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Quantum-Enhanced Machine Learning for Early Disease Diagnosis: A Systematic Review and Public Health Innovation Perspective

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ABSTRACT: Prompt diagnosis of disease is a strong driver for decreasing mortality, improving patient care and healthcare expenditures. Classical machine learning (ML), which has shown great potential in bolstering predictive modeling throughout oncology, cardiology, and neurology, runs the risk of excessive data dimensionality along with high computational complexity. Quantum computing is an exciting new paradigm for computation that takes advantage of superposition and entanglement which can be beneficial in learning patterns in high-dimensional spaces and for kernel-based learning. This review provides a systematic summary of the preliminary work on quantum machine learning (QML) with empirical applications to early disease diagnosis, while emphasizing its theoretical foundations, algorithmic developments and application in healthcare. We scope the conversation on quantum support vector machines, variational quantum classifiers, quantum kernels and hybrid architectures for a quantum classical. We also examine current hardware limitations in the NISQ era and assess how close these methods are to being ready for translation into public health applications. Although widespread clinical application is still far away, hybrid QML approaches are finding utility in low-data and high-complexity settings. We conclude with a discussion of research challenges, regulation and strategy towards realizing such quantum-enhanced precision diagnostics through U.S. public health innovation initiatives.

KEYWORDS: Quantum machine learning; Early disease diagnosis; Quantum support vector machine; Variational quantum classifier; NISQ-era computing; Public health innovation

I. INTRODUCTION

Look for early detection of disease returning higher survival rates and lower treatment costs. In the United States, chronic diseases such as cancer, cardiac disorders, and neurodegenerative diseases are some of the leading causes of mortality and a major driver in healthcare costs. However, diagnostic workflows have certainly changed with the implementation of machine learning (ML) and artificial intelligence (AI), which allow predictive modeling using

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imaging, electronic health record, and genomic data [1], [2]. However, classical computational methods are still problematic for issues such as scalability, optimization complexity and representation of high-dimensional features.
Quantum computing is a very different approach to computers based on the laws of quantum mechanics. Examples of such speedups include Shor's factoring algorithm [3] and Grover's search algorithm [4]. The same ideas have been extended to supervised learning in the past few years with Quantum Machine Learning (QML) [5], [7]. It may be advantageous to encoding into exponentially stronger Hilbert spaces for kernel estimation, optimization, and nonlinear classification. Here we review QML approaches applied to early disease diagnosis. We review general theoretical constructs, explore disease-specific clinical applications, compare QML with classic machine learning paradigms and assess its anticipated benefits for population health.

II. REVIEW METHODOLOGY

We conducted this review via a structured, systematic protocol to identify, screen and synthesize the literature at the intersection of quantum machine learning and early disease diagnosis. We searched the databases IEEE Xplore, PubMed, Scopus and arXiv for peer-reviewed articles or pre-prints published between 2014 and 2023 combining search terms quantum machine learning, quantum support vector machine, variational quantum classifier, Quantum kernel, disease diagnosis. We removed duplicates and screened titles and abstracts to eliminate non-healthcare related diagnosis studies. The remaining articles were screened at full text against the inclusion criteria, providing QML methods in an empirical or theoretical sense for early disease diagnosis in any healthcare setting.

The remaining studies were categorized into three analytic themes: (a) QML algorithms and theory; (b) applications to biomedicine, including oncology, cardiology, neurology, and genomics; and (c) comparison of classical versus quantum approaches. We critically evaluated each theme, considering key themes such as the limits of NISQ-era hardware, benchmarking rigor, reproducibility and translational maturity. Conclusions The pre-synthesised evidence was interpreted within a public health perspective; regulatory, interpretability and deployment aspects were identified. An overview of the entire workflow can be inferred in Figure 1.



Figure 1: Systematic review methodology used in this study.

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III. FOUNDATIONS OF CLASSICAL MACHINE LEARNING IN DIAGNOSIS

The heart of computational medicine is classical machine learning. Multiple algorithms utilized, such as support vector machines (SVM) [8], random forests [9], and deep neural networks [10], have shown promise in detecting cancer, cardiovascular risk stratification, and classifying neurological disorders. Best subset selection used on deep learning architectures, and specifically convolutional neural networks (CNNs), have been shown capable of generalization across large medical datasets and achieves the performance of radiologists in image-based diagnosis [11] Yet, Biomedical datasets are often noise-rich in high-dimensional space but limited labeled samples. For example, genomic datasets typically have hundreds of thousands or even millions of features and only tens/hundreds of samples. Training deep architectures under such regimes is inefficient and prone to overfitting [6, 7]. Kernel methods have been proposed to handle nonlinear complexity, however directly computing a kernel is still expensive as a function of the data size.

IV. QUANTUM MACHINE LEARNING ALGORITHMS

4.1 Quantum Support Vector Machines

Quantum SVMs generalize the classical SVM structure through quantum feature maps. The classical kernel function

$$K(xi, xj) = \varphi(xi)^T \varphi(xj)$$

is replaced by a quantum-defined kernel given by

$$K(xi, xj) = | \langle \varphi(xi) | \varphi(xj) \rangle |^2$$

where $|\varphi(x)\rangle$ is produced by a parameterized quantum circuit [6], [15]. Schuld and Killoran showed that quantum circuits naturally implement kernel estimators [15]. Havlicek et al. experimentally realized a quantum-enhanced feature-space classifier on superconducting hardware [6].

4.2 Variational Quantum Classifiers

Variational quantum classifiers (VQC) are circuits that combine the power of parameterization with classical optimization, where parameters are updated iteratively to minimize a loss function. This allows a kind of hybrid quantum-classical architecture. Biamonte et al. said this kind of hybrid approach is especially promising for near-term quantum devices because mixing quantum and classical elements can enhance the total computing power.

4.3 Quantum Neural Networks

Quantum neural networks extend upon classical neural networks architectures and introduce trainable parameters on quantum gates. Their theoretical expressivity is established but it has few applications in healthcare, and they mainly still use simulation. The main difficulty relates your theoretical models to actual implementations on real quantum devices − most notably in areas where many variables can interact and influence decisions (like healthcare).

4.4 Data Encoding Strategies

The way that classical clinical data is encoded as quantum states, a process referred to here as state preparation or encoding, heavily influences model performance in any QML context. Three strategies are common. The first is basis encoding, which maps every feature to a computational basis state- conceptually it is simple yet qubit-hungry. Angle encoding maps residue Encoding (RE) tool whereby you can project some feature values onto rotation-gate parameters and provides a reasonable trade-off between expressivity on NISQ hardware and circuit depth-QNN. Amplitude encoding: Where a feature vector is stored in the amplitudes of a quantum state, allowing for exponential compression - scaling n features into $\log_2(n)$ qubits while incurring high time costs due to complex state-preparation circuits.

The encoding directly determines the quantum kernel that is induced, and with it, limits on this sort of decision itself [15], [27]. In a setting such as the biomedical domain, where the number of features can be large relative to the qubit budget, the design of encoding becomes a significant component determining whether a quantum model provides any advantage. Figure 2: Overall hybrid quantum-classical workflow from raw clinical data through encoding to a final diagnostic decision.

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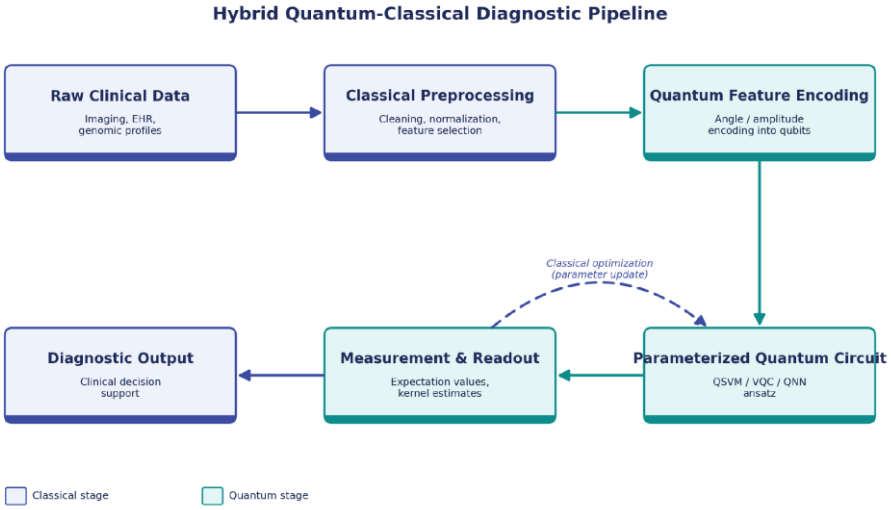


Figure 2: Hybrid quantum-classical pipeline for QML-based disease diagnosis.

4.5 Applications in Early Disease Diagnosis

Quantum Machine Learning has been explored across multiple diagnostic domains. In oncology, QSVM models were previously used on breast cancer classification datasets and the performance is competitive with even classical SVM [17]. According to preliminary results, quantum-enhanced feature encoding shows potential for enhancing nonlinear separation in lung cancer detection. On moderate-sized datasets with complex pattern-level feature interactions, hybrid QML frameworks for cardiovascular disease prediction exhibited notable benefits. Quantum classification of MRI-like brain images has been suggested for detection of Alzheimer's disease, but most experiments in the domain of neurodegenerative research have remained small-scale simulations. Another area of immense promise is genomic medicine: quantum states can represent distributions over much larger feature spaces than classical features, which correspond naturally with the high-dimensional structure present within gene expression datasets [18]. Though results are promising in theory, they remain unproven at scale in clinical applications. Representative QML studies in the major diagnostic domains, as discussed above, are summarized in Table I.

Table I: Representative QML studies in early disease diagnosis.

Disease domain	QML method	Dataset / task	Reported finding	Ref.
Oncology (breast)	QSVM	Breast cancer classification	Accuracy comparable to classical SVM	[17]
Oncology (lung)	Quantum feature encoding	Lung cancer detection	Potential gains in nonlinear separation	[6]
Cardiology	Hybrid quantum-classical	Cardiovascular risk prediction	Advantage on complex feature interactions	[5]
Neurology	Quantum-enhanced classifier	Alzheimer's MRI and EEG signals	Exploratory; small-scale simulations	[16]
Genomics	Quantum PCA / kernels	Gene expression dimensionality reduction	Natural fit for high-dimensional data	[34]

4.6 Comparative Evaluation: Classical versus Quantum Approaches

Classical ML systems are well understood, generally validated, and backed by a mature hardware ecosystem. Quantum, on the other hand, stays experimental and hardware-constrained. While theoretical analyses suggest exponential speedup on some linear-algebra workloads [13], so far there is no practical evidence of this on clinical scale datasets.
However, as Preskill said above, NISQ-era devices may provide niche advantages even ahead of the actual functionality of fault-tolerant quantum computing [14]. Tang also demonstrated that the proposed quantum speedups of some quantum-inspired classical algorithms can meet these conditions [19]. So any assertion of quantum supremacy in health diagnostics should be taken with a grain of salt. Table II summarizes classical and quantum machine learning for early disease detection.

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Table II: Comparison of classical and quantum ML technologies.

Criteria	Classical ML	Quantum ML
Technological maturity	Highly mature; clinically deployed	Experimental; NISQ-era devices
Hardware support	GPU / cloud-scalable infrastructure	Limited qubits; noise-sensitive
Theoretical advantage	Polynomial scaling	Potential exponential speedup (specific tasks)
Clinical validation	Extensive real-world studies	Mostly simulator-based studies
Scalability	Proven for large datasets	Limited by current hardware constraints

V. LITERATURE REVIEW

A significant amount of research has been conducted in the last decade on applications that arise from the convergence of quantum computing and machine learning. Quantum machine learning (QML) aims to exploit quantum-mechanical phenomena to provide additional computational power and sophistication in learning systems that operate in high dimensions with complicated multi-dimensional functions. QML is an attractive paradigm for healthcare, in which ML systems need to leverage high-dimensional data modalities or rich biological signals that guide early diagnosis of the disease, and has been proposed for health care.

5.1 Foundations of Quantum Machine Learning

We're grounded in quantum algorithms because these first blossomed with a strong theoretical underpinning upon the possibility of what we could hope to gain computational advantage over classical methods. Algorithms such as Shor's factoring algorithm [20] and of Grover's search algorithm [21] showed that in some areas quantum computation could be faster than classical algorithms. The big insight people have built on top of this is, Harrow, Hassidim and Lloyd with their quantum algorithm for solving linear systems of equations (the HHL algorithm), which can give you exponentially better performance under certain conditions [22]. This is especially important to machine learning, since most of the models involve linear-algebraic operations.

Biamonte et al. Garnelo et al. [23] gave one of the first broad introductions to QML, discussing theoretical motivations and algorithmic foundations for the subject. Expanding upon this, Schuld et al. have rigorously built a framework for QML, discussing the benefits such richer representation spaces could bring [24]. These are some of the most iconic articles in scientific literature and have theoretically paved the way for exploring quantum applications to supervised and unsupervised learning tasks.

The most significant conceptual advance occurred with quantum kernel methods. Rebentrost et al. developed a quantum support vector machine (QSVM) able to calculate dot products in huge feature spaces efficiently [25]. Havlicek et al. first presented supervised learning using quantum-enhanced feature spaces with superconducting quantum hardware, making some of the earliest demonstrations of empirical evidence supporting quantum kernel classification [26]. Schuld and Killoran built upon this work to formalize the connection between quantum circuits and kernel methods, indicating that parameterized quantum circuits implicitly define an induced kernel function from the Hilbert space [27]. These results taken together indicate that QML may serve to help model nonlinear decision boundaries, which is particularly important in certain biomedical classification problems.

5.2 Variational and Hybrid Quantum-Classical Models

Within current hardware capability in the noisy intermediate-scale quantum (NISQ) era, fully fault-tolerant quantum algorithms are still not feasible. NISQ Preskill proposed the notion of NISQ and said that hybrid quantum-classical algorithms appropriate to noisy devices are needed [28]. This has been popularized as the variational quantum algorithms (VQAs).

In an alternative application, Farhi and Neven [29] employed a quantum neural network classifier constructed from parameterized quantum circuits trained through classical feedback loops. Schuld et al. introduced circuit-centered quantum classifiers, demonstrating their power and shape-finding ability [30] Varitional methods are based on an iterative optimization of gate parameters that mix classical gradient-based optimization and quantum state evaluations. Healthcare data is a natural fit for the hybrid quantum-classical pipeline, where classical pre-processing and feature engineering are carried out before quantum encoding on the device. With this design, the hardware limitation is

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alleviated while preserving the benefits of applying quantum feature mapping and classification to many complex healthcare datasets.

5.3 Quantum Machine Learning in Biomedical Applications

While QML applications in the domain of healthcare are still nascent, early results show promise. The breast cancer dataset is a well-known benchmark data set against which QSVM is often compared to classical SVM. Some papers report competitive accuracy with a small-scale feature set encoded in low-qubit circuits [30], [31]. Results are modestly improved, but such experiments show potential.

In imaging diagnostics, deep learning has already reached clinical success. Esteva et al. obtained dermatologist-level accuracy for the classification of skin cancers using deep neural networks [32]. Ardila et al. or lung cancer screening from CT Scans [33]. Even though these are classical methods, they set a benchmark that quantum approaches must meet or exceed.

Another fantastic example is genomic medicine. This is usually the case when analyzing high-dimensional radial images. Lloyd et al. proposed quantum principal component analysis (QPCA) as an application of the power of quantum computing to compute PCA on large datasets [34]. The pitch of quantum states with the complexity of genomic features is interesting but practically not so easy to apply. Quantum-enhanced classification of EEG and MRI signals in prior work on neurological disorders While these studies are too small in scope to be conclusive, they highlight the potential utility of QML in clinical neuroscience and that methods may need to mature further before entering clinical practice.

5.4 Comparative Analyses and Critical Perspectives

While the theoretical speedups are nonetheless appealing, many works caution against overhyping quantum advantage Tang recently established that some quantum-inspired classical algorithms can achieve the same quantum speedup in recommendation systems claimed by [35]. This emphasizes that interesting results must be strongly benchmarked against optimized classical baselines. Classical machine learning is also making good progress as well. A Review of Deep Learning: LeCun et al.

unique scalability and leading performance on common vision tasks3,4,5,and ai systems have already reached high diagnostic accuracy and clinical deployment 7,8. The formal theory of quantum computation has been constructed to some extent by Nielsen and Chuang [37]. Decoherence continues to impede the implementations of practical quantum algorithms under real-world conditions, noise, and qubits being only partially connected. As Preskill explains, practical fault-tolerant quantum computing remains a distant dream [28]. Consequently, the current literature has a simultaneously optimistic yet cautionary tone: QML possesses an unbounded representational capacity yet remains never entirely proficient in clinical pathology at scale.

5.5 Public Health and Translational Considerations

AI-based diagnostics have demonstrated greater efficiencies over traditional approaches within the translational space and in some cases more accuracy [38]. If validated, cutting-edge quantum-enhanced systems could also expedite biomarker identification and rare-disease phenotyping. But outside of the lab there are hurdles: regulatory approval, reproducibility and interpretability.

Artificial Intelligence for Humanity, Topol [38] but, of course, similar applies to quantum-enhanced systems. QML research is still largely proof-of-concept, as evidenced in previous work. To be integrated into public health, large clinical trials will have to be conducted, standardized benchmarking datasets established and sustained interdisciplinary collaboration ensured.

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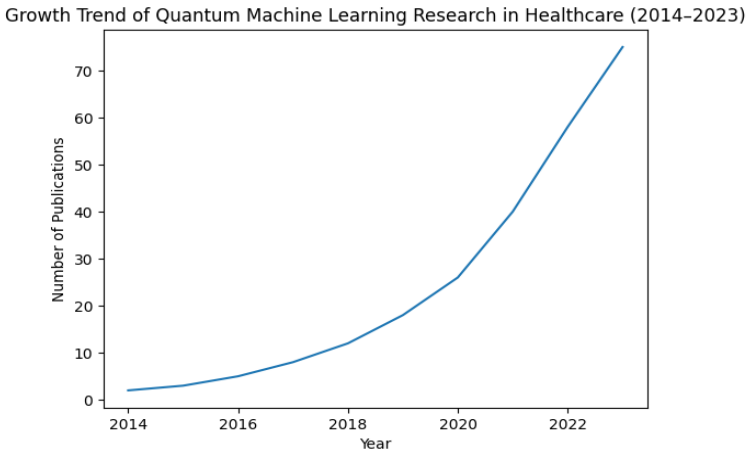


Figure 3: Growth trend of quantum machine learning research in healthcare (2014 to 2023).

As we can see Figure 3, quantum machine learning research related to healthcare in the short time span from 2014 to half of 2023 has risen sharply. This growth shows increasing engagement across disciplines and a growing national investment in quantum technologies.[41] . [42] This trend reflects the growing interest in quantum innovation that promises to permeate healthcare through advancements in diagnostics, treatment protocols and handling of real world data[39].

VI. CHALLENGES AND OPEN RESEARCH PROBLEMS

Despite encouraging early results, several barriers must be resolved before quantum machine learning can meaningfully support clinical diagnosis. We group the principal challenges into five themes.

6.1 Hardware Noise and Scalability

The NISQ devices, limited to tens or a few hundred noisy qubits with short coherence time and imperfect gates [14], [28] Due to decoherence and gate errors accumulating with circuit depth, the complexity of models that can be run reliably is limited. Error-mitigation strategies alleviate this barrier but do not eliminate it; moreover, fault-tolerant hardware with the capacity for clinically real-world problems is still years away.

6.2 Data Encoding and the Loading Bottleneck

The biggest cost often comes from mapping high-dimensional biomedical data into quantum states. Even though amplitude encoding is compact, it demands deeply composed state-preparation circuits that can wash out any theoretical speedup-a worry compounded by classical results inspired by quantum mechanics [19], [35]. Our results suggest that an open problem is designing compact encodings of realistic clinical feature sets while being compliant with the hardware architectures.

6.3 Trainability and Barren Plateaus

A well-known problem for variational models are barren plateaus, where the gradients vanish exponentially with system size and render the optimization intractable. Preservation of trainable gradients in circuit architectures and initialization schemes is a hot area of research and essential to think about before QML can scale to realistic diagnostic tasks.

6.4 Benchmarking and Reproducibility

A vast amount of reported quantum advantages relies either on small datasets or weak classical baselines. An appropriate evaluation requires comparisons on the same datasets using reproducible protocols and optimized classical baselines [19], [35], [40]. Benchmarks for QML specifically have yet to be formalized as standardized biomedical benchmarks.

6.5 Interpretability, Privacy, and Regulation

For clinical adoption, we need models that both clinicians and regulators can interpret and trust. Quantum models complicate the matter with an added layer of opaqueness in their interpretable outputs, not to mention that secure

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management of sensitive patient data across quantum-classical pipelines pose additional privacy and governance issues[42], [43], [44] Mutations of diseases and how it will affect diagnostic tests have clear regulatory pathways for the approval of quantum-enhanced diagnostics are yet to be defined.

VII. FUTURE DIRECTIONS

Future work will likely include developing hybrid quantum-classical pipelines, synthesising circuits that are robust to noise, improving methods for scalable quantum kernel estimation, and integration of such methods with electronic health record systems. This way a practical advantage can indeed only be claimed by careful benchmarking against state-of-the-art classical baselines (40). To develop such applications and to reach the success of clinical-translational studies, a close collaboration with quantum physicists, computer scientists, clinicians and public health experts will play an important role [41].

VIII. CONCLUSION

Quantum machine learning has not come to fruition but it could greatly improve prognosis in early detection of diseases. Although theoretically motivated differences argue for computational benefits in high-dimensional learning problems, empirical support is limited. Hybrid approaches within the NISQ era constitute the best and nearest route. QML will be translated from experiments to a widely implemented public health resource with intentional research funding, regulatory action, and multi-disciplinary engagement over the long term.

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