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Quantum 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 key determinant in reducing mortality, improving patient care and decreasing healthcare costs. Despite the success of classical machine learning (ML) in improving predictive modeling across oncology, cardiology, and neurology, growing data dimensionality and computational complexity remain ongoing barriers. Quantum computing based on superposition and entanglement is a promising computational paradigm that shows potential advantages in high-dimensional pattern recognition and kernel-based learning. This review aims to systematically summarize preliminary work on quantum machine learning (QML) with empirical applications for early disease diagnosis, focusing on its theoretical underpinnings in addition to its algorithmic design and use in healthcare. We then frame the discussion with respect to quantum support vector machines and variational quantum classifiers, quantum kernels, as well as hybrid quantum-classical architectures. We further evaluate existing hardware constraints in the noisy intermediate-scale quantum (NISQ) era and appraise translational maturity for integration into public health. While clinical deployment is still far from broad, hybrid QMLs are proving useful in low-data and complex-feature contexts. We end with research challenges, regulatory guidance, and strategic directions towards enabling quantum-enhanced precision diagnostics aligned with U.S. public health innovation initiatives.

Keywords: Quantum Machine Learning; Quantum SVM; classifiers; Quantum modelling

1. Introduction

Survival rates increase, and the cost of treatment decreases with the earlier detection of disease. Chronic diseases, including cancer, cardiovascular disorders, and neurodegenerative conditions, are among the top causes of death in the United States as well as the top contributors to healthcare costs. Machine learning (ML) and artificial intelligence (AI) have revolutionized diagnostic workflows by allowing predictive modeling from imaging, electronic health records, and genomic data [1], [2]. Despite these advancements, classical computational methods show drawbacks in scalability, optimization complexity, and high-dimensional feature representation.

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Quantum computing is a radically different computational paradigm that utilizes the laws of quantum mechanics to analyze information. Examples of such speedups are reflected in Shor's factoring algorithm [3] and Grover's search algorithm [4]. Recently, these ideas have been generalized to supervised learning tasks, leading to quantum machine learning (QML) [5]–[7]. The capability to encode information into exponentially growing Hilbert spaces might provide benefits for kernel estimation, optimization, and nonlinear classification tasks. Here, we review the QML methods that have been applied to early diagnosis of disease. We discuss theoretical frameworks, summarize clinical applications, compare QML to classical ML paradigms, and evaluate its public health impact.

2. Foundations of Classical Machine Learning in Diagnosis

Classical machine learning is at the core of computational medicine. Different algorithms, including support vector machines (SVM) [8], random forests [9], and deep neural networks [10], have reported excellent performance in cancer detection, cardiovascular risk stratification, and neurological disorder classification. Deep learning architectures, specifically convolutional neural networks (CNNs), have generalized well on large medical datasets to achieve radiologist-performance levels in diagnosing from images [11]. However, biomedical datasets are usually highly noisy and high dimensional with limited labeled samples. Genomic datasets typically have many tens of thousands of features and comparatively few observations. The training of such regimes with deep architectures becomes computationally inefficient and has a high overfitting risk. To address nonlinear complexity, while kernel methods were suggested, straightforwardly evaluating a kernel is expensive in terms of data size

3. Quantum Machine Learning Algorithms

3.1. Quantum Support Vector Machines

Quantum SVMs generalize classical SVM structures through the use of quantum feature maps. The classical kernel function

$$K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$$

is replaced by a quantum-defined kernel, which is given by

$$K(x_i, x_j) = |\langle \phi(x_i) | \phi(x_j) \rangle|^2$$

where $|\phi(x)\rangle$ is obtained by a parameterized quantum circuit [6], [15]. The naturalness of quantum circuits in implementing kernel estimators is proved by Schuld and Killoran [15]. Havlíček et al. experimentally realized a quantum-enhanced feature space classifier on superconducting hardware [6].

3.2. Variational Quantum Classifiers

Variational quantum classifiers (VQC) combine parameterized quantum circuits and classical optimization, iteratively updating parameters to minimize loss functions. This forms hybrid quantum–classical architectures. Biamonte et al. noted that hybrid methods hold great potential, particularly for near-term quantum devices; the blending of quantum and classical components can increase computational power.

3.3. Quantum Neural Networks

Quantum neural networks generalize classical neural architectures through the inclusion of learnable parameters on quantum gates. While their theoretical expressivity has been established, there are only a few applications in healthcare settings, and they still rely primarily on simulations. The challenge is translating theoretical models to real-world implementation on quantum devices, especially in multifactorial areas such as healthcare.

3.4. Applications in Early Disease Diagnosis

Quantum machine learning has been investigated in multiple diagnostic fields. In the field of oncology, QSVM models have been utilized on breast cancer classification datasets, demonstrating comparable performance with classical SVM [17]. Preliminary results suggest that quantum-enhanced feature encoding might improve nonlinear separations in the context of lung cancer detection. Hybrid QML frameworks for predicting cardiovascular disease have shown significant advantages with moderate-sized datasets having complex feature interactions. While quantum-enhanced MRI classification has been suggested for the detection of Alzheimer's disease, most experiments in neurodegenerative disease research have largely been restricted to small-scale simulations up to October 2022. One area of strong potential

application is genomics medicine. Quantum states can represent many more feature spaces than their classical counterparts, which correspond to a naturally high-dimensional space of gene expression datasets [18]. While promising theoretical results exist, clinical validation at scale is lacking.

3.5. Comparative Evaluation: Classical vs Quantum Approaches

Classical ML systems are well established, widely validated and backed by a solid hardware ecosystem. Quantum approaches are still experimental and limited in hardware. Whereas theoretical analyses propose such exponential speed-ups in some linear algebra tasks [13], practical evidence on clinical scale sets is lacking.

As Preskill points out, NISQ-era devices may offer specialized advantages before quantum computing is yet fault-tolerant [14]. Tang proved that some quantum inspired classical algorithms may achieve a similar speedup to suggested quantum algorithms under certain conditions [19].

As such, any claims of quantum supremacy in healthcare diagnostics should be treated with skepticism. The primary comparison of classical versus quantum machine learning for early disease detection is shown in Table X.

Table 1 ML Technology Comparison

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

4. Literature Review

Over the last decade, there has been a considerable amount of research on what new possibilities lie around the corner as quantum computing and machine learning converge. Quantum machine learning (QML) endeavors to capitalize on quantum mechanical phenomena, adding computational power and sophistication to learning systems operating within the realms of high dimensions and complex functions. QML has been suggested as a promising computational paradigm for the healthcare domain, whose machine learning systems inherently harness rich biological signals and multidimensional datasets that require early disease diagnosis.

4.1. Foundations of Quantum Machine Learning

It was on solid theoretical ground that quantum algorithms first began to flourish, providing a pathway toward computational speedup relative to classical methods. Shor's factoring algorithm [20] and Grover's search algorithm [21] indicated that quantum computation may outpace classical algorithms in certain areas. Harrow, Hassidim, and Lloyd built on this insight and presented a quantum algorithm for solving linear systems of equations (the so-called HHL algorithm), potentially leading to exponential gains under certain conditions [22]. This becomes particularly relevant to machine learning because a lot of models use linear algebraic operations.

Biamonte et al. were one of the first to give a broad overview of QML, including its theoretical motivations and algorithmic frameworks [23]. Building upon this, Schuld, Sinayskiy, and Petruccione rigorously developed the framework of quantum machine learning (QML), emphasizing the unique advantages that QML agents may provide through enhanced feature spaces [24]. A significant influence in scientific literature; they laid the theoretical groundwork for quantum computation being used on supervised and unsupervised learning tasks.

The largest conceptual breakthrough came with the development of quantum kernel methods. Rebentrost et al. introduced a quantum support vector machine (QSVM) which can efficiently compute inner products in supersized feature spaces [25]. Later, Havlíček et al. experimentally showed the supervised learning using quantum-enhanced feature spaces, performed on superconducting quantum hardware, thus offering one of the first empirical evidences for quantum kernel classification [26]. Schuld and Killoran continued this work by providing a more formal link between

quantum circuits and kernel methods, showing that parameterized quantum circuits implicitly induce kernel functions in Hilbert space [27].

These results suggest that QML may provide a means to classify certain nonlinear decision boundaries, which is especially relevant in biomedical classification problems.

4.2. Variational and Hybrid Quantum-Classical Models

With the current hardware constraints in the noisy intermediate-scale quantum (NISQ) era, fully fault-tolerant quantum algorithms are still impractical. Preskill proposed the idea of the NISQ era, showing that hybrid quantum-classical algorithms suited for noisy devices are necessary [28]. Variational quantum algorithms (VQAs) have since then become a mainstream method.

Classification using quantum neural networks was suggested by Farhi and Neven, employing parameterized quantum circuits that are optimized through classical feedback loops [29]. Schuld et al. introduced circuit-centric quantum classifiers later [30], showcasing how flexible and expressive they can be. These variational techniques depend on a process of iteratively optimizing the gate parameters using some mixture of classical gradient-based optimization and quantum state evaluation.

Healthcare data suits the hybrid quantum-classical pipeline, where classical pre-processing and feature engineering take place before encoding on the quantum device. This method overcomes hardware challenges and still preserves the advantages of quantum computing in feature mapping and classification. Leveraging quantum capabilities and classical techniques works to its advantage, allowing it to perform efficiently on many complex healthcare data sets.

4.3. Quantum Machine Learning in Biomedical Applications

Although applications of QML in healthcare are still nascent, the preliminary findings have been promising. The breast cancer dataset is frequently used as a benchmark for evaluating the performance of QSVM as compared to classical SVM implementations. There are several studies reporting competitive accuracy with a minimum feature set encoded in low-qubit circuits [30], [31]. Improvements are modest, yet these experiments show feasibility.

Deep learning has already been clinically successful in imaging diagnostics. Esteva et al. performed at dermatologist levels in classifying skin cancers using deep neural networks [32]. Ardila et al. built on this work to create deep-learning systems for lung cancer screening from CT scans [33]. Although these works are classical, they set a standard that quantum approaches must match or exceed.

Another area for promising applications is genomic medicine. Gene expression datasets are high-dimensional and exhibit a complex correlation structure. Quantum principal component analysis (QPCA), introduced by Lloyd et al, proved the effectiveness of quantum computing in extracting principal components from large datasets [34]. The theoretical alignment between quantum state and genomic feature complexity is compelling, though a practical implementation will be challenging.

Examples of prior work on the diagnosis of neurological disorders include quantum-enhanced classifications in EEG and MRI signals. Despite being too small-scale to be definitive, these studies demonstrate the exploratory promise of quantum machine learning (QML) in clinical neuroscience. Although QML could provide higher-level insights, further development is required to render it useful in diagnosing neurological disorders.

4.4. Comparative Analyses and Critical Perspectives

Though theoretical speedups are enticing, numerous works warn against overhyping quantum advantage. Tang showed that some quantum-inspired classical algorithms can reach the claimed quantum speedup in recommendation systems [35]. This suggests that the compelling results of these findings often necessitate strong benchmarking against optimized classical baselines.

Additionally, classical machine learning is still moving fast and advancing rapidly. Focusing on the major advancements of deep learning, LeCun et al. [36] have summarized how classical architectures have led to unprecedented scalability and performance in common vision tasks. AI systems had already achieved high diagnostic accuracy and translational deployment in clinical contexts [32], [33].

Nielsen and Chuang [37] offer a detailed theoretical basis for understanding limits on quantum computation. As a result, building practical quantum algorithms is still hindered in real-world implementations due to constraints such as decoherence, gate noise and qubit connectivity. As Preskill explains, practical fault-tolerant quantum computing is still a distant goal [28].

As a result, the current literature has an optimistic and cautious tone. Although QML provides unprecedented representational ability, it has yet to empirically demonstrate superiority in clinical pathology at scale.

4.5. Public Health and Translational Considerations

At the translational level, AI-based diagnostics have proven more efficient in healthcare than traditional ones and even demonstrated better results [38]. If proven, state-of-the-art, quantum-boosted systems might also further accelerate biomarker discovery and uncommon illness classification. But clinical deployment is dependent on regulatory approval, reproducibility, and interpretability. Yet Topol emphasizes that artificial intelligence in healthcare should remain humane [19]. This also applies to quantum-enhanced systems. Previous work has already shown that QML research remains predominantly proof of concept. Integration of the public health will be primeval, which involves detailed clinical trials at scale, a defined and standardized benchmarking data set, as well as interdisciplinary collaborations.

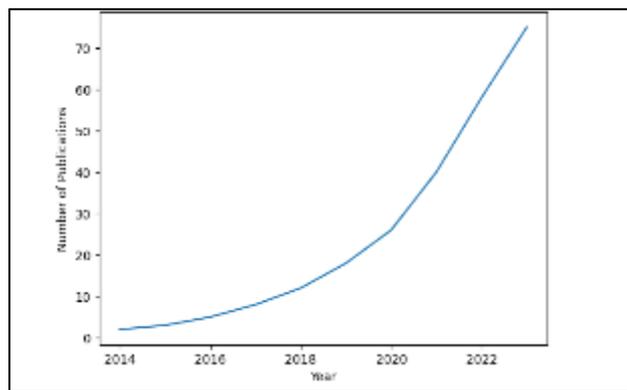


Figure 1 Growth trend of quantum machine learning research in healthcare

Figure 1 shows an explosion of quantum machine learning research in healthcare from 2014 to mid-2023. This growth reflects the increasing cross-disciplinary engagement and growing national commitment to quantum technologies. The data highlights the growing interest in quantum innovations and their promise for a radical impact on healthcare — from improving diagnostics to optimizing treatment protocols to analyzing large amounts of data.[39]

5. Future Directions

We envisage future work to include establishing hybrid quantum-classical pipelines, devising noise-resilient quantum circuits, developing scalable techniques for the estimation of quantum kernels, and integrating these methods with electronic health record systems. A practical advantage can only be achieved through rigorous benchmarks against state-of-the-art classical baselines.[40] A close collaboration between quantum physicists, computer scientists, clinicians and public health experts will be necessary to ensure that meaningful applications are delivered to the world and that clinical translation is successful.[41]

6. Conclusion

Quantum machine learning would significantly enhance the capability of disease diagnosis in its early stages, though it remains an unrealized proposition. Theoretical foundations suggest potential computational advantages for high-dimensional learning tasks, but empirical validation in clinical contexts is still lacking. Hybrid approaches in the NISQ era offer the most viable near-term path. But moving QML from the experimental stage to a widely used public health tool relies on strategic research funding, regulatory alignment, and interdisciplinary collaboration.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed

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