classical models [63]. In cardiac pathology classification, the HQMC-CPC model utilized a 30-qubit circuit with a ZZFeatureMap and a series of controlled-Z gates, with a modified hardware-efficient ansatz (MHEA) to improve accuracy and reduce complexity [64]. Lastly, a study in quantum pre-training used a Restricted Boltzmann Machine (RBM) in a D-Wave quantum annealer. Quantum pre-training provided classical neural networks with initial weights, illustrating the scalability of quantum techniques in the face of limitations in devices [65].

5.2.2. Quantum convolutional neural network

Quantum Convolutional Neural Networks (QCNNs) form a new combination of classical neural networks' popular architecture and techniques in quantum information processing, opening new avenues for effectively processing complex patterns in data. QCNNs

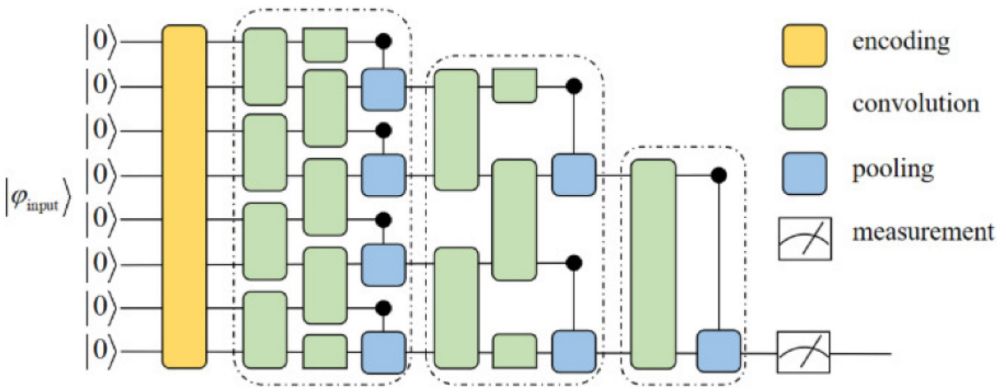


Fig. 11. Schematic representation of a quantum convolutional neural network (QCNN), illustrating the encoding, convolution, pooling, and measurement stages [68].

use quantum information processors to efficiently carry out complex tasks in different applications [66]. The difference in design between a QCNN and a Classical Convolutional Neural Network (CCNN) in feature detection strategy is that CCNNs use a combination of a convolutional and a pooling layer to carry out feature detection in images, whereas QCNNs transform a pixelated image into a quantum circuit through a feature map, e.g., a ZFeatureMap. In QCNNs, the Quantum Convolutional Layer consists of two-qubit unitary operators that determine relationships between qubits. The quantum pooling layer then lowers circuit dimensions, and classification ultimately results from one or more qubits, subject to a particular quantum circuit's design [19].

Another significant advantage of QCNNs is that they efficiently handle an input size of N qubits with variational parameters O(log(N)), thus offering good training performance on near-term quantum hardware [56]. Recent works have demonstrated this efficiency, showing that QCNNs outperformed classical CNNs and Artificial Neural Network (ANN) models in accuracy and efficiency under virtually all scenarios [67]. Fig. 11 demonstrates the process through which classical CNNs are embedded within QCNNs by incorporating quantum layers.

QCNNs and hybrid quantum-classical models represent a promising frontier in medical image classification, blending quantum computing's potential with the well-established strengths of classical neural networks. The studies summarized below explore various implementations of these advanced techniques, each addressing unique challenges in the medical imaging domain.

The development of the RANet model, paired with a Quanvolutional Neural Network (QNN), marks a significant effort in leveraging quantum computing to detect rheumatoid arthritis from thermal hand images. Here, quantum filters played a crucial role in enhancing image processing capabilities, showcasing the potential of quantum-classical integration, even within the constraints of simulated environments [69]. Expanding on this integration, a hybrid quantum-classical CNN was tailored for the detection of COVID-19 through chest X-ray analysis. The quantum layer, with the use of Random Quantum Circuits, enhanced the feature extraction process by showing how quantum circuits can be effectively embedded into traditional neural networks to enhance diagnostic accuracy [70]. The same principle was followed in brain tumor classification, where a revised HQC-CNN adopted a Parameterized Quantum Circuit (PQC) for early feature extraction. This method illustrated the capability of quantum preprocessing in simplifying complicated image classification tasks, particularly under quantum hardware constraints [71]. Another model, the adaptive HQCNN, was designed for the classification of brain MRI images using quantum convolutional layers. The rotation gates in the quantum layer, optimized by a Genetic Algorithm, have demonstrated how quantum techniques can accelerate convergence and improve the overall performance of models in medical imaging [72]. Another example is the classification of diabetic retinopathy using a quantum-enhanced deep CNN employing multi-qubit gates to extract features. This approach was tested in a simulated quantum environment and allowed quantum circuits to solve multiclass classification problems with high precision [73]. The contribution of quantum computing to securing image classifiers has been demonstrated by generating universal adversarial perturbations. A QCNN architecture, with a 12-qubit, 20-layer quantum circuit, has been tested to identify vulnerabilities that indicate a need for more robust quantum algorithms in practical scenarios [74]. In classifying child obesity using thermal imaging, a variational quantum classifier has been incorporated into the process. This work showed how even shallow quantum circuits can provide advantages in image classification when quantum resources are limited [75]. Quantum optimization merged with deep learning in the diagnosis of dystrophinopathies using muscle MRI images. The integration of the Multi-Objective Quantum Tunicate Swarm Optimization (MOQTSO) algorithm within a Capsule Network (CapsNet) framework showed how effectively quantum principles might be applied to enhance not only the efficacy of feature selection processes but also to improve accuracy [76]. A hybrid neural network was proposed for Alzheimer's disease diagnosis, embedding a QVC into the ResNet34 architecture. This demonstrated how feature dimensions can be effectively reduced by quantum circuits and, in return, improve classification performance [77]. Building further on the hybrid model concept, a transfer learning approach with a quantum method was implemented in detection in diabetic retinopathy. Combining a 4-qubit VQC with a classical Inception-V3 model highlighted the potential of collaboration between quantum and classical in achieving high accuracy, especially in binary classification tasks [78]. Osteoarthritis classification in the knee was carried out using a QCNN in which classical deep learning methods were combined with quantum convolutional layers. This paper showed how feature extraction can be improved by angular encoding and application using quantum circuits and thereby classification performance [6]. Combining the classical method with the quantum method, a brain disorder classification model like Parkinson's Disease and Alzheimer's Disease has been suggested. Combining a QVC with AlexNet showed how performance in diagnostic models can be improved with upgrades using quantum [79]. Combining the classical approach with the quantum one, a model has been proposed for the classification of brain disorders such as Parkinson's Disease and Alzheimer's Disease. The integration of a QVC within the AlexNet framework showed how quantum enhancements can improve the accuracy of diagnostic models [80]. A novel approach for detecting respiratory lung diseases, including COVID-19, was explored through a hybrid CNN-quantum classifier framework. The use of several qubit settings in quantum classifiers demonstrated the versatility of quantum computation in multiclass classification in a medical context [81]. The concept of collaborative QL gained prominence with the Federated Quanvolutional Neural Network that used quantum convolutional layers in a federated learning setup.

Quantum-enhanced models have the potential to retain high accuracy when handling medical data while reducing data exchange demands [82]. In a bid to counter insufficient labeled medical data, scientists have merged supervised contrastive learning with variational quantum classifiers. In a basic quantum implementation, scientists used the VQC in a contrastive learning model. The results indicated that model performance could be improved by quantum computing on a wide range of datasets [83]. Researchers used quantum adaptive machine learning to classify brain tumors into several categories. They were able to integrate quantum convolution and pooling layers into a working hybrid model. The process enhanced model training and classification accuracy, demonstrating the potential of medical imaging with quantum computation [10]. Generally, this research is a demonstration that quantum computation and classical neural networks are malleable and have a lot of potential. The methods are both purely quantum convolutional neural networks and hybrid quantum-classical. This is a demonstration that humans never stop experimenting with ways of making use of quantum technology in enhancing medical image classification in spite of having hardware constraints.

5.3. Hybrid approach

Hybrid Approach refers to a developing endeavor to unify computational power in quantum algorithms with advanced pattern recognition capability in deep learning architectures. It endeavors to reconcile in a balanced manner both efficiency and accuracy in classifying medical images using complementary powers in Quantum Machine Learning (QML) and Quantum Deep Learning (QDL). Researchers continue to search for optimal ways to connect quantum technologies with classical deep learning methods to provide improved performance in sophisticated diagnostic applications in medicine. In a detection research paper in Retinopathy of Prematurity (ROP), a Quantum Support Vector Machine (QSVM) was applied after segmentation of retinal images using SegNet. The QSVM applied a 10-qubit quantum circuit implemented with IBM Qiskit using quantum kernels to transform selected features into quantum space for classification [84]. Another study integrated quantum computing into the Inception-ResNet-V1 model for multi-class skin image classification. This approach involved a quantum convolutional layer using quantum gates like CNOT and rotation gates to enhance feature extraction, with classification handled by an SVM, improving accuracy through quantum-enhanced processing [85]. The findings from the reviewed studies are summarized in Table 1.

Table 1. Summary of reviewed studies on QL for medical image classification.

Ref.	Scope	No. Qubits	No. Parameters	Quantum Circuit Depth	Gates Used	Encoding Type	Pre-processing of Images	Core Technique	Challenges and Limitations
Quantum Machine Learning									
[53]	Binary	5614	-	-	-	-	Images resized; flattened to 1D arrays of 40,000 pixels	Classical SVM for baseline + Quantum and simulated annealing for optimization of SVM through QUBO formulation + Graver Augmented Multi-Seed Algorithm for hybrid optimization.	Quantum annealing methods have long queue times; limited number of qubits restricts large data processing
[54]	Binary	2	-	-	H, ZZFeatureMap	Angle	K-means clustering for segmentation of hot spots	K-means clustering + Feature extraction (BRISK, MSER, FAST, Harris, ORB) + LogitBoost + QSVM.	Complexity of quantum kernel methods, hardware noise in quantum systems
[57]		-	-	-	-	-	Data cleansing and partitioning into cytoplasm and nucleus parts	Data cleansing + Quantum-based Grasshopper Computing Algorithm for feature selection + Fuzzy C-means for feature extraction and classification using the proposed PQSO classifier.	Requires accurate feature selection
Quantum Deep Learning									
[61]	Binary	5	-	2	Ry, X, XX, ZZ	Angle	Data normalization including erosion and dilation, de-noising	Image resizing + Angle Encoding for quantum state preparation + Unitary Matrix for quantum feature transformation + Quantum Channels for feature extraction + Designing quantum circuits for classification task.	Limited dataset size, focus on only COVID-19 positive cases.
[58]	Binary	5 to 16	-	-	X, Y, Z, H, RX, RY	amplitude	Principal Component Analysis (PCA)	Quantum-assisted neural networks + classical backpropagation + orthogonal neural networks.	Quantum hardware instability; noise during quantum computations; dimensionality reduction limits accuracy

(Continued)

Table 1. Continued.

Ref.	Scope	No. Qubits	No. Parameters	Quantum Circuit Depth	Gates Used	Encoding Type	Pre-processing of Images	Core Technique	Challenges and Limitations
[62]	Binary	4	-	Shallow	Ry, Rz, CNOT, H	Angle	Image smoothing, feature extraction using Contourlet Transform, PCA and mRMR	Median filter + Contourlet Transform + Contour detection + mRMR + VQC + Rule-based system	Since we have developed a Quantum-Classical approach so this research may not justify the power of quantum computation precisely, and this is a fundamental incompleteness of our work. To elucidate the mentioned drawback, in the future with the arrival of actual quantum hardware, we will transfer this research to the quantum computer for determining outcomes.
[63]	Multi	4	MMS4: 1.0 million parameters, MMS6: 1.1 million parameters	MMS4: Qdepth=4, MMS6: Qdepth=6	H, RY, RX, RZ, CNOT	Angle	the image data is adjusted to fit within the quantum feature extraction process.	Quantum-Based Multi-Multi-Single feature extraction + Custom Classical Classifier.	Quantum circuit development on real-time quantum processors is challenging due to small qubit sizes; pre-processing of high-resolution images faces noise issues
[64]	Multi	30	-	1	Ry, Rz, CNOT	Angle	-	Classical Feature Extraction + Recursive Feature Elimination + Angle Encoding for quantum state preparation + Modified Hardware Efficient Ansatz in VQC.	Quantum circuit depth, optimization challenges, 30 qubits limitation
[65]	Binary	-	64	-	-	-	Compressed using autoencoder	Classical Convolutional Autoencoder for data compression + Quantum Pre-training using Restricted Boltzmann Machine on a quantum device (D-Wave) + Classical Neural Network for final classification.	Quantum hardware limitations, data compression challenges

(Continued)

Table 1. Continued.

Ref.	Scope	No. Qubits	No. Parameters	Quantum Circuit Depth	Gates Used	Encoding Type	Pre-processing of Images	Core Technique	Challenges and Limitations
[69]	Binary	4	-	-	Ry	Angle	Resized, grayscale normalization	Angle Encoding for quantum state preparation + Unitary Quantum Circuit for applying spatial transformations on the image + Quanvolutional Layer with 4 Quantum Channels for further feature extraction + Classical CNN Layers for final classification.	Real-time data limitations, resolution issues in quantum kernel
[70]	Multi)	4	119 645	Shallow	Ry, RX, Pauli-Z	Angle	Resize, data augmentation	Random quantum circuits for feature extraction + Quantum convolutional layer + Classical CNN layers for final classification.	The HQ CNN model does not work efficiently with large datasets and multiclass classification
[71]	Multi	4	1.96 million	Shallow	Ry	Angle	Resized, normalized	Quantum Convolutional Layer (using parameterized quantum circuits) + Classical CNN layers (including Convolutional layers, Max-pooling, and Fully connected layers).	Quantum circuit depth, dataset imbalance
[72]	-	4	9160	1	Ry, Rz,	Angle	normalized	Classical CNN layers for initial feature extraction + Angle Encoding for quantum state preparation + Quantum Convolutional Layer (PQC-based) for further feature extraction and final classification.	Adversarial attacks
[73]	Multi	-	-	-	H, CNOT, CCZ, X, Y, Z	Angle	Resizing of images, checking for missing values.	Pre-processing images + Encoding data into quantum states + Applying Hadamard and coupling gates + Executing quantum convolutional layers + Quantum pooling for dimensionality reduction + Residual blocks to enhance learning + Final classification through fully connected layers.	Hardware limitations with quantum computing; noisy qubits and expensive error correction; challenging pre-processing to quantum format
[74]	Binary	12	12	20	H, Rx, Rz, CNOT	Amplitude	Images resized and normalized to fit the input requirements for quantum state encoding	Quantum Continual Learning using elastic weight consolidation + Quantum adversarial perturbations through Quantum Basic Iterative Method (qBIM).	Vulnerability to adversarial attacks, hardware limitations with qubit size, complexity of generating universal perturbations

(Continued)

Table 1. Continued.

Ref.	Scope	No. Qubits	No. Parameters	Quantum Circuit Depth	Gates Used	Encoding Type	Pre-processing of Images	Core Technique	Challenges and Limitations
[75]	Multi	2	-	6	RX, RY, RZ, CNOT	Amplitude	DCGAN used to generate additional images; data augmentation, resizing; region of interest segmentation using thermal camera FLIR tools	Amplitude Embedding for feature data + VQC + Measurement in Pauli-Z basis for final classification	Lower performance of VQC due to fewer qubits High computational cost, small dataset, overfitting risks
[76]	Binary	-	-	-	-	-	Region of interest detection using an optimized region growing approach based on multi-objective quantum tunicate swarm optimization (MOQTSO)	Capsule Network (CapsNet) for initial feature extraction + Quantum-enhanced parameter optimization using Multi-objective Quantum Tunicate Swarm Optimization + Extreme Learning Machine for final classification.	Limited dataset information, generalization concerns with limited computational resources
[77]	Binary	4	-	6	H, R, CNOT, Pauli-Z	Angle	Center cropped, converted to PyTorch tensor, image normalization performed	Lassical pre-trained ResNet34 for feature extraction + QVC for dimensionality reduction and classification.	Requires high computational resources for training and tuning; performance depends on the quality of pre-trained models.
[78]	Binary	4	-	6	H, Ry, CNOT	Angle	Resizing, removal of extra black pixels, conversion to tensor vectors, normalization	Inception-V3 for feature extraction + Dressed Quantum Circuit for classification.	Imbalanced dataset, variability in quantum device performance, potential overfitting
[6]	Multi	4	-	4	H, RX, RY, RZ, CNOT, Pauli-Z	Angle	Image resizing, normalization	Image resizing + Normalization + Angular Encoding for quantum state preparation + Random Quantum Circuit for feature extraction + Variational Quantum Circuit for feature optimization + Quantum Measurement + Classical Convolutional Layer for final classification.	Imbalanced dataset, with fewer high-grade images (Grade 3 and 4), quantum circuit complexity
[79]	Binary	4	4096	6	H, CNOT, Rx, Ry, Rz	Amplitude	Normalization, Data augmentation	AlexNet CNN for feature extraction + Variational Quantum Circuit (VQC) for dimensionality reduction + Fully connected layer for final classification	Complexity of quantum circuits, small dataset size

(Continued)

Table 1. Continued.

Ref.	Scope	No. Qubits	No. Parameters	Quantum Circuit Depth	Gates Used	Encoding Type	Pre-processing of Images	Core Technique	Challenges and Limitations
[80]	Binary	4	2,070	1	H, Ry, CNOT, Pauli-Z	Angle	Data augmentation, normalized	Pretrained ResNet18 (without the final linear layer) + Dressed Quantum Circuit (DressedQuantumNet) with variational quantum circuits	Quantum hardware limitations, accuracy trade-offs
[81]	Multi	4	MSMS4: 1.4 million parameters, MSMS6: 1.4 million parameters	MMS and MSMS quantum classifiers: Qdepth = 4 and Qdepth = 6	H, RY, RX, RZ; CNOT	Angle	Min–Max normalization applied to images, scaling pixel values between [0, 1]	Hybrid framework combining Custom CNN for feature extraction + Quantum Classifiers (MMS and MSMS) for final classification	Developing quantum circuits for real-time quantum processors due to limited qubit sizes; noise restrictions during high-resolution image pre-processing
[82]	Multi	16	11 788	1	H, RX, Rz	Angle	Not detailed	Classical CNN layers for initial feature extraction + Quantum layer (VQC with Angle Encoding) for final classification.	Data heterogeneity, communication costs, quantum hardware limits
[83]	Binary	2	2048	-	ZZFeature Map	Angle	Data augmentation, outlier removal, scaling, and normalization; Principal Component Analysis (PCA) for dimensionality reduction	Supervised Contrastive Learning for feature extraction + Principal Component Analysis for dimensionality reduction + VQC for final classification using quantum processing.	quantum hardware limitations, sensitivity to noise, challenges with complex datasets, and long training times, which affect the scalability and generalization of the model.
[10]	Binary	-	-	-	RZ, U	Angle	Images were resized, down-sampled, and normalized; noise resistance through quantum algorithms	Quantum Adaptive Machine Learning combining quantum convolution and pooling layers + classical fully connected layers for classification.	Quantum hardware constraints, training time, and generalization across different datasets need further exploration
							Hybrid Approach		
[84]	Binary	10	-	-	H, Phase shift (P), R	Angle	Noise removal, segmentation using SegNet CNN	SegNet CNN for segmentation + SIFT-SURF feature extraction + QSVM classifier.	Segmentation errors, computational complexity in feature extraction
[85]	Multi	-	-	-	CNOT, Rx(θ)	Angle	Data augmentation (rotation, cutting, flipping), Min-Max normalization	Data augmentation + Min-Max normalization + Inception-ResNet-V1 with quantum convolutional + SVM classifier.	Imbalanced dataset leading to potential bias, addressed by weighted random sampling method

6. Discussion

Quantum Learning (QL) combines quantum computing principles with classical learning techniques to revolutionize medical image classification, offering solutions for the high dimensionality and complexity of medical imaging data. This systematic review explored the rapidly evolving landscape of Quantum Machine Learning (QML) and Quantum Deep Learning (QDL) techniques that are transforming medical image analysis. Different quantum algorithms leverage the unique characteristics of quantum systems to enhance efficiency and accuracy in image classification.

6.1. Quantum algorithms utilized in medical image classification

Our analysis reveals a diverse range of quantum learning (QL) techniques applied to medical image classification, categorized into three major approaches based on the technology utilized.

One approach focuses on enhancing classical machine learning algorithms with quantum computing techniques. This includes methods such as the Quantum Support Vector Machine (QSVM) and Quantum Grasshopper Optimization using Fuzzy C-Means, which improve classification efficiency for simpler data. The second and most prevalent category is Quantum Deep Learning, representing roughly over 70% of the studies. This approach integrates quantum neural networks with classical techniques—such as Quantum Neural Networks (QNN) and Quantum-Classical Convolutional Neural Networks (Q-CCNN)—and demonstrates notable effectiveness in analyzing complex patterns in medical data for feature extraction. It leverages deep learning's ability to handle multidimensional data while boosting accuracy and speed through quantum enhancements. The third category involves hybrid methodologies that combine machine learning and deep learning with quantum techniques. These methods integrate the strengths of both approaches, enhancing overall classification accuracy by effectively analyzing both simple and complex patterns.

Hybrid models, which combine quantum and classical components, emerge as a practical pathway to exploit quantum advantages without abandoning proven deep learning techniques. Many reviewed studies adopted a hybrid design to address the limitations of purely quantum models. A common pattern is using classical deep networks for pre-processing or feature extraction, then a quantum circuit for classification (or vice versa). For example, in one approach a quantum CNN was first trained on a brain MRI dataset, and its learned weights were then transferred and fine-tuned classically on a knee X-ray dataset - a QCTL pipeline [6]. This hybrid transfer learning improved accuracy slightly (as noted, $\sim$1% boost) over training a classical model alone, indicating the quantum initialization introduced a beneficial representation. Another study extracted deep features with a custom CNN (RANet) and then fed them to a classical SVM, achieving higher accuracy (97%) than either the CNN or a standalone quantum network [69]. This showcases a useful trade-off: the quantum component (quanvolutional layer) provided an alternate representation of the data, but the classical machine learning ultimately decided the class – leveraging the strength of both. Hybrid models can mitigate the input size problem of quantum classifiers. Rather than encoding an entire high-resolution image into qubits (which is infeasible for current hardware), a classical CNN can compress the image into a manageable feature vector, which a quantum classifier (e.g., a variational circuit or quantum kernel SVM) then processes [63]. This approach was effective in the HQF-CC framework, where a custom quantum feature extractor (MMS algorithm) distilled chest X-rays into quantum-friendly features, and a classical network achieved nearly 99% accuracy on diagnosis. Another advantage is robustness and generalization: by combining modalities, models can avoid some pitfalls of either method alone. Quantum circuits might find global data patterns through entanglement, while classical nets capture local textures; together, they can improve overall detection rates. There is also a potential computational benefit – if the quantum part reduces dimensionality significantly, the classical part has less data to crunch. In a hybrid SVM example for pneumonia, the quantum-inspired feature mapping led to fewer errors with faster prediction times than a deep CNN approach. The flipside is increased complexity. Hybrid systems must orchestrate two different computing paradigms. Data must be transformed from pixel values to quantum states (e.g., via amplitude or angle encoding) and back, which introduces overhead and potential information loss during encoding. Moreover, the quantum component itself might be a bottleneck – if the quantum model underperforms or is too small, the overall system may not justify its complexity. For instance, in the RA classification case, the quantum layer (quanvolution) alone was weaker than the classical model, so only by adding classical feature selection did the hybrid approach excel. This indicates a trade-off: hybrids only help if the quantum part adds unique value; otherwise, they could complicate an already working classical solution. Another limitation is that current hybrid demonstrations are largely experimental – integrating them into real clinical pipelines would require stable quantum hardware or fast simulators, which are still in development. There is also a maintenance trade-off classical ML engineers and quantum specialists must collaborate, as tuning a hybrid model means tuning classical hyperparameters (learning rates, CNN architecture) *and* quantum hyperparameters (circuit depth, type of ansatz, number of qubits). Despite these challenges, the case studies so far illustrate real-world effectiveness. The hybrid chest X-ray model (HQF-CC) effectively detected COVID-19 and pneumonia from radiographs, and a hybrid quantum SVM has been piloted for a common diagnostic task (pneumonia vs normal) with success. These examples build confidence that even with today's hardware, quantum-classical hybrids can tackle practical medical imaging problems. The key trade-off is complexity vs. payoff: hybrids are worthwhile when the quantum component addresses a specific weakness of the classical approach (such as feature dimensionality or linear separability), thereby improving accuracy or efficiency modestly. As quantum hardware improves, we expect the cost-benefit balance of hybrid models to further tilt in their favor, unlocking greater performance gains.

The diversity in quantum and classical technologies for medical image classification spans these three categories. While Quantum Deep Learning dominates the research landscape, the integration of quantum with classical techniques in all categories demonstrates flexibility and significant potential for improving performance and classification accuracy in medical imaging applications, as detailed in Tables 1 and 2.

6.2. Medical imaging applications of quantum learning

The review of 28 studies shows that QL applications span a wide range of diseases and offer innovative solutions for rapid diagnosis.

The most significant application involves using QL for diagnosing brain diseases such as Alzheimer's and Parkinson's, or brain tumors, using MRI images. Hybrid models that combine quantum approaches with traditional models can identify subtle patterns in images, improving classification accuracy and enabling faster analysis for better treatment decisions. For cardiac diseases, the classification of conditions like cardiomegaly and cardiomyopathy using cardiac MRI has been enhanced through hybrid models combining deep learning and quantum technologies, improving classification accuracy and reducing analysis time for large datasets.

Quantum approaches have been utilized to classify chest X-rays during the COVID-19 pandemic, facilitating rapid and accurate identification and diagnosis of COVID-19 and pneumonia to enhance healthcare responses and crisis management. Quantum models have demonstrated superior performance in ophthalmology by analyzing fundus images for diabetic retinopathy, efficiently identifying disease instances and enabling early detection to prevent vision complications. One important application is in thermal imaging for rheumatoid arthritis diagnosis, with quantum models aiding in quantifying thermal fluctuations in inflamed joints to improve diagnostic performance at various stages of the disease. Quantum models perform complex thermal data better compared to conventional methods. Quantum Learning (QL) has proved to be useful in MRI imaging of pathologic muscles, e.g., muscles affected by Duchenne muscular dystrophy, to improve detection of common patterns with shorter processing time. Quantum transfer learning has been utilized to classify mammography images as benign or malignant, a very critical application in breast cancer detection. These quantum models have improved diagnostic performance with a reduction in computational complexity and have proved effective in early detection of breast cancer. These applications indicate that QL methods offer improved diagnostic performance, improve processing times for medical images, and result in faster and improved medical decision-making for severe diseases, as evident in Table 3.

6.3. Medical image datasets used in quantum learning research

An examination of datasets used in Quantum Learning (QL) research highlights critical variations in their size, availability, and complexity. These factors have a significant influence on both performance outcomes and on the generalizability of quantum models to medical image classification.

Large open-access repositories like the COVID-19 Radiography database (15,153 images) and the ACDC 2017 collection (more than 15,000 MRI scans) enable researchers to thoroughly analyze intricate patterns in high-dimensional medical data. The sheer volume of information in these large repositories has been particularly valuable in studying intricate pathologies; it has greatly improved diagnosis capability in cardiovascular and respiratory diseases by providing researchers with rich, heterogeneous input data.

The Brain Tumor MRI dataset is another abundant source with 7,023 high-quality images that researchers have employed to detect fine-grained morphological features essential in tumor detection at

Table 2. Comprehensive overview of QL algorithms for medical image classification applications.

Technology Category	Models/Algorithms	Reference
Quantum Machine Learning	Quantum Support Vector Machine	[53, 54]
	Quantum Grasshopper Optimization with Fuzzy C-Means	[57]
Quantum Deep Learning	Quantum Neural Network	[61, 69]
	Quantum-Classical Convolutional Neural Network	[70, 71, 72, 73]
	Quantum-Assisted Classical Neural Networks	[58]
	Quantum Orthogonal Neural Network	[58]
	Quantum Continual Learning with Universal Perturbation	[74]
	Variational Quantum Circuit	[62]
	Variational Quantum Classifier with Customized Convolutional Neural Network	[75]
	Quantum Variational Circuit with ResNet34	[77]
	Hybrid Quantum-Classical Transfer Learning with 4-Qubit Variational Classifier	[78]
	Hybrid Quantum-Classical Convolutional Neural Network with Quantum Transfer Learning	[6]
	Hybrid Quantum Feature Extraction and Custom Classification Model	[63]
	Hybrid AlexNet-Quantum Variational Circuit	[79]
	Hybrid Classical-Quantum Neural Networks with Transfer Learning	[80]
	Hybrid Classical Convolution and Quantum Variational Classification Framework	[81]
	Federated Learning with Variational Quantum Convolutional Neural Network	[82]
	Supervised Contrastive Learning with Quantum Variational Classification	[83]
	Quantum Adaptive Machine Learning	[10]
	VQC with Hybrid Evolutionary Algorithm	[64]
	Autoencoder with RBM Pre-trained on D-Wave Quantum Device	[65]
	Multi-Objective Quantum Tunicate Swarm Optimization with Deep Learning	[76]
Hybrid Approach	SegNet-SURF-QSVM	[84]
	Quantum Inception-ResNet-V1 with SVM Classifier	[85]

an early stage. In contrast, researchers are faced with severe methodological challenges when working with small collections. MIAS and DDSM mammography databases with a mere 322 and 2,750 images, respectively, suffer from a lack of sample diversity and cannot be used to extract fine-textured features that are essential in analyzing abnormalities in breast tissue in cancer screening protocols [93]. In these cases, quantum transfer learning is often employed, where models are first trained on larger datasets and then fine-tuned on smaller ones to enhance performance.

In addition to differences in size, many datasets used in both quantum machine learning and deep learning have inherent limitations. For instance, the Osteoarthritis Initiative (OAI) dataset comprises 9,516 knee X-ray images but suffers from class imbalance-with severe cases (Grade 4) making up only about 3%—and potential inconsistencies in grading. Similarly, the Brain Tumor MRI dataset from Kaggle, with 3,264 images from 233 patients, is limited by its moderate size and single-source origin, which raises concerns about distribution shifts and bias. The IDRiD dataset, offering 516 retinal fundus images, is divided into a very small split (approximately 80% for training and 20% for testing), increasing the risk of overfitting and limiting demographic diversity. Even the COVID-19 Radiography Database, despite its large volume, faces class provenance bias due to images being sourced from different institutions, requiring rigorous validation to prevent overestimation of performance.

Specialized datasets further illustrate these challenges. Datasets for Retinopathy of Prematurity (ROP), which may include around 6,000 retinal images from 188 infants, often suffer from limited access, small size, class imbalance, and high variability-complicating quantum encoding. Likewise, the RA Hand Thermogram dataset, which contains 600 thermal images from only 100 subjects (later augmented to 1,440 images), is prone to selection bias, limiting the generalizability of its findings. Even large multi-center datasets like ADNI, despite

Table 3. Classification based on dataset usage.

Dataset Category	Disease	Dataset Name	Image Type	Number of Images	Data availability	Link to available dataset	Ref.
Neurological Imaging	Alzheimer's	Alzheimer's Dataset	MRI	6400	PV	Alzheimer's Dataset (4 class of Images) (kaggle.com)	[77]
	Alzheimer's	ADNI	MRI	787	PV	ADNI | Alzheimer's Disease Neuroimaging Initiative (usc.edu)	[79]
	Parkinson's	PPMI	MRI	621	PV	Home | Parkinson's Progression Markers Initiative (ppmi-info.org)	[79]
Ophthalmic Imaging	Blindness Detection	APTOS 2019 Blindness Detection Dataset	Fundus photography	3,662	PV	APTOS 2019 Blindness Detection | Kaggle	[78]
	Diabetic retinopathy	Retina-MNIST	Fundus Camera	1480	PV	MedMNIST	[58]
	Retinopathy of Prematurity		Fundus Camera	200	NPV	_	[84]
	Diabetic Retinopathy	IDRID	Fundus Photography	516	PV	Indian Diabetic Retinopathy Image Dataset (IDRiD) | IEEE DataPort (ieee-dataport.org)	[73]
Pneumological Imaging	COVID-19	CT scans for COVID-19	CT scans	10,000	PV	GitHub - UCSD-AI4H/COVID-CT: COVID-CT-Dataset: A CT Scan Dataset about COVID-19	[61]
	COVID-19	COVID-19 Radiography Database	X-ray	5,445	PV	COVID-19 Radiography Database (kaggle.com)	[70]
	Pneumonia-infected	Pneumonia-MNIST	X-Ray	5332	PV	MedMNIST	[58]
	COVID-19	CC-19	CT scan	34,006	PV	https://paperswithcode.com/dataset/cc-19	[82]
		ChestMNIST	X-Ray	58,954	PV	MedMNIST	[82]
	Pneumonia	Pneumonia X-Ray Images	X-Ray	3267	PV	Pneumonia X-Ray Images (kaggle.com)	[53]
	COVID-19	COVID-19 Radiography	X-Ray	15,153	PV	GitHub - rgbnihal2/COVID-19-X-ray-Dataset	[63, 81]
Musculoskeletal Imaging	Rheumatoid Arthritis	_	Hand Thermal Images	240	NPV	_	[54]
	Osteoarthritis	OAI	X-ray	9,516	PV	Knee Osteoarthritis Dataset with KL Grading - 2018 (kaggle.com)	[6]
	Dystrophinopathies	_	MRI	_	NPV	_	[76]
	Rheumatoid Arthritis	_	Hand Thermal Images	600	NPV	_	[69]
Cancer cells Imaging	Breast Cancer	MIAS	Mammography	322	PV	https://www.kaggle.com/datasets/kmader/mias-mammography	[80]
	Breast Cancer	DDSM	Mammography	2750	PV	http://www.eng.usf.edu/cvprg/mammography/database.html	[80]
	Brain Tumor	Brain Tumor MRI	MRI	7,023	PV	Brain Tumor MRI Dataset (kaggle.com)	[71, 72, 10]
	Brain Tumor	REMBRANDT	MRI	110,020	PV	The REMBRANDT study, a large collection of genomic data from brain cancer patients - PubMed (nih.gov)	[10]
	Cervical	DTU/HERLEV	Pap smear	2600	PV	https://mde-lab.aegean.gr/index.php/downloads/	[57]
	Skin Damage	Dermoscopic	ISIC 2019	25,331	PV	https://challenge.isic-archive.com/landing/2019/	[85]
Miscellaneous	Child Obesity	_	Thermal Images	150	NPV	_	[75]
	fluoroscopic venogram	Taken from 10 patients. Taken from 12 patients	X-ray	650	NPV	_	[65]
	Malaria	RBC images	Microscopic RBC images	27,558	PV	https://www.kaggle.com/iarunava/cell	[62]
	Various	MedMNIST	Various	120 samples per dataset	PV	MedMNIST	[83]
	Various	MedMNIST	MRI	1200	PV	MedMNIST	[74]
	Cardiac Pathologies	ACDC 2017	MRI	15,153	PV	https://www.creatis.insa-lyon.fr/Challenge/acdc/databases.html	[64]

*PV: Publicly Available.

*NPV: Not Publicly Available.

offering thousands of brain scans for Alzheimer's Disease and related conditions, encounter issues with subtle class differences, heterogeneous data from multiple scanners, and persistent class imbalance-especially with fewer advanced Alzheimer's cases.

Overall, while classical deep learning thrives on large, diverse datasets, current QML approaches are often constrained to smaller or more structured datasets due to hardware and encoding limitations. The seemingly perfect performance observed on small datasets like IDRiD may reflect overfitting rather than true model advantage, whereas larger datasets such as the COVID-19 chest X-ray collection have enabled hybrid quantum-classical models to achieve accuracies as high as 98.8%. Therefore, meticulous data curation—through stratified sampling, augmentation, and cross-site validation-is essential to ensure balanced and normalized input distributions before any claims of quantum advantage in medical image classification can be substantiated. The impact of dataset size and complexity on model performance is further detailed in Table 1.

6.4. Performance metrics and evaluation of quantum learning models

Empirical results across the 28 studies show that quantum-enhanced models can achieve competitive accuracy to state-of-the-art classical models, but improvements are often modest. For example, Dong et al. report that a Quantum-to-Classical Transfer Learning (QCTL) approach improved knee osteoarthritis X-ray classification accuracy to 98.36%, about a 1.08% gain over a purely classical deep CNN baseline [6]. Similarly, a hybrid quantum feature extractor reached 98.8% accuracy in COVID-19 pneumonia detection, slightly outperforming conventional CNNs on the same data [71]. These gains, while noteworthy, are relatively small-highlighting that classical deep learning models remain very strong performers in vision tasks. In some cases, classical models still outperform quantum ones: a quanvolutional network for rheumatoid arthritis achieved 93.3% accuracy, trailing a custom CNN (95%) and even a CNN + SVM ensemble (97%) on the same thermal image test [76]. This underscores that current quantum models are not yet universally superior; their success can be task-dependent. That said, certain quantum approaches have matched classical performance with far fewer trainable parameters. A quantum SVM classifier for pneumonia was "pretty competitive" with deep learning and *"makes fewer mistakes, and it takes less time"* in inference, hinting at potential efficiency gains.

Classical deep learning enjoys mature frameworks and hardware (GPUs/TPUs) that scale to millions of parameters and large inputs (e.g., 224×224 or higher resolution images). In contrast, quantum models are currently limited by qubit counts and circuit depth on quantum hardware. This means QML experiments often use downscaled images or focus on small regions of interest to fit data into a quantum circuit. For instance, many QML studies encode only a few dozen features or small image patches as qubit states, whereas a CNN can ingest the full image. Consequently, classical models can leverage the full richness of high-resolution medical images, while quantum models might miss some detail unless hybrid techniques are applied. Moreover, training a classical CNN on a large dataset can be time-consuming but is straightforward, whereas training a quantum model may involve significant overhead in data encoding and is presently restricted to simulated environments or very small quantum processors. As hardware advances (more qubits, lower noise), the scalability gap is expected to close, but for now classical DL has an edge in handling large-scale data.

When considering resources and speed, there are trade-offs. Classical deep networks require substantial memory and compute power; for example, a ResNet or EfficientNet model demands GPUs and can take hours to train on thousands of images. Some hybrid quantum models have shown advantages in memory efficiency – the HQF-CC model (quantum feature extractor + classical classifier) was reported as more memory-efficient than a purely deep model for chest X-ray classification. Quantum algorithms also hold the promise of faster computation for certain operations (like kernel evaluations in SVM) once true quantum hardware is used. In the pneumonia SVM study, the quantum-inspired SVM ran faster in inference than a deep learning approach. However, currently most QML models are tested via quantum simulators running on classical hardware, incurring extra overhead. Thus, training times can actually be longer for QML in practice today. In summary, classical DL is more mature and scalable for large datasets, while quantum-enhanced models can be competitive in accuracy and hint at efficiency gains in specific scenarios. A balanced evaluation needs to consider that pure performance metrics (accuracy, AUC, etc.) are often comparable within a few percentage points, so factors like model size, inference speed, and resource usage become distinguishing factors between quantum and classical approaches.

Various performance metrics are employed to evaluate QL solutions in medical image classification, as accuracy alone may be misleading, especially with unbalanced datasets where high accuracy might indicate that the model excels at classifying majority classes but fails to detect rare positive cases. In such contexts, metrics like precision and recall are emphasized.

Precision is necessary to avoid false positives in critical diagnoses like cancer and recall to avoid missing real positives and thereby missing critical disease diagnoses. F1 score provides a balanced score between recall and precision, particularly with unbalanced data, and reflects how a model's performance varies in different scenarios. Other critical metrics in measuring quantum models are sensitivity and specificity, with high sensitivity to avoid missing disease cases and high specificity to reduce false positives and enhance diagnostic performance. Comparison in terms of performance can be made between different QL models in terms of numbers of parameters, circuit depths, and types of gates, as shown in Table 1. High numbers of parameters in models refer to complex systems with advanced architectures that enhance the capacity of quantum circuits to extract more detailed and accurate features. The model in [88], with a parameter number of 1.4 million and a circuit depth of 6 and with a combination of gates like RY, RX, RZ, and CNOT, shows high complexity in feature extraction and classification processes. This multi-class classification model has better performance in handling complex health-related data but has limitations in terms of computational complexity and added quantum noise that has to be tackled with caution. Models with fewer parameters, such as that in [87], with a parameter count of 2,070 and a depth of 1, may be less effective in complex feature extraction but have a low computational complexity and therefore less noise and thus can be operated faster and more stably, particularly in binary classification. Such models may be limited in handling very complex or high-dimensional data and therefore can be comparatively less effective in comparison to more parameterized models. This difference in parameter counts and circuit depth goes hand in hand with performance metrics such as accuracy and F1 score in Table 4. More complex models have better scores in challenging tasks with high resource utilization and error rates due to quantum circuit noise. The challenge lies in balancing these metrics to achieve effectiveness in quantum models in medical image classification. Deep analysis using a combined set of metrics is needed to assess stability and effectiveness in quantum models.

6.5. Image preprocessing and encoding methods

Image preprocessing and encoding in QL's domain have a very significant role and a strong influence on model performance. Success in achieving correct results greatly depends on visual data preprocessing to accommodate the limitations and computational power of a quantum model. Advanced preprocessing has to be carried out in complex data like those in medical images in order to preserve details that may be very critical to model performance and correctness. Out of standard image preprocessing techniques, resizing has been extensively utilized to reduce the size of images to be able to exist in a finite number of qubits in a quantum system. This helps in reducing computational complexity by reducing data to a manageable, easier-to-process level, albeit with a possibility of losing valuable details which may be critical to ultimate model accuracy. Another standard technique utilized is normalization, whereby pixel intensities are normalized to a specific value range, e.g., [0,1], to aid encoding in a quantum system. This enhances processing time and eliminates distortions during encoding.

Principal Component Analysis (PCA) is applied to reduce high-resolution images like MRI scans to a lower dimension to handle more complex scenarios. It makes processing easier and reduces the use of quantum resources at the risk of losing some critical details. At encoding level, Angle Encoding has been predominantly used in most studies. It encodes pixel values into angle in quantum space to facilitate effective processing. It has a disadvantage in being vulnerable to quantum noise; interference with a system can reduce result accuracy. Amplitude Encoding is another encoding technique for complex data whereby a single quantum state contains all information, particularly for complex and high-level data. It has a disadvantage in terms of high computational cost and challenges in minimizing noise and maintaining accuracy.

Overall, a balance between preprocessing and encoding has to be established to have good performance with quantum models. Preprocessing simplifies processing, and encoding must keep essential details in images. While some advances have been made in using quantum models in medical image processing, the limitation in terms of accessible qubits, depth in quantum circuitry, and challenges in managing quantum noise severely limit such models. These encoding and preprocessing methods have been explained in Table 1.

6.6. Key challenges and hurdles in quantum learning for medical image classification

The challenges facing quantum and hybrid models in medical image classification stem from several key areas, including technical constraints, computational

Table 4. Performance metrics for quantum models.

Ref	Model	Training Acc (%)	Testing Acc (%)	Acc (%)	Precision (%)	Recall (%)	F1 Score (%)	Sensitivity (%)	Specificity (%)
[65]	A-RBM-DWave	-	-	99.8	-	-	-	-	-
[62]	VQC	99.12	98.93	99.06	99.08	99.05	-	-	99.07
[61]	QNN	-	-	96.92	97.11	97.8	-	-	-
[85]	QIRV1-SVM	-	-	98.76	98.26	-	-	98.4	99.81
[57]	QGH-FCM	-	-	-	98.8	94	95	-	-
[77]	QVC-ResNet34	99	93	97.2	90	88	87	-	-
[78]	QCTL-VQC	-	-	93-96	95.59	92.10	93.80	-	92.81
[70]	HQ-CNN	-	98.6	98.6	98.2	99	98.6	-	98.2
[58]	QANN	93	85	-	-	-	-	-	-
	QONN	86	81	-	-	-	-	-	-
[80]	HQC-NN-TL	-	-	81	83	80	81	-	84
[71]	HQC-CNN	-	-	97.85	98	98	98	-	-
[84]	QSVM	-	-	95.5	-	-	-	93	98
[54]	QSVM	-	-	92.7	93	96	94	-	-
[6]	HQCNN-QTL	-	-	98.36	99.2	98.10	98.60	-	-
[75]	VQC-CNN	-	-	84.4	-	-	-	-	-
[82]	FL-VQC-CNN	-	-	97	-	-	-	-	-
[79]	AlexNet-QVC	-	97	-	93	92	93	-	-
[72]	HQ-CNN	-	-	-	97.74	97.33	97.53	-	-
[76]	MOQTSO-DL	-	-	96.45	88.18	-	92.99	98.46	95.83
[53]	QSVM	-	-	92.5	97.6	92.7	95	-	-
[73]	QCNN	-	-	100	100	100	100	-	100
[69]	QNN	-	91.6	93.33	96	92	93	-	-
[74]	QCL-UP	-	-	89.7	-	-	-	-	-
[83]	SCL-QVC	-	-	90	-	-	-	-	-
[10]	QAML	-	-	-	96.37	96.10	96.49	-	-
[63]	HQFE-CCM	97.2	98.8	87	91.4	N/R	90.1	88.7	97.8
[64]	VQC-HEA	-	-	-	-	-	-	-	-
[81]	HCC-QVCF	98.9	98.1	98.9	98.7	-	97.6	96.5	99.6

complexity, and effective model training management. The most significant among these are instability in quantum systems and the emergence of noise. Quantum systems rely on sensitive properties such as entanglement and superposition, making them highly vulnerable to noise and external disturbances. Since pure quantum models, such as variational quantum circuits (VQC), depend entirely on quantum computing for feature extraction and classification, noise significantly contributes to accuracy variability. Stabilization and noise reduction are two of the biggest obstacles to more extensive application of quantum models.

Another significant limitation is that only a limited number of qubits are available. Most of the models require many qubits in order to effectively process large-scale multidimensional medical data. Even with improved devices, current hardware constraints make it unfeasible to process complex classification on large-scale medical data. Depth in a quantum circuit is a major problem as more operations are performed in deeper circuits and more noise is introduced with more error accumulation. Hybrid quantum-classical approaches add an additional layer of complexity. Optimal balance between classical and quantum computation is critical due to medical data's nature. Careful balancing is required so that advantages of quantum computation are not offset by additional complexity.

Recent studies have attempted to address these challenges by implementing error mitigation strategies. For instance, study [66] shows that employing shallow variational circuits combined with adaptive optimization techniques can significantly reduce error accumulation during training, leading to improved convergence and stability. Similarly, study [70] demonstrates that using noise-aware encoding methods-particularly angle encoding-helps preserve model accuracy despite hardware imperfections. Moreover, study [81] provides precise quantitative evidence of the impact of noise: when a universal adversarial perturbation with a strength of 0.02 is applied, the classifier's average accuracy drops from 93.3% to 28.5% (with fidelity of 0.79); when analyzed by task, the accuracy declines from 94.5% to 24.5% (fidelity 0.84) for the previously trained task and from 92.0% to 32.5% (fidelity 0.76) for the later trained task. These results underscore the severe impact that noise has on quantum learning (QL) models and provide a benchmark for assessing the effectiveness of mitigation strategies.

While these error mitigations approaches-such as shallow circuit design, adaptive optimization, and noise-aware encoding-offer promising improvements, they only partially counteract the detrimental effects of quantum noise. This highlights the urgent need for future research to integrate robust quantum error correction (QEC) techniques with current error mitigation methods to fully realize the potential of QL in practical medical image classification applications.

Although only a subset of the 28 reviewed studies offer detailed quantitative evidence regarding noise mitigation, these examples underscore the potential of current strategies-such as shallow circuit design, adaptive optimization, and noise-aware encoding-in partially offsetting the detrimental effects of quantum noise. Nevertheless, the persistent challenge of noise and the limited scalability of current devices emphasize the need for future research to integrate full quantum error correction techniques with these mitigation approaches. Such advancements will be essential to fully realize the potential of QL in practical medical image classification scenarios.

Another challenge that is confronted by quantum models is that they are reliant on simulators. Since most research is conducted on quantum computing simulations and not on actual quantum devices, outcomes might not be representative of challenges that would be confronted by models when implemented on true quantum systems. Creating a quantum circuit is not easy and is a lot of design and development effort. Any increase in the number of qubits or in quantum layers increases model complexity and train times and consumes a lot of computation resources.

In terms of medical data size, most medical images are large and complex and must be processed with precision and a lot of computation. Data imbalance also affects classification accuracy because rare cases are likely to be misclassified when classes are unbalanced. Other models, such as QCNN, require a large number of parameters in order to be very accurate. With each increase in parameters, the model is more complex and more difficult to train because certain quantum systems may not be well-suited to process structures with such a large amount of information. These challenges are summarized in Table 1. Currently, the major obstacles to large-scale implementation of quantum models in medical image classification are technical and practical. Novel approaches that can overcome these challenges remain essential for effectively leveraging quantum computing in this field.

7. Feasibility and real-world data challenges in quantum learning for medical imaging

Quantum learning (QL) has demonstrated promising potential in medical imaging, achieving competitive accuracies in tasks such as brain tumor, retinal disease, and COVID-19 classification. However, the practical implementation of QL models is currently hindered by both technical limitations and the nature of the available datasets. Below, we present two key dimensions of these challenges.

7.1. Key technical constraints

QL models offer theoretical speedups through quantum parallelism, yet they are largely confined to experimental settings due to several hardware and algorithmic constraints. Preparing and encoding high-dimensional medical images into quantum states often incurs significant computational overhead. The preprocessing and quantum-state encoding steps are non-trivial and can be computationally expensive, especially as the data size grows. For instance, even with small images, converting them to quantum format and managing quantum error-correction protocols is challenging and costly in terms of computation. This overhead can offset QL's speed advantages, making it difficult to scale up medical image analyses. Current quantum hardware provides only a limited number of qubits, severely restricting the size of data and complexity of models that can be run. This limited scalability of NISQ devices means QL methods often must use drastically reduced input sizes or hybrid approaches. In fact, basic encoding schemes are directly capped by qubit availability, as each pixel or feature may require a qubit; today's devices simply do not have enough qubits to encode high-resolution images without downsampling. As a result, most QL experiments in imaging are confined to small-scale problems, since it remains difficult to operate quantum computers with a sufficient qubit count and low error rates for large datasets. Besides qubit count, the depth of quantum circuits (number of sequential gate operations) is sharply limited by noise and decoherence in current hardware. As circuit depth increases, computational complexity and error rates escalate, undermining the reliability of the results. In practice, quantum neural networks must be kept shallow; deeper circuits on NISQ machines accumulate noise faster than error-correction can handle. This constraint means QL models cannot yet match the layer depth of classical deep networks, potentially limiting the representational power unless combined with classical layers (as done in hybrid models).

In summary, while early studies underline the feasibility and potential of QL in medical imaging-even reporting high accuracy gains under certain conditions these advantages come with significant hardware and algorithmic limitations. Overcoming the computational overhead of quantum data encoding, the qubit scarcity, and the circuit depth (noise) constraints is essential before QL can be widely integrated into clinical image analysis workflows. Each of these challenges is an active research area, and addressing them will be crucial to fully realize quantum learning's promise in healthcare imaging.

7.2. Bridging the gap between curated and real-world data

While the publicly available datasets used in QL research-such as MedMNIST, MNIST, and other curated medical image benchmarks-are indeed derived from genuine clinical data, they are typically curated and preprocessed to facilitate controlled experiments and benchmarking. This means that although the data are "real" in origin, they often do not capture the full complexity, variability, and heterogeneity inherent in raw clinical data. For example, these datasets are usually standardized to a fixed resolution (e.g., 28×28 or 64×64 pixels) and may have undergone noise reduction, cropping, and normalization, which, while useful for research, may oversimplify the challenges encountered in a hospital setting. In contrast, real-world clinical data collected from hospitals tend to be more diverse, with variations stemming from different imaging devices, patient demographics, and clinical protocols. These factors introduce additional noise and complexity that curated datasets may not reflect. Consequently, while the available datasets are genuine, their controlled nature may limit the external validity of QL model evaluations. To bridge this gap, future research should emphasize the following: Conduct extensive model validation on heterogeneous datasets sourced directly from clinical environments or through multi-center collaborations, ensuring that QL models can handle the variability encountered in practice. Engage in partnerships between institutions to gather diverse, high-quality clinical data that better represent real-world scenarios, thus Assess clinician trust and acceptance of quantum-assisted diagnostic tools through both qualitative and quantitative studies, which will be essential for the clinical adoption of these models. These measures will help ensure that QL models are not only technically advanced but also clinically relevant and robust when deployed in actual healthcare settings.

8. Challenges and future trends

Quantum learning (QL) has garnered significant attention for its potential to revolutionize medical image classification, leveraging quantum mechanical principles to address limitations inherent in classical approaches. However, while its theoretical advantages are well-documented, the practical implementation of QL in healthcare remains fraught with challenges. These challenges stem not only from the nascent stage of quantum hardware but also from technical, computational, and integration complexities. Addressing these obstacles is crucial to transitioning QL from a research focus to a practical tool in clinical settings. In parallel, advancements in methodologies and collaborative initiatives are paving the way for overcoming these barriers. Below, we explore the key challenges and identify future trends that can shape the trajectory of QL in medical imaging.

8.1. Challenges

- At the core of QL's challenges lies the limited capability of current quantum hardware. Devices are constrained by a small number of qubits, which directly impacts the size and complexity of problems they can handle. Furthermore, issues such as noise, decoherence, and high error rates compound these limitations, making it difficult to execute robust quantum algorithms for medical imaging tasks. These constraints hinder QL's scalability and its ability to process large and intricate medical datasets effectively.
- Medical imaging datasets are inherently high-dimensional and complex, posing a significant challenge in their preparation for quantum processing. Encoding these datasets into quantum-compatible formats, such as amplitude or angle encoding, requires significant computational resources and precision. Current techniques, while theoretically effective, often struggle with efficiency and accuracy when applied to large-scale datasets, making this a critical bottleneck in QL applications.
- The adoption of QL in clinical settings depends heavily on the interpretability of its models. While QL models often demonstrate promising accuracy, their "black-box" nature limits their transparency. Clinicians need to understand the reasoning behind model outputs to trust and effectively utilize these tools in decision-making processes. This lack of interpretability presents a significant hurdle to the clinical adoption of QL-based systems.
- Hybrid quantum-classical systems represent a practical approach to leveraging QL's capabilities

alongside classical computing's strengths. However, integrating these paradigms is not without challenges. Effective task allocation between quantum and classical components requires careful optimization, algorithm design, and resource management. The immature state of quantum software ecosystems further complicates this integration, creating a significant technical challenge for researchers and developers.

8.2. Future trends

- To navigate the current limitations of quantum hardware, hybrid quantum-classical models are poised to play a central role in QL's advancement. These models strategically allocate tasks, using quantum systems for computationally intensive processes such as feature extraction or classification, while relying on classical systems for data preprocessing and augmentation. This approach not only enhances the feasibility of QL but also allows researchers to exploit the strengths of both paradigms effectively.
- As encoding complexities remain a major bottleneck, developing more efficient and adaptive encoding schemes is critical. Research efforts should prioritize lightweight techniques that reduce computational demands without compromising the fidelity of encoded data. Simplified and scalable encoding methods tailored to the unique requirements of medical imaging will significantly expand the practical applications of QL.
- The absence of standardized benchmarks for evaluating QL models in medical imaging has hindered consistent comparisons and slowed progress. Establishing benchmark datasets and protocols specific to quantum applications will provide a unified framework for assessing model performance, enabling researchers to validate and refine their approaches more effectively.
- The integration of explainable AI (XAI) techniques into QL frameworks is essential for bridging the gap between advanced quantum computations and clinical usability. Transparent models with built-in interpretability tools can help clinicians trust and adopt QL systems, ensuring their outputs are actionable and aligned with clinical requirements.
- Collaboration between academia and industry is crucial for accelerating the practical implementation of QL. Joint efforts can lead to the development of application-specific quantum devices optimized for tasks such as tumor classification or anomaly detection, fostering a more targeted and impactful approach to medical imaging applications.

By addressing these challenges and focusing on these future trends, QL can evolve into a transformative tool in medical image classification, bridging the gap between theoretical innovation and practical application in healthcare.

9. Conclusion and recommendations

Quantum computing shows significant potential in enhancing medical image classification, especially in hybrid models where quantum elements are used to enhance classical processing. However, the field remains in its early stages, with many of the theoretical advantages of quantum computing yet to be fully realized due to current hardware limitations. At present, classical models continue to dominate the field, with quantum models serving primarily as enhancements rather than full replacements. The ongoing reliance on classical preprocessing and feature extraction underscores the importance of hybrid approaches in the current landscape. To fully harness the potential of quantum computing, continued investment in quantum hardware development is crucial. This includes increasing the number of qubits, reducing noise, and improving error correction techniques. Furthermore, advancements in quantum circuit optimization are necessary to develop more efficient architectures tailored for medical image processing. Reducing quantum circuit depth and exploring novel error mitigation strategies will be essential for improving quantum model stability and scalability. Given the current state of quantum computing, hybrid models offer the most effective way forward, allowing quantum computing to leverage its strengths while compensating for its weaknesses through classical preprocessing. Additionally, larger and more diverse datasets should be used to test quantum models to ensure their ability to generalize across different types of medical images and conditions, which is vital in proving the effectiveness of quantum models in real-world applications. Integrating quantum learning with federated learning frameworks could provide a path toward more scalable and privacy-preserving applications, enabling decentralized training on multi-institutional medical datasets. Establishing standardized metrics for evaluating quantum models is essential to ensure consistent and fair comparisons across studies. These metrics should include, besides accuracy, other measures such as precision, recall, F1-score, and computational efficiency. Furthermore, developing advanced preprocessing techniques tailored for quantum computing can help maximize the effectiveness of quantum models, including advanced dimensionality reduction methods and optimized data encoding techniques. Research should focus on refining encoding schemes, such as adaptive quantum embeddings, to better align with medical imaging features and reduce information loss during quantum state preparation. Multidisciplinary collaboration between quantum computing experts, medical imaging specialists, data scientists, physicists, and healthcare professionals are critical for advancing the field. Such collaboration will ensure that quantum models are not only technically advanced but also clinically relevant and applicable in healthcare settings. Expanding interdisciplinary research initiatives and establishing dedicated research consortia could accelerate the translation of quantum medical imaging from experimental models to real-world applications. There is a need to explore and develop new quantum algorithms capable of efficiently handling large datasets and complex image features, potentially leading to more significant quantum advantages in the future. Beyond classification tasks, the exploration of quantum models for segmentation, anomaly detection, and multi-modal imaging analysis represents a promising research direction.

While this review primarily focuses on the technological feasibility of QL models in medical imaging, it is important to acknowledge that their clinical adoption will require careful consideration of regulatory and ethical challenges. Ensuring compliance with healthcare privacy standards (e.g., HIPAA, GDPR) and developing interpretable quantum AI models will be essential for responsible deployment in real-world healthcare settings. Future research should explore secure quantum computing frameworks and fairness-aware quantum algorithms to address these concerns.

Adopting these recommendations will contribute to the evolution of the quantum medical imaging field, offering improved diagnostic tools and advancing the capabilities of medical technology.

CRediT authorship contribution statement

Eman A. Radhi: Conceptualization, literature review, data extraction, analysis of existing methods, and original draft preparation. Mohammed Y. Kamil and Mazin Abed Mohammed: Supervision, critical revision of the literature synthesis, validation of the findings, and manuscript review and editing. The authors employed GPT exclusively to improve linguistic clarity and readability; no alterations were made to the manuscript's scientific content or conclusions.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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