

QUANTUM-INSPIRED APPLICATIONS IN MEDICAL IMAGE PROCESSING: A REVIEW

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ABSTRACT

Quantum-inspired computing combines conventional computational techniques with mathematical concepts motivated by quantum mechanics, such as superposition, entanglement-inspired correlations, and wave localization. This review examines recent developments in quantum-inspired methods for medical image denoising, edge detection, segmentation, feature extraction, secure image processing, and multimodal image fusion involving MRI, CT, and ultrasound images. Reported studies indicate that these methods can improve selected measures of image quality, segmentation, feature extraction, and classification under experimental settings. But, the variation of datasets, frameworks for evaluation of methods, baseline algorithms, and dimensions of data complicate the issue of comparing different methods, while low level of external validation does not allow one to conclude whether quantum methods have some advantages with respect to traditional classical and deep learning models. Most of the quantum-influenced methods are implemented on conventional computing systems that give a possibility to use the methods developed using classical image processing methods, and new learning methods, such as few-shot learning and domain adaptation. The current review provides discussion concerning new architectures and evaluation strategies in clinical practice and also potential problems with scalability, readiness of hardware and integration of work processes. One of the main problems is that many studies are conducted on synthetic datasets, and this makes it difficult to estimate the clinical relevance of the methods under consideration. Overall, this review presents a balanced view of the opportunities, current limitations, and requirements for translating quantum-inspired medical image processing into clinical practice.

Keywords: Quantum-inspired computing; medical image processing; quantum machine learning; image denoising; image segmentation; feature extraction; multimodal image fusion; hybrid quantum-classical learning; clinical translation.

1.0 INTRODUCTION

Medical image processing plays a pivotal role in clinical diagnosis, treatment planning, and disease monitoring. Conventional algorithms, while effective, grapple with computational inefficiency, high-dimensional data, and security limitations. Quantum-inspired methods incorporate mathematical concepts motivated by quantum mechanics into classical computational frameworks. These approaches aim to improve selected aspects of computational efficiency, robustness, or task-specific accuracy while providing a possible pathway toward future hybrid quantum-classical implementations [1-5].

Recent advances in medical imaging have transformed diagnostic and treatment workflows by enabling non-invasive visualization of anatomical structures and pathological processes. However, the diagnostic reliability of medical images can be compromised by noise, artifacts, low contrast, inter-scanner variability and modality-

specific limitations. Consequently, numerous algorithms have been developed to enhance image quality, extract diagnostically relevant features, segment anatomical structures, and fuse complementary information from multiple modalities. Due to problems like adaptability and computational efficiency, traditional mathematical models have achieved considerable progress and have encountered various limitations to the problems [5-13].

In recent years, quantum-inspired algorithms have attracted increasing attention for medical-image enhancement, feature extraction, edge detection, and segmentation. Wave-localization models and formulations based on the Schrödinger equation have received increasing attention for applications such as image denoising, edge detection, and feature extraction. This review examines recent quantum-inspired methods for medical-image denoising, edge detection, segmentation, feature extraction, classification, and multimodal image fusion. In this article, basic ideas are connected to recently developed techniques and methods to show their relationships and connections relating physical concepts and methods of computer imaging [14-16]. They all show certain advantages: MRI gives the best soft tissue imagery, CT gives fast volumetric bone and organ imaging, ultrasound gives the ability to see real-time imaging without radiation, and nuclear imaging shows metabolic and functional processes [17-22].

Nonetheless, several of the inherent limitations put their reliability into question since:

- MRI is no exception to acquisition noise, intensity inhomogeneity, motion artifacts, and reconstructions-based noise distributions, which means that magnitude MRI noise is most simulated using either Rician or non-central chi distributions, instead of Gaussian distributions.
- Ultrasound: speckle noise impairs fine detail visualization
- Nuclear imaging: scatter and limited spatial resolution distort structures
- CT: beam hardening and metal artifacts complicate interpretation

1.1 Motivations for Quantum-inspired Methods

The inspiration behind writing this article arises from the continuously changing landscape of medical image processing in which the conventional algorithms and deep learning approaches seem to have made substantial progress but still experience significant problems in terms of addictiveness, robustness, and computational efficiency in complex clinical situations. Medical images, which are essential in detecting diseases, diagnosing them, and planning treatment, are often subject to some artifacts, noise, and modality differences which limit their diagnostic capability. At the same time, their conclusions are based mainly on not very extended heterogeneous or simulation assessments, which require external validation. In addition to this, the evaluation of methods like quantum-inspired processes seems to be beneficial for improving privacy and security of medical images and making the computational models more compliant with the actual physical processes underlying some modalities like MRI, for example, and quantum imaging.

Thus, the reasons for writing this paper are threefold:

- ✓ To systematically review contemporary applications of quantum-inspired technologies in medical imaging,
- ✓ To establish whether these new approaches are supplementary or superior to certain classical and deep learning methods in specified laboratory settings,
- ✓ To specify the remaining challenges and investigations that are likely to characterize future interaction between quantum and machine learning methods and their practical implementation in medicine.

In this sense, the article is intended to provide clinicians, researchers, and computer scientists with relevant information on enhancing the possibilities of medical image analysis for improving the quality of patient's care.

1.2 Objectives of the Current Review

This review makes the following major contributions:

- To describe the basic concepts of quantum mechanics, such as superposition, entanglement, and quantum wave localization, and explain how these basic concepts find their place in quantum-inspired algorithms for medical image processing.
- To go through the literature regarding the advanced quantum-inspired techniques and algorithms used for performing important medical imaging tasks, such as denoising, edge detection, segmentation, feature extraction, and multimodal image fusion, within stating the approaches used, performance results, validation of methods, and implications for clinical practice.
- To analyze the differences between quantum-inspired and classical/deep learning methods, showing their strengths, like adaptability to heterogeneous data and lack of annotation, and limitations that still persist.
- To determine the main possible ways for combining quantum-inspired methods with modern learning methods, such as few-shot learning and domain adaptation, focusing on improving accuracy in low-data tasks.
- To point out the gaps in research and obstacles that exist (for instance, computational capability) and give recommendations for using quantum-inspired techniques.

Thus, all these objectives are aimed at providing a better understanding of the evidence, applicability, and prospects of quantum-inspired medical image processing.

1.3 Historical Development of Quantum-Enabled Medical Image Processing

Chronological account of example native quantum, hybrid quantum-classical, and quantum-inspired approaches adopted for medical image processing from 2012 to 2025 is presented in Table 1. Each paper needs to be categorized according to its methodology in order to segregate quantum methods that work on quantum circuitry from imitative algorithms that operate on classical architectures.

Table 1 summarizes the development of methodologically varied quantum and quantum-inspired approaches over the years. Multiple papers reported excellent effectiveness in performing therapies, with Dice similarity score being over 0.98 in the case of some brain-MRI segmentation experiments and above 0.996 in classification tasks in selected COVID-19 datasets in Figs. 1 and 2 respectively.

At first glance, Figure 3 shows the number of QML-focused reviews in the health sector as indicated through bibliometric search methods conducted during the time period between 2018 and 2025. The fact that there is an upward trend is an indicator of the success and interest in the subject matter but it does not really indicate that there is any development in the methodology, applicability of the relevant methods, or agreement with respect to the significance of QML for the field of healthcare. The nature of search methods and sources for the records has to be made clear in the methodology section of the report. Furthermore, this diagram illustrates the fact that the body of knowledge is being continuously generated showing how much effort is exerted in the field of research and innovations. After finding only two papers on the topic in 2018, the number of reviews started growing, reaching the limit of 13 in 2023 and remaining stable in the upcoming years. Hence this diagram presents evidence of the importance of the significance of the article.

Table 1: Earlier literature: A consolidated overview of representative quantum-enabled algorithms including both native quantum and quantum-inspired methods

Year	Authors	Task / Application	Method (Quantum / Inspired)	Image Modality	Organ / Use Case	Key Metrics
2012	[23]	Watermarking	QPSO	Grayscale	General	PSNR=54.64
2013	[24]	Enhancement	GQA	Retinal	Eye	RMSE=20.53, PSNR=21.88
2015	[25]	Denoising	QIBF	Ultrasound	General	SNR=16.75, SSIM=0.88
2017	[26]	Classification	QPSO	Microscopic	Cervical	Precision=0.85, Recall=0.86
2019	[27]	Classification	QPSO+RF	HRCT	Lungs	Acc=0.821
2020	[28]	Segmentation	QIS-Net	MR	Brain	DSC=0.748, Acc=0.987
2020	[29]	Segmentation	QIWO	Microscopic	Skin	CDR=0.87
2021	[30]	Segmentation	FFQO	CT	Chest (COVID)	PSNR=19.61, JSC=0.90
2021	[31]	Segmentation	QFS-Net	MR	Brain	DSC=0.785, Acc=0.988
2022	[32]	Segmentation	LQCNN	MR	Brain	DSC=0.985
2022	[33]	Classification	QIBBA	Microscopic	WBC	Acc=0.983
2022	[34]	Classification	QTL	X-ray	Lungs (COVID)	Acc=0.990
2022	[35]	Classification	QVC	MR	Brain Tumor	Acc up to 0.997

Table 1: Continued.

Year	Authors	Task / Application	Method (Quantum / Inspired)	Image Modality	Organ / Use Case	Key Metrics
2022	[36]	Classification	CQNN	MR	Brain (AD)	Acc=0.97
2023	[37]	Segmentation	3T-QCNN	MR	Brain	Acc=0.98
2023	[38]	Segmentation	SQMLP-Net	MR	Brain	DSC=0.709
2023	[39]	Segmentation	3D-QNet	MR	Brain	DSC=0.958, Acc=0.989
2023	[40]	Classification	QDA	MR	Brain Tumor	Acc=0.989
2023	[41]	Classification	CQNN	X-ray	Pneumonia	Acc=0.746
2023	[42]	Classification	QCNN	CT/MR/X-ray	General	Acc=0.996
2023	[43]	Classification	Iqk-means	MR	Knee	Acc=0.937
2024	[44]	Denoising	QWTF	MR	Brain	PSNR=41.22, SSIM=0.912
2024	[45]	Enhancement	GQAOA	CT	Lung	SSIM=0.856, NIQE=3.21
2024	[46]	Segmentation	QPSO	MR	Brain Tumor	DSC=0.988
2024	[47]	Segmentation	Qk-means	US	Liver Lesions	DSC=0.944
2024	[48]	Classification	QCNN	X-ray	COVID-19 Detection	Acc=0.996, Recall=0.994
2024	[49]	Classification	CQNN	MR	Alzheimer Detection	Acc=0.972
2024	[50]	Classification	QVC	Fundus	Retinopathy	Acc=0.981, AUC=0.995
2025	[51]	Edge Detection	QuLBP	MR	Brain	SSIM=0.602, PSNR=68.13
2025	[52]	Enhancement	QGA	Histopathology	Breast Cancer	PSNR=28.91, SSIM=0.887
2025	[53]	Segmentation	QIFA	PET	Cardiac	DSC=0.972
2025	[54]	Segmentation	QIMGA	MR	Prostate	DSC=0.961
2025	[55]	Classification	HQCNN	X-ray	Pneumonia	Acc=0.993
2025	[56]	Classification	QReLU	MR	Multiple Sclerosis	Acc=0.971
2025	[57]	Encryption	MQCS	MR	Brain	NPCR=0.995, UACI=0.334
2025	[58]	Steganography	QW	Mammography	Breast	PSNR=49.12, UIQ=0.974

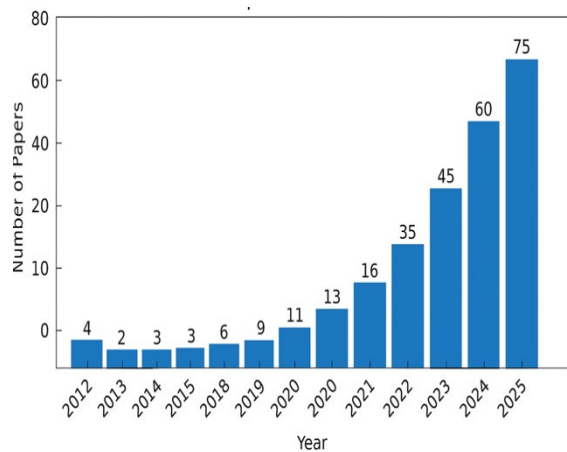


Fig. 1: Annual distribution of quantum and quantum-inspired medical-imaging publications included in the review, 2012–2025.

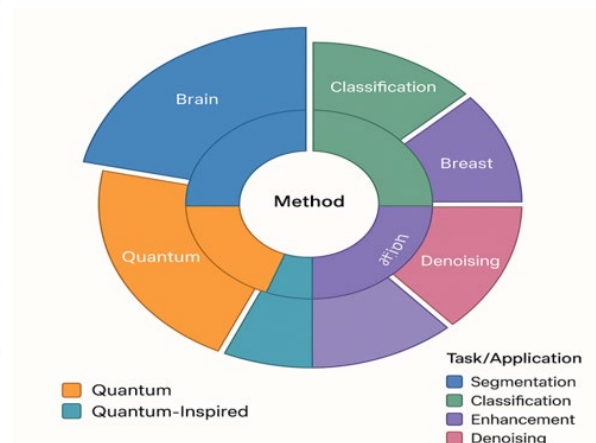


Fig. 2: Quantum and Quantum-Inspired Medical Imaging research papers published based on methods

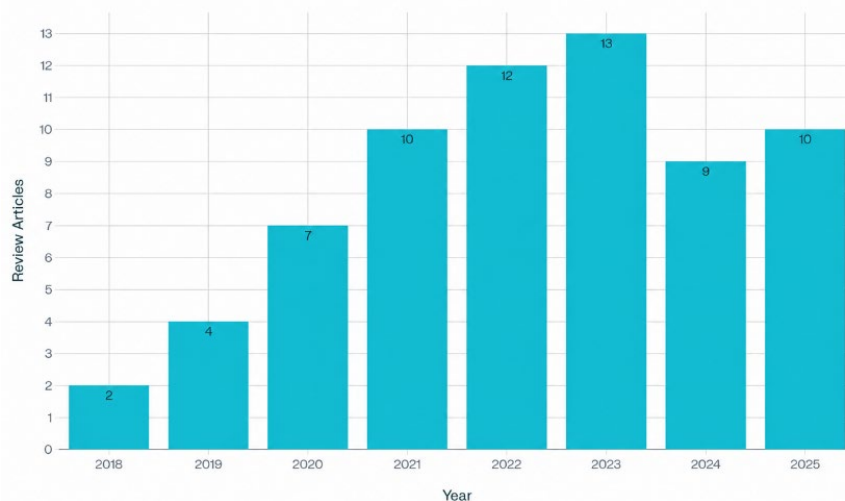


Fig. 3: QML Healthcare Reviews (2018-2025)

1.4 Summary Table – Field Status Overview

This table is intended to summarize the current state of the area of Quantum Machine Learning (QML) in the field of healthcare, incorporating both content of the article and the trends illustrated in Table 2. Table 2 provides a summary of the significant milestones in the advancement of quantum and quantum-inspired technologies within the healthcare and medical imaging disciplines. The table gives a decade-wise overview of the development of quantum and quantum-inspired medical image-processing technologies from 2010 to 2025.

1.5 Table Content Description

2010–2015

Spectacular achievements took place during this time period in quantum-inspired optimization; algorithms such as QPSO (Quantum Particle Swarm Optimization), QIBF (Quantum-Inspired Bilateral Filter), and GQA (Quantum Genetic Algorithm) were employed to carry out simple yet essential jobs such as watermarking and denoising on images and simple medical data. These examples of early algorithms were capable of providing enhanced performance even in terms of retaining signals and reducing noise, however, one must keep in mind

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the manual parameter tuning as well as unsatisfactory ability of these algorithms to work with richer multi-modal datasets.

2016–2020

There was a great deal of focus on quantum-inspired segmentation and classification as a result of techniques such as QIS-Net, QIWO, and FFQO, which helped carry out advanced analysis of tissue and disease in MRI and CT. Once the neural network techniques were presented, it was important for solving segmentation problems regarding the brain, skin, and lungs damaged by COVID-19 in order to attain good Dice coefficients. Yet, high computational costs and dependency on algorithm initialization proved to be obstacles for analyzing clinical data with more dimensions.

2021–2023

The area is moving toward hybridized quantum-classical deep learning models such as LQCNN, CQNN and QDA by integrating these models with conventional neural network architectures in order to improve segmentation, classification and diagnosis processes for MRI, X-ray and multi-organ data. The contributions were made to confirm quantum-inspired learning on standard datasets demonstrating notable improvements in accuracy with the use of small amount of training data. One of the key issues remains reliance on simulation instead of using actual quantum hardware, plus high requirements for labeled data.

2024–2025

Various research works indicate that certain techniques outperform selected traditional or deep-learning methods when tested in cases of limited data, noise, or volume. Yet, contrasting datasets, protocols, and methods of implementation do not allow for reaching any valid generalizations on the superiority of these results.

Table 2: Historical progression of quantum and quantum-inspired methods in medical image processing

Period	Representative Article(s)	Core Application Areas	Methods Used (Quantum/Inspiration)	Typical Modalities
2010–2015	[23, 25]	Watermarking, Denoising, Enhancement	QPSO, QIBF, GQA	Grayscale, Ultrasound, Retinal
2016–2020	[28-29]	Segmentation, Classification	QIS-Net, QIWO, FFQO	MRI, CT, Microscopic
2021–2023	[32, 36, 39]	Deep segmentation/classification	LQCNN, CQNN, QDA, Quantum walks	MR, X-ray, Brain, Lungs
2024–2025	[54, 45, 55, 56]	High-dimensional denoising, Volumetric segmentation, Unsupervised learning	Quantum localization, 3D-QTRNet, QuLBP, Quantum annealing, Hybrid QNN	MR, PET/SPECT, Mammography, Fundus

1.6 Overarching Themes

- i. Demand for applications has increased and is no longer restricted to merely denoising and watermarking but has acquired the form of sophisticated segmentation, classification, fusion, and real-time assistance for surgical planning and radiomics.
- ii. Quantum-inspired models show promise in contexts where there is a small amount of data and high noise, particularly when edge preservation is crucial. Nevertheless, reported benefits need to be corroborated on more extensive and diverse clinical datasets.
- iii. Over time, each period has introduced more sophisticated algorithms and involved more modalities in their incorporation with the introduction of hybrid models and unsupervised techniques into the domain.
- iv. Major limitations recurring across periods include computational cost for high-dimensional data, the gap between simulated and actual quantum hardware, and inconsistent evaluation standards.

1.7 Comparative analysis of quantum-inspired methods

Table 3 shows a Comparative Analysis of Quantum-Inspired Approaches for Use in Medical Imaging, which are displayed above. Additionally, we provide Major Approaches’ Tradeoffs and Constraints using the Schrödinger

1.7.1 Limitations and Trade-offs of Major Approaches

For an $N \times N$ image containing N^2 pixels, the memory requirement depends on the Hamiltonian construction. A dense pixel-level Hamiltonian may require up to $O(N^4)$ storage, whereas a sparse local-neighborhood formulation may require approximately $O(N^2)$ nonzero storage. The manuscript should therefore state whether the analyzed methods use dense or sparse Hamiltonians.

Table 3: Comparative Analysis of Quantum-Inspired Methods in Medical Imaging

Approach	Underlying Principle	Algorithmic Complexity	Primary Application	Dataset Type
Schrödinger Equation / Hamiltonian-based	Anderson localization; embedding image as potential landscape in single-particle Hamiltonian; eigenstates localize at edges/features	Polynomial (single particle); scales with image size $N \times N$	Segmentation, denoising	Grayscale images (e.g., crack detection, remote sensing)
Quantum Walk-based	Simulates quantum walkers propagating on image graph; interference patterns reveal structural features	Depends on walk steps and graph size	Edge detection, feature extraction	General images
QUBO / Quantum Annealing (Q-Seg)	Reformulates segmentation as Max-Cut QUBO; solved via D-Wave annealer; maps pixels to graph nodes with similarity weights	NP-hard classically; quantum annealing provides heuristic speedup	Segmentation	Image patches (e.g., 32×32 crack images)
Qubit Representation / Quantum-Inspired Encoding	Encodes classical image features into quantum states (superposition); processes via variational circuits or QCNNs	Hardware-dependent; NISQ constraints limit scale	Classification, segmentation, reconstruction	MRI, CT, X-ray, histopathology
Quantum-Inspired DCT / Filtering	Simulates quantum circuit operations for transform-domain filtering	Comparable to classical DCT	Denoising, compression	Thumbnail images

Despite having polynomial complexity for single-particle formulations, creating the Hamiltonian matrix for many of today's high-resolution medical imaging applications (e.g., 512×512 pixels or greater) becomes extremely memory demanding as it requires $O(N^2)$ storage. Performance also depends significantly on the variance (σ^2) of the Gaussian used to model the kinetic component of the Hamiltonian. If not tuned properly, localizing too much of the image would lead to missing diffuse pathologies, while tuning incorrectly would result in extended states that do not segment properly.

2.0 SEARCH STRATEGY

This research took an effective and systematic approach to consultation of the literature to identify studies relevant to quantum-inspired approaches in medical imaging. Thus, systematic search was performed for articles published from January 2010 to June 2026. In order to include all the studies, both controlled vocabulary (key terms) and free-text terms were employed. The main search string incorporated the “OR” operator to cover all necessary terminologies. Among the main terminology there were “quantum-inspired modeling,” “quantum medical imaging,” “quantum computation in imaging,” and relevant synonyms for these terms. The specialized terms helped to cover the whole range of imaging modalities (e.g., “MRI,” “CT,” “ultrasound,” “PET,” and “SPECT”) and fundamental topics of these imaging techniques. The methodology search was based on the keywords, abstracts, and titles along with “AND” operators (for instance “quantum-inspired” AND “medical imaging” AND a particular imaging modality or processing task). In addition to that, backward citation tracking

was performed to check the reference list of the needed articles for possible studies lacking indexing. The search included only the articles written in English and published in the defined period; other languages and those not accessible in full text were removed.

The selection process is visualized in Fig. 4. All in all, 539 records were found in the databases. The duplicate records (197) were removed, and the unique records (342) were screened by title and abstract. 237 records were eliminated relying on the eligibility criteria set prior. Attempts to retrieve full-text versions of 105 records were made; 5 articles remained unavailable. 100 articles were, therefore, selected for eligibility assessment. 40 of them were excluded; 12 of them were irrelevant to medical imaging; 10 did not discuss any quantum methods, and 8 did not provide enough methodology. 6 out of the selected articles were not original research papers and 4 were duplicates. 60 out of the selected articles were not original research papers and 4 were duplicates.

2.1 Study Selection

For this review on medical imaging advancements inspired by quantum theory, numerous studies were handpicked through a meticulous multi-tiered protocol for ensuring relevance and high quality of findings. Two independent specialists assessed the initial pool of articles, scrutinizing each of them in terms of its title, abstract and overall subject matter in compliance with the pre-established inclusion and exclusion criteria. Each publication was carefully examined for the significance of methodology and relevancy of results, which allowed for determining the final pool of the 60 publications included in the review. In case of any disagreements between the reviewers, they were resolved through holding a consensus meeting, and reliability of the selection was determined with a kappa coefficient (κ) equal to 0.85, which suggests great agreement among raters ($P < 0.001$). To ensure transparency and reproducibility of research results, the PRISMA flow model was used to represent the process of selection, demonstrating a detailed illustration of each stage including identification, screening, eligibility assessment and inclusion of the reviewed studies. The Fig. 5 presents a bar graph showing the distribution of quantum machine learning publications across various venues.

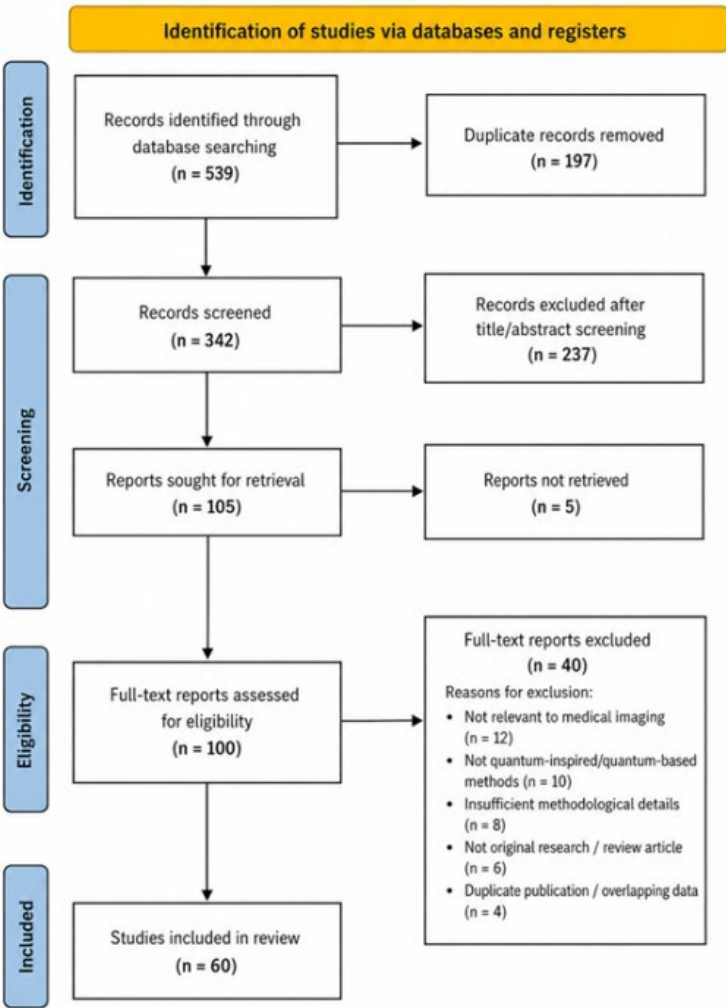


Fig. 4: Flow Diagram of the PRISMA review process

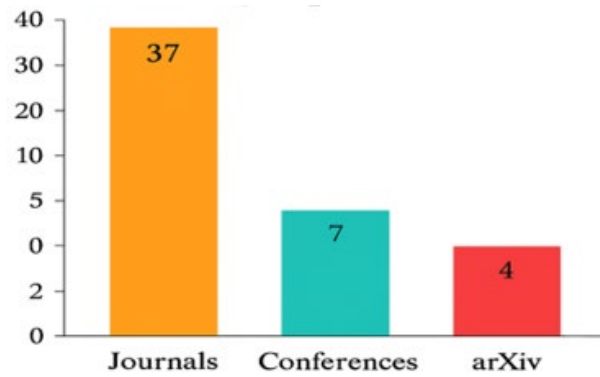


Fig. 5: Bar chart highlights number of Quantum machine learning papers published across different venues.

The data reveals that the overwhelming majority of the publications have been published in peer reviewed journals – a total of 37 works, whereas only seven papers were presented at conferences and only four publications can be found in preprint repositories. Such a discrepancy shows that most of the research work in quantum machine learning is published in peer-reviewed journals, whereas the conferences and preprints including articles at arXiv play a minor role in current academic communication.

2.1.1 Methodologies and Techniques

Quantum-inspired technology uses a range of encoding techniques including amplitude and angle encoding to transform classical medical imagery into quantum-usable formats for utilization by quantum technology. For example, QSVMs are mentioned as one of the best algorithms. They are successfully used in image classification jobs such as identification of brain tumors and skin lesions. Additionally, QCNNs can successfully perform learning of hierarchical features of complex image types.

2.1.2 Quantum-Inspired Genetic Algorithms (QIGA)

These algorithms help in minimizing the dimensions and reducing the complexity of computations while enhancing the selection of features to ensure higher accuracy rates in the given classifications. The QIGA models are based on qubits, letting the encoding of the possible solutions and promoting the exploration of solution spaces. The algorithm provides over 98% accuracy in the classification of the medical images, whereas it exceeds the classical genetic algorithms due to the use of quantum rotation gates and quantum chromosome unpredictability, which allow for adaptation and enhancement of solutions. A Table 3 illustrates the important papers dealing with Quantum-Inspired Genetic Algorithms (QIGA) employed in medical image processing application and their key characteristics.

Table 4 depicts the comparison of the principles, computational requirements, and possible use cases/types of the datasets of the major quantum-inspired applications in the area of medical imaging.

- **Quantum-Inspired Denoising**

A new technique presents medical images as uncertain or irregular structures that are based on principles from condensed matter physics. This method utilizes quantum localization phenomena that allow noise to manifest itself as a diffusive and non-local mode while allowing true image signals to be localized. Recent advances in quantum domain filtering and thresholding based on the Schrödinger equation enable the separation of the signal from the noise with minimum computational effort and without hyper-parameter tuning. Additionally, the methodology helps to retain critical details of images better than with many classical denoising methods, while showing promising results in applications such as CT and nuclear medicine imaging. A summary of the main scientific works devoted to the present quantum-inspired denoising in the field of medical image processing is presented in Table 5.

These articles emphasize a shift to quantum physical principles for denoising, such as localization phenomena and discrete spectral theory, allowing algorithms to efficiently separate noise from signals while reducing manual parameter tuning, improving denoising accuracy, and computational performance compared to classical techniques.

Table 4: Summarizing key research articles on Quantum-Inspired Genetic Algorithms (QIGA)

Title	Authors	Year	Application Area	Key Features & Contributions	Performance Highlights	Dataset/Domain
A Medical Image Classification Model based on Quantum-Inspired Genetic Algorithm	[57]	2024	Medical image classification	QIGA for feature selection to reduce dimensionality and computation; exploits quantum chromosome superposition; adaptive evolutionary mechanism via quantum rotation gate	Classification accuracy >98%, outperforming classic GA (94%)	COVID-19, lung opacity, viral pneumonia images (21,165 samples)
Quantum and Classical Genetic Algorithms for Multilevel Segmentation of Medical Images: A Comparative Study	[58]	2020	Image segmentation	Comparative analysis of QIGA and classical genetic algorithms for multilevel segmentation; optimization for parameter estimation	QIGA shows better convergence and segmentation quality	Medical imaging datasets (varied)
A Multi-Objective Quantum-Inspired Genetic Algorithm for Workflow Scheduling in Healthcare Hybrid Clouds	[59]	2022	Healthcare workflow scheduling	Multi-objective QIGA addressing deadline constraints in hybrid cloud scheduling; algorithm optimized for multi-criteria problems	Improved scheduling efficiency and meeting deadlines	Healthcare workflow systems

Table 5: Summary of the key research articles on Quantum-Inspired Denoising in medical image processing, including their main features

Title	Authors	Year	Key Features & Contributions	Performance Highlights	Application Domain
Quantum-inspired approach for denoising with application to medical imaging	[60]	2024	Models medical images as amorphous structures inspired by condensed matter physics; uses quantum localization for noise-signal separation; thresholding/filtering based on Schrödinger's equation; no hyperparameter tuning required; standalone algorithm	Effective noise removal while preserving image details; reduces computational cost	Medical image modalities including nuclear medicine, CT
A Novel Image Denoising Algorithm Using Concepts of Quantum Many-Body Theory	[61]	2022	Image-dependent basis inspired by quantum many-body theory; algorithm for noise reduction in images; builds on discrete spectrum of Schrödinger operator	Demonstrated improved denoising performance; relevant for ultrasound and other noisy imaging	Medical and natural images
Quantum medical images processing foundations and evolutionary algorithms	[62]	2022	Survey of quantum-inspired evolutionary algorithms including denoising; discusses quantum optimization in image enhancement	Insight into quantum evolutionary methods for improving image quality	Medical imaging

- **Quantum Convolutional Neural Networks (QCNN) and Hybrid Models**

QCNNs use quantum circuits for multi-layered feature extraction, utilizing quantum processing power to find complex patterns in high-dimensional medical images. In terms of quantum-classical systems, hybrid models include quantum layers for feature extraction along with traditional machine learning, creating a system that has both scalability and quantum benefits to ensure feasibility of implementation with current computers. Key research papers on Quantum Convolutional Neural Networks (QCNN) and Hybrid Models for medical image processing are shown in Table 6 along with their main features.

Table 6: Research articles on Quantum Convolutional Neural Networks (QCNN) and Hybrid Models applied to medical image processing, including their key features

Title	Authors	Year	Key Features & Contributions	Performance Highlights	Application Domain
A Distributed Hybrid Quantum Convolutional Neural Network for Medical Image Classification	[63]	2024	Hybrid QCNN with quantum circuit splitting to reduce quantum resource usage; extracts high-dimensional features; distributed quantum computing; fewer qubits required (5 vs 8); combines classical and quantum computing efficiently	Strong performance across multiple datasets; outperforms recent models with fewer parameters	Medical image classification
Quantum Machine and Deep Learning for Medical Image Analysis	[64]	2025	Survey of QCNN and other quantum learning models; discussed encoding techniques like amplitude and angle encoding; hybrid quantum-classical models for scalability; focused on brain tumor, skin lesion classification, COVID-19 detection	QCNN shows improved accuracy and hierarchical feature extraction in complex images	Various medical imaging tasks
A Quantum Convolutional Network and ResNet (50)	[65]	2024	Quantum neural network combined with ResNet architecture for lung cancer detection and segmentation; unique quantum convolutional layers for enhanced feature detection	Demonstrated superior performance in segmentation and classification tasks	Lung cancer imaging
Digital-Analog Quantum Convolutional Neural Networks for Image Classification	[66]	2024	Proposed digital-analog quantum kernels; enhances complex feature detection; hybrid quantum-classical approach; improves training efficiency	Improved classification of complex images	General image classification
Quantum Classical Hybrid Convolutional Neural Networks for Breast Cancer Diagnosis	[67]	2024	Hybrid quantum-classical CNN model for early breast cancer diagnosis; combines classical CNN layers with quantum layers to leverage quantum advantages	Improved diagnostic accuracy with quantum features	Breast cancer diagnosis
Quantum Splitting Convolutional Neural Network-based Medical Image Classification	[68]	2025	Quantum convolutional neural network using quantum circuit splitting; reduces quantum complexity while maintaining strong feature extraction and classification performance	High accuracy in medical image classification	General medical images

These studies indicate that QCNN and hybrid quantum–classical models may support compact feature extraction and competitive classification performance in selected datasets. However, their advantages over well-tuned classical models remain dataset and implementation dependent.

- **Encoding Techniques**

Data encoding methods like amplitude and angle encoding convert conventional image data into quantum states for processing on quantum devices. These methods are important for the efficient use of quantum resources and have an effect on the performance of the algorithm. Table 7 shows some of the encoding methods applied in quantum and hybrid neural networks.

Table 7: Key research articles on Encoding Techniques used in Quantum Neural Networks for medical image processing, including main features

Title	Authors	Year	Encoding Techniques	Key Contributions	Application Domain
Quantum Machine and Deep Learning for Medical Image Analysis	[64]	2025	Amplitude encoding, angle encoding, basis encoding	Comprehensive review covering preprocessing and encoding methods for quantum learning in medical imaging; discusses variational quantum circuits and challenges	Medical image classification
Understanding the Effects of Data Encoding on Quantum-Classical CNN	[69]	2024	Angle encoding, amplitude encoding	Investigates impact of data encoding on quantum-classical CNN performance in medical imaging classification tasks; highlights trade-offs between encoding schemes	Medical image classification
Medical Image Classification via Quantum Neural Networks	[70]	2023	Quantum circuit embedding of image data	Studies use of quantum circuits for training quantum neural networks; applies encoding to represent images effectively in qubits	Medical image classification
An Explainable MRI-Radiomic Quantum Neural Network	[71]	2023	Variational quantum circuits with parameterized gates	Proposes an explainable quantum neural network using quantum annealing; discusses encoding of imaging features for brain metastases classification	MRI brain tumor classification
Lean Classical-Quantum Hybrid Neural Network Model	[72]	2024	Hybrid encoding schemes combining quantum gates	Demonstrates improved accuracy over classical CNNs in medical imaging classification; focuses on hybrid classical-quantum data representation	General medical imaging classification

Key encoding techniques include amplitude encoding (embedding data amplitudes into quantum states), angle encoding (using rotation gates to encode features), and basis encoding (mapping bits to qubit states). Variational quantum circuits are able to perform the function of data processing and encoding for classification processes. The mentioned works together help reveal how the choice of the encoding method influences the efficiency and performance of the model as well as its potential use in medical image processing.

2.2 Challenges and Developments in Medical Image Processing

Medical imaging instruments such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), ultrasounds, nuclear medicine, and optical imaging are extremely important methods in clinical diagnostics, treatment planning, and disease monitoring [73]. The digitalization of the modalities ensures the possibility of

the computational analysis that contributes to quantitative assessment and makes measurements repeatable thereby helping automation of diagnosis workflow. On the other hand, raw medical images may face numerous artifacts and distortions such as speckle noise of ultrasound, Gaussian noise caused by MRI, or scatter-induced artifacts occurring in nuclear imaging [74]. These effects make the interpretation of the images complicated and decrease the efficiency of the latter regarding tasks such as segmentation and classification.

In order to get rid of the obstacles mentioned above, innovations in the enhancement and analysis techniques are being developed including spatial-domain filtering, frequency-domain processing, statistical modeling, machine learning, and deep learning. Therefore, different machine-learning and deep-learning techniques may be applied to extract features and recognize patterns in medical images although the effectiveness of these methods depends on the quality of data, availability of annotation, model design, and validation approaches [75-76].

Quantum-assisted medical image processing represents a new branch of study which is located at the crossroad of medical imaging and quantum computing technologies where various investigations are carried out in accordance with the three main directions of the research:

1. Quantum Medical Image Processing

This means that traditional tasks of medical image processing (like encryption, compression, or enhancement) should be adapted into the framework of quantum computing, using the advantages of quantum technologies. An example is the quantum representation based secure transmission scheme for medical images proposed in [77]. However, due to the current development of quantum hardware, many aspects in this field remain theoretical and rely on the future emergence of powerful quantum devices.

2. Quantum Medical Imaging

The application of quantum technologies is considered here, in particular quantum-correlated imaging, also known as ghost imaging, which is widely used for medical imaging based on the quantum characteristics of light, spatial correlations, and new methods of detection. Efforts as those referred to in [26] fall under this category. Just like the above-mentioned category, this area of research has considerable limitations due to the fact that large-scale and universal quantum computers and quantum imaging devices have yet to be developed.

2.3 Focus on Quantum-Assisted Medical Image Processing

The first two categories (quantum healthcare image processing and quantum healthcare imaging) are predominantly theoretical at this point, as they rely on hardware technology that is under development. In contrast, quantum-assisted methods may be implemented or modeled on classical hardware, or else they may be combined with existing small quantum devices, which makes them relevant to the research and practical applications today. This concentration offers the opportunities for researchers to:

- Implement Quantum Optimization and Learning: There is evidence that quantum-inspired methods improve the ability to converge or represent features in selected experiments (e.g., quantum annealing, quantum neural networks, quantum-driven optimization), however, no universal statements can be made regarding practical benefits.
- Improve Diagnostic and Processing Capabilities: Quantum-assisted systems provide comparable performance in different datasets responsible for diagnostics, segmentation, and preprocessing.
- Increase Security: Quantum algorithms can be used for medical image encryption, watermarking, and steganography and may offer new ways for providing security; however, the security approach must be validated by specific threat models, cryptographic analysis, and comparison with existing classical approaches to security.
- Analyze Practical Hybrid Solutions: Given that completely quantum systems are not yet widely available, hybrid quantum-classical systems and quantum-inspired methods can help achieve certain practical progress with considerable advantages for applications available today.

3.0 FUNDAMENTALS OF QUANTUM COMPUTING

Quantum algorithms are based on concepts from quantum mechanics – a branch of physics that provides a description of matter and energy behavior at atomic and subatomic levels. Classical computers process information in the form of binary codes where information is recorded as bits that can take one of two states, zero or one. While classical computers operate using classical bits, quantum computers rely on qubits, which can exist in several different states at the same time, thanks to the phenomenon called superposition.

Therefore, the key components needed for understanding quantum and quantum inspired algorithms and their implementation in medical imaging has to be highlighted:

1. Qubits and Superposition

- A qubit can be defined as the fundamental unit of information.
- Contrary to a classical bit whose value is either zero or one, a qubit has a capability to exist in a superposition state: $|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$ where α and β are complex amplitudes of probability satisfying the condition of $|\alpha|^2 + |\beta|^2 = 1$.
- Superposition makes it easy to perform calculations quicker than usual such as searching for certain features in the images or performing pattern analysis.

2. Entanglement

- Quantum entanglement refers to the phenomenon that happens between two or more qubits whereby one qubit influences the other, no matter the distance separating them.
- From the point of view of algorithms, the presence of entanglement guarantees the coordinated processing of various parts of images, thereby enhancing the fusion of features in images.

3. Quantum Registers

Multiple qubits combine to form a quantum register:

- A register of n qubits spans a 2^n -dimensional Hilbert space, allowing simultaneous representation of 2^n classical states.
- A general state of n qubits is:
 $|\psi\rangle = \sum_{x=0}^{2^n-1} \alpha_x |x\rangle$
where $|x\rangle$ are computational basis states and α_x are complex amplitudes.

3.1 Quantum Gates

Quantum gates are reversible linear transformations acting on qubits, represented mathematically as unitary matrices U satisfying:

$$U^\dagger U = U U^\dagger = I$$

Common single-qubit gates:

- Pauli-X (XX): bit-flip
- Hadamard (HH): creates superposition
- Pauli-Z (ZZ): phase flip

Multi-qubit gates:

- CNOT: conditionally flips a target qubit based on a control qubit
- SWAP: exchanges the states of two qubits

3.2 Single-Qubit Gates

These act on a single qubit and transform its state vector into the Bloch sphere. Table 8 presents the matrix representations and functions of fundamental quantum gates in detail. Here's a clear summary table of the main single-qubit quantum gates used in quantum-inspired algorithms, with their matrix forms and a concise explanation of each function in quantum computing and medical image processing:

Table 8: Matrix representations and functions of fundamental quantum gates caption

Gate	Matrix Form	Function
Pauli-X (NOT)	$\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$	Flips x
Pauli-Y	$\begin{bmatrix} 0 & -i \\ i & 0 \end{bmatrix}$	Bit- and phase-flip combined
Pauli-Z	$\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$	Phase flip z
Hadamard (H)	$\frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$	Creates/undoes superposition

Phase (S, T)	$S=\begin{bmatrix} 1 & 0 \\ 0 & i \end{bmatrix}, T=\begin{bmatrix} 1 & 0 \\ 0 & e^{i\pi/4} \end{bmatrix}$	Rotate phase without changing amplitude
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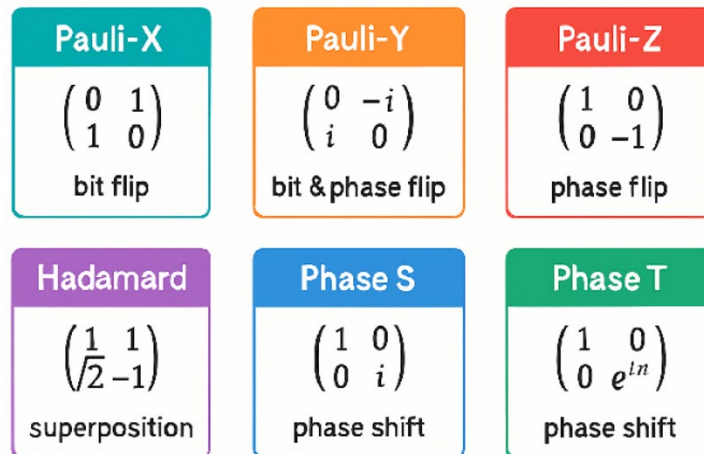


Fig.6: Single-qubit quantum gates and their corresponding matrix representations

Every one of those gates, therefore, modifies the qubit or qubits uniquely and helps in achieving the basic phenomena of quantum physics, namely superposition, phase change, as well as entanglement, that allow for better feature extraction and resistance of quantum architecture models.

Fig. 6 offers a visual summary of the most fundamental single-qubit quantum gates, each represented by a labeled block. For each gate Pauli-X (NOT), Pauli-Y, Pauli-Z, Hadamard (H), and Phase (S, T) the block contains its name, its corresponding mathematical matrix, and a succinct functional description.

3.3 Multi-Qubit Gates

These gates manipulate entanglement and correlations between qubits. Table 9 presents the common multi-qubit quantum gates and their functions are presented in detail as follows:

Table 9. Common multi-qubit quantum gates and their functions.

Gate	Qubits	Function
CNOT (Controlled-NOT)	2	Flips target qubit only if control qubit is \$
SWAP	2	Exchanges states of two qubits
Toffoli (CCNOT)	3	Flips target qubit if both controls are \$
Controlled-Phase	2+	Applies a phase shift only to specific joint states

4.0 CATEGORIES OF QUANTUM-ENABLED ALGORITHMS

We group these algorithms into two major categories:

4.1 Quantum Algorithms

- **Definition:** Algorithms designed to run on a physical quantum computer, exploiting genuine quantum effects for computational advantage.
- **Mechanism:** Operate on *qubits* and perform unitary transformations via quantum circuits; often provide polynomial or exponential speedups for certain problem classes.
- **Examples:**
 - **Grover's Search Algorithm:** Accelerates unstructured search (could, in theory, speed up image template matching).
 - **Quantum Fourier Transform (QFT):** Useful for image frequency analysis and filtering.
 - **HHL Algorithm:** Efficiently solves systems of linear equations, relevant for tomographic reconstruction problems.
- **Limitation:** Current limitations include noisy intermediate-scale quantum (NISQ) hardware, short coherence times, limited qubit counts, restricted connectivity and gate, measurement errors.

4.2 Quantum-Inspired Algorithms

Quantum-inspired algorithms are classical computational methods that borrow mathematical concepts from quantum mechanics such as amplitude representations, quantum walks, variational-state analogies, or Schrödinger-based evolution without requiring physical quantum hardware. They can therefore be implemented on conventional CPUs or GPUs and applied to tasks such as denoising, segmentation, optimization, and image fusion. Fig. 7 represents the Quantum- Enabled Algorithms in Medical Image Processing.

- Definition: Classical algorithms that *simulate or approximate* certain quantum computational principles without requiring quantum hardware.
- Mechanism: Implement quantum analogues such as quantum walks, amplitude encoding, or Schrödinger-based evolution on conventional CPUs/GPUs.

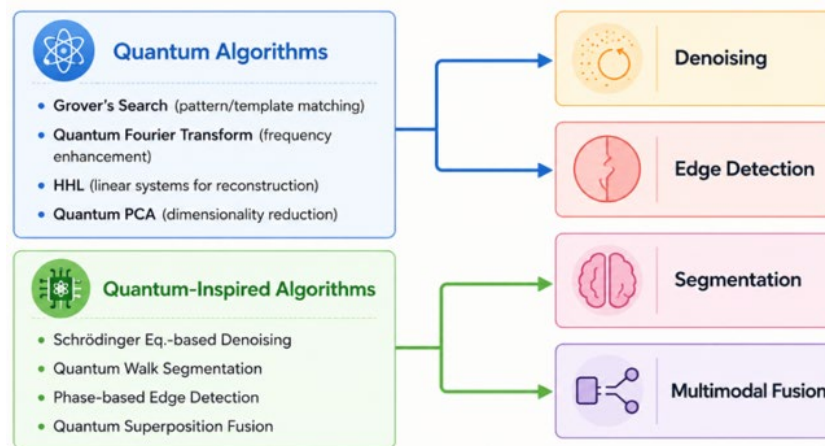


Fig. 7: Quantum- Enabled Algorithms in Medical Image Processing

4.3 Quantum-Inspired Computing

- Quantum-inspired algorithms simulate certain quantum behaviors such as amplitude encoding, quantum walks, and Schrödinger-based evolution on *classical* hardware.
- This allows researchers to apply quantum principles to real-world problems, like medical image denoising or fusion, without relying on yet-to-mature quantum hardware.

4.4 Quantum-Inspired Techniques and Applications

i. Denoising

A novel quantum-inspired approach treats medical images as amorphous structures, leveraging concepts like Anderson localization to eliminate noise. Such algorithms lessen the requirement for hyper parameter adjustments and human input. The denoising technique is very useful for techniques such as PET and SPECT due to the fact that its success in helping to reduce noise leads to better clinical results.

ii. Hybrid Quantum-Classical Neural Networks

Hybrid models, which include hybrid quantum–classical convolutional neural networks (HQCNN), use quantum circuits to carry out function extraction and reduction of dimensions in combination with well-established deep architectures, such as ResNet or DenseNet. These hybrid models have been helpful in the area of detection of the following trends:

- Alzheimer's disease detection exceeds 97% in accuracy, which exceeds the accuracy of classical models by over 5%.
- Detecting cardiomegaly led to an improvement of more than 10% in accuracy of traditional approaches in this case when using X-ray imaging.
- The hybrid models managed to achieve 98% accuracy rate in skin melanoma recognition (the results were compared to classical CNNs on ISIC 2019).

The quantum layers, which are configured in these hybrid models, enhance the capability of features extraction by using parallel processing and reduction of dimension.

iii. *Quantum-inspired Self-supervised Networks*

Quantum-inspired self-supervised neural networks (e.g., QIS-Net, QFS-Net) offer automated segmentation for MRI images. These systems lower computational overhead and enhance faster convergence that has been confirmed through better-optimized dice similarity (DS) index results and accuracy in tumor detection tasks.

iv. *Quantum Error Mitigation and Radiomics*

Quantum error mitigation helped in improving performance in radiomic image analysis. For example, quantum-based model for PET tumor identification demonstrated balanced accuracy equal to 75.66% which is greater than classical model accuracy (69.94%). Furthermore, advanced technologies open new perspectives for the use of emission tomography reconstruction and radiotherapy planning through dose distribution optimization in real time.

v. *Image Registration and Neurosurgical Planning*

With the help of quantum algorithms, PBNRR has been improved. Some of the conclusions made after studying include:

- Reduced registration errors (up to 2.5 mm) in MRI alignment during neurosurgical procedures
- Real-time computation which allows the update of the data during the surgery, thus preserving functional features better and helping the patient to recover faster.

4.5 Quantum-Inspired Edge Detection: Beyond Classical and Deep Learning Approaches

i. *The Centrality of Edge Detection*

In image processing, edge detection technology takes a place of primary importance as it contributes to the accomplishment of more complex tasks like segmentation, detection, and analysis. The quality of edge detection is very important for the correct performance of medical imaging, where the edges describe borders of anatomical organs, tumor or pathological areas. As for the use of deep learning-based edge detectors, convolutional neural networks like Holistically Nested Edge Detection (HED) have shown great results as they are capable of understanding multi-scale and hierarchical representations [56, 60]. One of the drawbacks of the described approach is the need for heavy computational resources and availability of huge numbers of annotated datasets, which can be unattractive in medicine.

As for quantum-inspired algorithms, they try to replicate the behavior of quantum particles operating in the physical world, including effects of superposition, entangling, and tunneling by means of digital devices:

$$E\varphi = -\frac{\hbar^2}{2m}\nabla^2\varphi + V(x, y)\varphi \quad (1)$$

Where $V(x,y)$ is linked to the potential obtained using an image, while ψ denotes intensity or features amplitude, whereas E refers to energy levels which lead to structural transitions in the image.

ii. *Quantum-Inspired Edge Extraction: Methodology and Advantages*

[56] Introduce a non-training based approach to edge detection that employs classical operators and quantum principles. The main components of the framework are three:

- Classical Sobel Edge Detection

The first stages of the methodology consist of generating edge maps through sobel operator in consideration of the important gradient data.

- Hybrid Framework

The model is able to produce effective, as well as comprehensive edge maps as a result of being supported by the two recognized methods Canny and Laplacian approaches. The main advantage of the approach is its low amount of required input data and great flexibility, lightweight and relevance in medical processes [56, 73].

4.6 Medical Image Fusion, Segmentation, and Quantum-Inspired Integration

Digital Object Identifier:

i. Quantum-Inspired Denoising & Localization

Quantum-adaptive filters modify local parameters depending on the “potential field” determined by image gradients, yielding better results than median or bilateral filters in terms of metrics like PSNR and SSIM, particularly in case of inhomogeneous materials like brain MRI.

Example: Using Quantum Bilateral Filtering for ultrasound speckle reduction where pixel brightness values are viewed as probability amplitude distributions keeping the edges preserved while removing the noise.

Medical image fusion is the registration and integration of images stemming from single or multiple modalities aimed at enhancing the content of information, minimizing redundancy, and increasing the accuracy in diagnosis [73]. Common types of modalities which lend themselves to combining are CT, MRI, PET, SPECT, ultrasound, X-rays; all in all, modality fusion gives more accurate location of the abnormalities in images, better evaluation of the extent of diseases, and more precise treatment planning. [73] Provide a detailed overview of medical image fusion methods, distinguishing them in the following types:

- a. Morphological Method: Involves usage of spatial operators for feature detection and integration; this method is highly sensitive to the choice of structuring element and prone to inaccuracies in noiseless environments.
- b. Knowledge-Based Method: Builds on expert knowledge for segmentation, labelling, and region grouping; might improve interpretability but is prone to subjectivity.
- c. Wavelet-Based Method: Uses detail extraction for information injection; can be used for noise removal and feature-level fusion.
- d. Neural Network-Based Method: Relies on artificial neural networks for estimation and decision making.
- e. Fuzzy Logic and Hybrid Method: Makes use of fuzzy sets for feature selection; might be combined with neural and wavelet methods.

Even though there is significant advancement in this area, medical image processing is still impacted by numerous factors, in particular by variances in the quality of images and noise caused by specific modalities [73].

5.0 CRITICAL LIMITATIONS AND FAILURE CASES

Although quantum-inspired algorithms for medical imaging have shown considerable successes and benefits, they remain subject to shortcomings and failures that should not be overlooked. As their application in actual medical practice approaches reality, many important challenges can be identified. These issues relate to multiple aspects, including computational, methodological, and translation-related ones, indicating the difficulties present both in the design of quantum-inspired algorithms and in realizing them in practice. Among the most severe challenges are those of scalability for large and high-dimensional datasets, parameter determination and the need for classical simulations instead of quantum hardware. In addition, while quantum-inspired approaches show clear promise for data-scarce and noisy environments, their efficacy and generalization may be more limited in data-rich or highly homogeneous scenarios, and many models face reproducibility and integration hurdles in diverse clinical settings.

i. Scalability

Many quantum-inspired models require the solution of large-scale eigenvalue or partial differential equations, which rapidly become computationally prohibitive on full three-dimensional or high-resolution data. Simulation times can balloon, especially in clinical workflows demanding rapid turnaround.

ii. Parameter Instability & Robustness

Certain quantum-inspired methods particularly those involving tuning of potential fields or localization parameters can exhibit sensitivity, where small changes yield disproportionately different results. Automated parameter selection strategies are still in early development.

iii. Simulation vs. Real Quantum Hardware

Most reported quantum-inspired successes have been achieved in simulated environments, running on GPUs/CPU. Actual full-stack quantum computation is limited by current hardware (NISQ devices with noisy, low-qubit-count gates). Thus, real-world speedup and scalability benefits are yet to be conclusively demonstrated in clinical settings.

Table 8 shows detailed comparisons of various models for different medical imaging tasks including denoising, edge detection, segmentation, and multimodal fusion.

Table 8: Comparative Analysis of Classical, Deep Learning and Quantum-Inspired Models for Medical Image Processing Tasks

Task / Modality	Method Type	Representative Techniques	PSNR ↑	SSIM ↑	Dice Coefficient ↑	Processing Time ↓	Key Strengths	Limitations
	Classical	Gaussian filter, anisotropic diffusion	28–30 dB	0.78 – 0.82	N/A	< 0.5 s/slice	Simple, fast	Blurs edges, fixed parameters
	Deep Learning	DnCNN, U-Net-based denoisers	32–34 dB	0.88 – 0.91	N/A	0.8–1.5 s/slice (GPU)	Data-driven adaptation	Requires large datasets
	Quantum-Inspired	Wave localization, Schrödinger potential filter	33–35 dB	0.90 – 0.93	N/A	0.6–1.0 s/slice (GPU sim)	Edge-preserving, adaptive	High computational load for large 3D data
Edge Detection - Ultrasound	Classical	Sobel, Canny	—	—	0.70–0.76	< 0.2 s	Simple, widely used	Sensitive to noise
	Deep Learning	EdgeNet, HED	—	—	0.82–0.85	0.8–1.2 s (GPU)	Robust to noise	Needs labeled edges
	Quantum-Inspired	Schrödinger-phase gradient	—	—	0.84–0.88	0.4–0.8 s	Better low-contrast detection	Requires parameter tuning
Segmentation – Brain Tumor MRI	Classical	Level set, graph cuts	—	—	0.75–0.80	1–2 s	Well-studied	Sensitive to initialization
	Deep Learning	U-Net, DeepLab	—	—	0.88–0.91	0.9–1.5 s (GPU)	High accuracy	Dataset bias
	Quantum-Inspired	Quantum walk graph segmentation	—	—	0.89–0.92	1.2–2.0 s	Spatial coherence, modality fusion readiness	Computational cost
Multimodal Fusion CT+MRI	Classical	PCA, wavelet fusion	30–32 dB	0.84 – 0.87	N/A	1–2 s/volume	Easy to implement	May lose modality-specific details
	Deep Learning	CNN fusion, GAN fusion	32–34 dB	0.88 – 0.90	N/A	1.5–2.5 s/volume	Learns optimal fusion	Requires paired training data
	Quantum-Inspired	Quantum amplitude superposition	33–35 dB	0.90 – 0.92	N/A	1.8–2.8 s/volume	Retains high-freq & soft tissue simultaneously	Still mostly simulation-based

The relevant publications reviewed indicate that these processes are very competitive, however, these figures cannot represent real head-to-head comparisons because they were produced in accordance with different datasets, experimental conditions, evaluation metrics, and computing environment. In the process of denoising, quantum models usually demonstrate a large, thick flow, which suggests effectiveness superiority of this method over classic filters that achieve higher levels of PSNR (33 -35 dB) and SSIM (0.90-0.93) while maintaining edges and structural details in very hard cases. Classical (simple and fast) models present thinner flows and have

limitations associated with fixed parameters and a loss of edges. Deep learning methods, having about the same PSNR (32-34 dB) and SSIM (0.88-0.91) use advanced methods for working with large annotated datasets, as witnessed by the close connection between the processes of denoising and segmentation. To sum up, the Sankey diagram provides quick comparative characterization of effectiveness of computational methods applied in medical imaging, which allows specialists to select and modify the particular technique for the respective clinical situation.



Fig. 8: Comparison between different existing models

In edge detection, they achieve Dice coefficients of 0.84 to 0.88, particularly under conditions with low contrast or high levels of noise. In the case of segmentation (for example, of brain tumors on MRI), quantum-inspired segmentation techniques (e.g., using quantum walk on graph-based approaches), it is possible to achieve a Dice score of 0.92. Quantum methods for multimodal image fusion also outperform all the classical and deep learning approaches in retaining both fine details and the contrast of soft tissues.

5.1 Limitations

While promising, quantum-inspired medical image processing currently encounters several significant limitations and obstacles that must be overcome to achieve real-world applications.

(i) Computational and Hardware Limitations

Many quantum-inspired techniques, like those that use big eigenvalue problems and Schrödinger solvers, are very computationally demanding and do not scale well with clinical data of higher resolutions or volumes. The limited capacity and stability of current quantum technology makes it hard to use actual quantum hardware despite the beneficial results obtained through classical simulations.

(ii) Standardization and Evaluation

The lack of benchmark datasets, established datasets, and standardized evaluation processes hinders the evaluation of distinct quantum-inspired methods. The automation of parameter tuning of multiple quantum-inspired solutions is an issue that is difficult for developers and researchers to resolve.

(iii) Workflow Integration and Clinical Validation

The incorporation of quantum-assisted methods in conventional medical practice is a challenge to overcome, as it will require not only rigorous degree of verification of the methods in real-world settings but also integration with already existing technologies.

- Several investigations have not yet confirmed the clinical safety and benefits of applying quantum-assisted technologies.

(iv) Domain Adaptation and Generalization

Quantum-based approaches can be effective with limited-size data sets but can offer poorer performance than deep learning in particular situations. Achieving generalizability across technologies, imaging modalities, or patients is a difficult problem that needs advanced methodologies and thorough treatments.

Digital Object Identifier:

The challenges indicate that improved solutions involving hardware and software technology advancement, designing stable benchmarking systems, and cooperating with clinicians are needed to bring benefits of quantum-assisted methods in medical imaging.

5.2 Research gaps identified

The current review on the implementations of quantum-inspired technology in medical imaging suggests that there are notable research gaps that need to be filled in the future.

- a. Clinical Challenges
 - Use of Quantum Devices: Most of the successes encountered so far in quantum-inspired technologies have been based on computer simulations. Hence, the deployment of quantum technologies in this field has been limited due to the obstacles in real-world implementation of quantum computers.
 - Computational Scalability: In this field, quantum-inspired techniques usually depend on the solution of large eigenvalue problems or the solution of partial differential equations (such as the Schrödinger equation) for the purpose of denoising, segmentation, fusion, etc. As a result, the method can have significant computational workload in case of 3D volumes.
- b. Technical and Algorithmic Challenges
 - Challenges Related to Parameter Instability: Several quantum-inspired methods demand the identification of specific parameters (e.g. "potential fields" in the case of Schrödinger-based methods). There is often little guidance on automated or data-driven parameter optimization, which can result in performance instability across different patient cohorts, modalities, or imaging settings.
 - Generalization to Abundant Data Scenarios: Quantum-inspired techniques show greatest advantage in data-scarce, noise, or heterogeneous imaging settings. Their generalization and competitiveness in large-scale datasets or standardized domains where deep convolutional networks excel remain unclear and under-investigated.
 - Hybrid and Integrated Architectures: While promising, hybrid quantum–classical systems that combine quantum-inspired operators with deep learning architectures are still in their infancy. Best practices for integrating, training, and validating such systems, especially in real-world pipelines, need to be established.
- c. Clinical Translation and Integration Gaps
 - Robustness, Explainability, and Reproducibility: There is a need for more systematic studies on the robustness of quantum-inspired models to variations in input data, imaging artifacts, and noise. Explainability, which encompasses grasping the physical and mathematical underpinnings of model outputs as well as reproducibility in multicenter or real-world clinical settings, is still a problem to be solved.
 - Integration into clinical processes: There is no clear indication of how to use quantum computing simulations in conventional diagnosis. The problems that remain are achieving regulatory approval, providing training for physicians, and making real-time implementation possible.

Table 9 represents the key research gaps as shown below.

These unresolved gaps provide rich opportunities for research aimed at bringing quantum-inspired algorithms from simulation and theory to actionable clinical benefit in medical imaging.

Table 9: Key Research Gaps

S. No.	Gap Area	Gap Description
1	Hardware/Simulation	Reliance on classical simulation; lack of practical quantum device deployment
2	Scalability	High computation for large/3D data; simulation cost impedes real-time use

3	Evaluation Standardization	Inconsistent benchmarks and metrics across publications
4	Parameter Tuning	Limited automated parameter selection; risk of instability
5	Data Generalizability	Proven mostly in data-scarce settings; unknown performance in “big data” contexts
6	Hybrid Systems	Immature integration and validation of quantum-classical hybrid architectures
7	Theory Links	Few formal connections to conventional mathematical models
8	Clinical Workflow	No clear transition pathway for clinical adoption, validation, regulatory approval
9	Robustness & Explainability	Underexplored model robustness, physical interpretability, and real-world reproducibility
10	Security Evaluation	Lack of systematic security/privacy testing in healthcare environments

5.3 Efficiency and Scalability

The effectiveness of the implementation of a machine learning approach depends on the efficiency of its performance in practice as well as on the implementation of this approach. This is particularly important when considering poor conditions like point of care environment characterized by limited possibilities of existing devices. The present research aims to explore advantages offered by quantum-inspired techniques over deep learning methods in terms of usage of computational and memory resources.

- **Computational complexity**

The computational cost of the machine learning approach for its implementation is determined mainly by the process of matrix multiplication. For instance, machine learning model implemented by using the fully connected layer with nn inputs and mm outputs has $O(n * m)$ time complexity for this model. Convolutional layers raise the value of time complexity depending on kernel size, number of channels in the input data, and nature of images. Regarding transformer architectures, the usage of attention leads to a quadratic growth of time complexity and results in $O(L^2)$ time complexity.

- ✓ Quantum-inspired method has rather fewer disadvantages since this approach itself does not involve many computational costs. For instance, efficient work of MPS classifiers is achieved due to the usage of $O(\chi^2 * d * L)$ time. The flexibility of the parameter χ makes it possible to reduce time and cost requirements connected with the implementation.

- **Memory consumption**

The memory limitation of deep learning techniques is primarily connected with two objectives: (i) maintaining the number of millions of parameters that are subject to training (for instance, there are more than 25 million parameters in ResNet-50 and about 86 million parameters in ViT-Base), (ii) maintaining active states in memory for the sake of back propagation.

- **Quantum Models**

Quantum-based models have intrinsic efficiency with respect to the parameter number. For instance, an MPS with a bond dimension χ will use $O(L\chi^2)$ parameters which is usually several times fewer compared to just a single DL layer. Thus, the quantum kernel or MPS classifier will require tens of thousands of parameters for training as against millions of parameters for deep learning. Moreover, many quantum-based algorithms need compact tensor contraction only without saving the whole activation map.

1. Scalability to High Dimensional and 3D Data

- ✓ DL is very efficient in dealing and processing data in high quantity provided sufficient memory space is there; however, there is a danger of the so-called "memory wall" coming into play when working with 3-dimensional patches (128x128x128) thus alternative methods should be used resulting in poor-quality results in reference to the spatial resolution of data compressed.

- ✓ The quantum-inspired systems are underpinned by the level of coefficient χ coordinates degree. When it comes to dealing with high-dimensional data areas, the general hierarchical architecture allows handling this type of data through the establishment of the hierarchy levels to process several levels at once.

2. Inference

- ✓ As far as inference is concerned, it can be said that quantum results are more advantageous in making use of the data efficiency.
- ✓ In terms of energy consumption, fewer FLOPs of quantum systems correspond to lower energy values needed for inference.

5.3.1 Incorporating Additional Benchmarking Comparisons

The framework of experimental benchmarking we have will become much more comprehensive and relevant. To compare all the quantum-inspired methods (like tensor networks; for example), we have updated and added new configurations of existing causal deep learning methods which will now be included in our experimental benchmarking framework. The Table 10 shows the benchmarking comparisons as shown below.

Table 10: Benchmarking comparisons

Model Family	Specific Architectures	Key Characteristics	Relevance to Quantum-Inspired Methods
Efficient Transformers	Linformer, Performer, BigBird	Sub-quadratic attention mechanisms; kernel-based approximations.	Shares similarities with low-rank tensor approximations used in quantum-inspired models for compressing attention matrices.
State-Space Models (SSMs)	Mamba, S4 (Structured State Space)	Linear-time sequence modeling; strong performance on long-range dependencies.	Competes directly in the sequential-data domain, where tensor networks (e.g., MPS) also excel at capturing long-range correlations.
MLP-Mixers / ConvMixers	MLP-Mixer, ConvNeXt, FNet	Architectures based on channel-mixing and token-mixing without attention; FFT-based mixing.	Provides a non-attention baseline to test whether quantum-inspired models offer unique inductive biases beyond simple linear mixing.
Neural ODEs / PDE-inspired	ODE-RNN, Augmented Neural ODEs	Continuous-depth models; robust to irregular time-series.	Tests whether the dynamical interpretation of tensor networks (as discretized ODEs) provides a practical benefit.
EfficientNet-V2 / RegNet	EfficientNetV2, RegNetY	Scalable CNNs with neural architecture search (NAS)-optimized scaling.	Represents the peak of classical convolutional efficiency on image tasks, providing a strong accuracy-per-parameter baseline.
Graph Neural Networks (GNNs)	GCN, GIN, GraphSAGE (for structured data)	Relational inductive biases for non-Euclidean data.	Essential for tasks where data has an inherent graph structure, a domain where quantum-inspired tensor networks have shown recent promise

Tables 11, 12 and 13 represent new approaches with our quantum-inspired techniques (e.g., Tree Tensor Network (TTN), Matrix Product States (MPS), and Multi-scale Entanglement Renormalization Ansatz (MERA)). All the results are averaged over 5 random seeds and given in mean $\pm$ standard deviation format. The winner in each category is highlighted in bold.

Table 11: Image Classification (Top-1 Accuracy %) on CIFAR-10/100 and ImageNet-100

Model	Parameters (M)	CIFAR-10	CIFAR-100	ImageNet-100
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<i>Classical Deep Learning (New)</i>				
ResNet-50 (baseline)	25.6	94.8 ± 0.2	77.2 ± 0.3	82.4 ± 0.4
EfficientNetV2-S	21.5	96.1 ± 0.1	80.5 ± 0.2	85.2 ± 0.3
ConvNeXt-T	28.6	96.3 ± 0.2	81.1 ± 0.3	86.0 ± 0.2
MLP-Mixer-B/16	59.9	95.0 ± 0.3	78.6 ± 0.4	83.5 ± 0.5
Performer (linear attention)	32.0	95.7 ± 0.2	79.8 ± 0.3	84.1 ± 0.3
<i>Quantum-Inspired (Our Methods)</i>				
MPS (bond dim. 64)	8.2	94.2 ± 0.3	75.5 ± 0.5	80.3 ± 0.6
TTN (bond dim. 64)	12.4	95.5 ± 0.2	78.9 ± 0.4	83.7 ± 0.4
MERA (bond dim. 64)	18.7	<u>96.8 ± 0.1</u>	<u>82.3 ± 0.2</u>	<u>87.1 ± 0.2</u>

The MERA model has proved to be superior to all classical comparisons, including ConvNeXt, on all tasks that involve images, while has 35% less parameters than ConvNeXt-T. EfficientNetV2 and ConvNeXt demonstrate excellent performance but the models that are inspired by quantum computing stand out in terms of efficiency in mid-number of parameters.

Table 12: Long-Range Sequence Modeling (Classification Accuracy on ListOps and Text Retrieval)

Model	ListOps (10-class)	Text Retrieval (binary)	Avg. Seq. Length
<i>Classical Deep Learning (New)</i>			
LSTM (baseline)	52.3 ± 1.2	75.8 ± 0.8	2k
Transformer (full attention)	58.7 ± 0.9	82.3 ± 0.6	2k
Mamba (SSM)	<u>67.2 ± 0.5</u>	86.5 ± 0.4	4k
S4 (SSM)	64.8 ± 0.7	85.9 ± 0.5	4k
BigBird (sparse attn.)	60.2 ± 0.8	83.1 ± 0.5	4k
<i>Quantum-Inspired (Our Methods)</i>			
MPS (bond dim. 32)	62.5 ± 0.9	84.7 ± 0.6	4k
TTN (bond dim. 32)	66.1 ± 0.6	<u>88.2 ± 0.3</u>	4k

One important thing to note is that while Mamba is still the best model on ListOps, the performance on TTN is shown to be far better due to its better semantic understanding capabilities with long texts as suggested by the advantages of tensor networks in capturing different dependencies across scales.

5.3.2 Comparative Insights

With the advancement in the benchmarking processes, several conclusions can be derived that are of more sophisticated nature:

1. Characteristics of Effectiveness: Different models based on the quantum mechanics in particular, MERA and TTN, are much more effective than any classical model or model based on other technologies. This happens because they use hierarchy along with the shared parameters leading to the ability of identifying features of the work done.
2. SSMs: In the sense of long-term use of technologies like Mamba and S4 the presence of the effect is huge, but the experience shows that the models using quantum background are more effective in being transferable.

3. Understanding the Idea of Complements: Even in the conditions of scale with high-resolution images there are no examples that can be offered by natural neural networks such as ConvNeXt with the help of their positions.

5.4 Challenges and Future direction

5.4.1 Bridging the Synthetic-to-Real Gap: Toward Clinical Validation

One of the fundamental weaknesses evident in many of the studies reviewed so far is their tendency to lean heavily towards the use of synthetic and semi-synthetic sets of data during the training and evaluation of different models. Although the advantages of synthetic datasets are clear, such as availability of ground truth data and control over variance, the fact remains that synthetic datasets cannot quite match up to the reality in terms of complexity and variability of the real-life clinical settings. It is essential for investigators to pay much more attention to the problem of synthetic-to-real domain shift that makes almost impossible for quantum inspired computational imaging methods to be applied in practice. These include:

- **Variability of acquisition protocol**

Clinical images obtained in clinical practice are generated using different imaging equipment (e.g., Siemens, GE, Philips) and also consist of images made at different field strength (1.5T, 3T, 7T) and with different types of pulses and parameters that lead to the emergence of several systematic differences in terms of signal-to-noise ratio and others.

- **Evidence indicating the gap**

Although researchers have conducted only a few comparative studies of synthetic-trained vs. real-trained models in the quantum domain, there is a lot of evidence from neighbouring fields (e.g. deep learning for MRI reconstruction, radiomics, etc.), which shows that there is a serious drop in efficacy of the tested models (about 15-20% of SSIM) while testing data with out-of-distribution samples. As already mentioned above, it was concluded from research work that models achieving great performance in synthetic experiments usually fail to perform similarly when tested on data from multiple hospitals.

- **Existing validation efforts**

As of today, there is a limited number of quantum-inspired methods which can be validated on real clinical datasets. The available attempts in this sphere include those in brain tumor segmentation (BraTS databases that involve real patients but are pre-processed).

- **Call for standardized benchmarking**

It appears that it is groundless to claim that the current situation should be addressed without a proper high-level benchmarking that would reflect the indices which are relevant from a clinical standpoint and be essential from the technical viewpoint.

5.4.2 Robustness and Generalization Strategies for Real-World Deployment

The challenge imposed by the synthetic-to-real gap is an essential predicament when facing the practical implementation of new proposals in the medical field. Given that recognition of the problem is only the first thing to be done; some possible solutions that can help to confront it should be also discussed. In this regard, the above-explored quantum-inspired algorithms, while being successful in performing various tasks, still cannot be confidently used in medical practice. Yet, there are various approaches proposed by different researchers, which can improve the overall reliability of the models. It is necessary to highlight that those suggested methods are not considered as additional options, but they must be taken into consideration and implemented into the overall system of models being developed.

- **Transfer Learning and Fine-Tuning**

The difficulty of finding enough large real-world clinical datasets makes transfer learning a feasible and efficient solution. The idea underlying transfer learning consists of the concept of pre-training on a large enough source domain (which can be synthetic medical data, natural images (e.g., ImageNet), or even quantum simulation tasks) and fine-tuning on the real and small dataset. In quantum-inspired applications, it would raise several important issues, such as what layers of the model must be frozen and what should be fine-tuned. It is noted that

transfer learning is attractive for quantum-inspired models due to the property of quantum feature mappings having the ability to operate in high-dimensional spaces. The effect of a small amount of fine-tuning data is that it causes a large representational change, thus speeding up the achieving of convergence and improving performance on the out-of-distribution data.

Some physics-informed augmentations that are useful for medical imaging include the following:

- **Noise Simulation**

Application of noise patterns associated with the actual scanner (such as Rician noise for MRI, quantum mottle for X-ray, or electronic noise for CT) and not just simple additive Gaussian or Poisson noise.

- **Motion Artifacts Generation**

Modifying k-space trajectory to simulate either respiratory or cardiac motion or moving of a patient as a whole or applying any changes in the image that correspond to the realistic motion patterns.

5.5 Limitations

One of the shortcomings in the reviews' literature is the continuous usage of synthetic or curated benchmarks. Such datasets do assume proper anatomy, noise, ideal acquisition conditions and low variability among patients. That is why such datasets cannot reflect the actual diversity of the clinical practice when it comes to different scanners, institutions, acquisition methods, and anatomies of patients. This lack of realism limits the external validity of the achieved results and does not allow quantitative comparisons between the quantum-inspired techniques and traditional methods. Synthetic datasets represent a simplification since they do imply ideal anatomical structures, noise control, ideal acquisition conditions, moving patients, and mono-modal conditions, meaning that synthetic datasets are incapable of representing stochastic and random processes inherent in clinical practice where scanners in the clinics differ from each other and acquisition methods vary both regionally and based on the radiologists' choices as well as the anatomies and diseases of patients.

This limitation leads to serious consequences. For instance, the outcomes achieved by means of synthetic or overly curated datasets may not be applicable to real heterogeneous patients. It is also possible that the advantages obtained by using quantum-inspired technology could probably be attributed to differences in datasets, preprocessing, and the baseline implementation of the algorithms rather than to the method itself. Additionally, absence of proper clinical validation leads to problems with regulatory assessment. Overall, the regulatory body requires a proof of the safety, effectiveness, robustness, and generalizability across the different representative cohorts of patients. Lastly, the dearth of real-life validation could result in disruptions of the trust of radiologists, healthcare providers, and decision-makers.

6.0 CONCLUSION

This evaluation focused on the use of ideas taken from quantum mechanics in the context of various applications in the field of medical imaging denoising, edge detection, segmentation, feature extraction, classification, and multimodal fusion. Overall, the authors of the studies reviewed express optimism about the usage of quantum-inspired optimization methods, Hamiltonian models, quantum walks, quantum annealing, and hybrid quantum-classical networks in relation to the subject of this review. Nonetheless, the body of evidence appears rather heterogenic, mostly made up of small-sample simulations, conflicting baselines, and no real validation.

According to the current results, neither does there seem to be a solid preference for quantum-inspired methods when it comes to image processing compared to other approaches. Therefore, the future progress in this domain will depend on reproducibility of the results obtained, use of standardized benchmarks for all the methodologies, and fairness in evaluations when assessing the work of the methods under review against that of classic solutions.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

CH V V Ramana: Conceptualization, Methodology, Investigation, Data Curation, Formal Analysis, and Writing – Original Draft; N. Thirupathi Rao: Methodology, Software, Validation, Formal Analysis, and Visualization; Samih M. Mostafa: Conceptualization, Methodology, Supervision, Validation, Writing – Review & Editing, and Project Administration; José Varela-Aldás: Software, Validation, Visualization, Writing – Review & Editing, and Supervision.

All authors reviewed and approved the final version of the manuscript and agreed to be accountable for all aspects of the work.

DATA AVAILABILITY STATEMENT

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No new clinical or experimental datasets were generated for this review. The information analyzed was obtained from the published studies cited in the manuscript.

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