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Quantum machine learning: A comprehensive review of integrating AI with quantum computing for computational advancements

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REVIEW HIGHLIGHTS

- The paper is about the integration of quantum computing and classical machine learning algorithms such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Naïve Bayes, K-Means, and Quantum Neural Networks, including their applications, mathematical contributions, significant findings, and limitations.
- The study categorizes quantum machine learning research contributions, prioritizing core mathematical techniques such as quantum feature mapping, distance metrics, and circuit design, while also pointing out the use of quantum-empowered models in applied domains such as medicine, finance, and image classification.
- The survey outlines open research problems in quantum machine learning, including improving quantum kernel methods, developing noise-tolerant quantum circuits, and scaling quantum models for practical use, as well as speculating on interdisciplinary applications and hybrid quantum-classical architecture innovations.

ARTICLE INFO

Method name:
Quantum Machine Learning

Keywords:
Quantum machine learning
Quantum computing
Artificial intelligence
Quantum neural networks

ABSTRACT

Quantum Machine Learning (QML) is the emerging confluence of quantum computing and artificial intelligence that promises to solve computational problems inaccessible to classical systems. Using quantum principles such as superposition, entanglement, and interference, QML promises exponential speed-ups and new paradigms for data processing in machine learning tasks. This review gives an overview of QML, from advancements in quantum-enhanced classical ML to native quantum algorithms and hybrid quantum-classical frameworks. It varies from applications in optimization, drug discovery, and quantum-secured communications, showcasing how QML can change healthcare, finance, and logistics industries. Even though this approach holds so much promise, significant challenges remain to be addressed-noisy qubits, error correction, and limitations in data encoding-that must be overcome by interdisciplinary research soon. The paper tries to collate the state of the art of QML in theoretical underpinnings, practical applications, and directions into the future.

Specifications table

Subject area:	Computer Science
More specific subject area:	Quantum Computing

(*continued on next page*)

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Name of the reviewed methodology:	Quantum Machine learning
Keywords:	Quantum Machine Learning, Quantum Computing, Artificial Intelligence, Quantum Neural Networks
Resource availability:	NA
Review question:	1. How do fundamental quantum principles, such as qubit representation, superposition, entanglement, and unitary evolution, contribute to the computational advantages of quantum algorithms in machine learning and optimization? 2. What is the Application Area, Mathematical Contributions, Key Findings and Limitations of previous studies on Quantum integrated with SVMs 3. What is the Application Area, Mathematical Contributions, Key Findings and Limitations of previous studies on Quantum integrated with KNN. 4. What is the Application Area, Mathematical Contributions, Key Findings and Limitations of previous studies on Quantum integrated with neural network.

Background

Quantum computing and artificial intelligence technologies have developed rapidly, earning a place for these realms among the most promising technologies and solving computational problems that, to this day, cannot be solved by systems of the classical world. In the intersection of these subjects Quantum Machine Learning (QML) must be understood as the unique features rooted in quantum mechanics, namely: superposition, entanglement, and quantum interference, which change the way machine learning models and algorithms function [1]. Fig. 1 illustrates the evolution of Quantum computing. Quantum computing describes a new paradigm for treating information, where quantum bits (Qubits) simultaneously are in several states [2]. By enabling quantum systems to apply computational operations across vast solution-spaces in parallel, this property facilitates a tremendous exponential speedup above those of classical systems specifically in certain classes of computation problems [3]. Therefore, these skills get absorbed into the adaptive and data-centered nature of artificial intelligence that empowers the creation of newer solutions in optimization, recognition of patterns, and generating models in various fields across healthcare, finance, cryptography, and logistics [4,5]. Fig. 1 illustrates the evolution of Quantum computing.

It is evident from Fig. 1 that the evolution of quantum computing represents a significant shift from classical computing, which relies on binary systems and transistors for processing information. Classical computers operate using bits—values represented as 0 s or 1s—and transistors, which are critical for their operation. However, the principles of quantum mechanics, such as superposition and entanglement, provide the foundation for quantum computing. Superposition enables quantum bits, or qubits, to exist in multiple states simultaneously, while entanglement allows qubits to share interdependent states, resulting in computational advantages far beyond classical systems [6]. Building on these principles, quantum computing introduces new concepts, including qubits and quantum gates, which perform operations analogous to classical logic gates but with far greater complexity and flexibility [7].

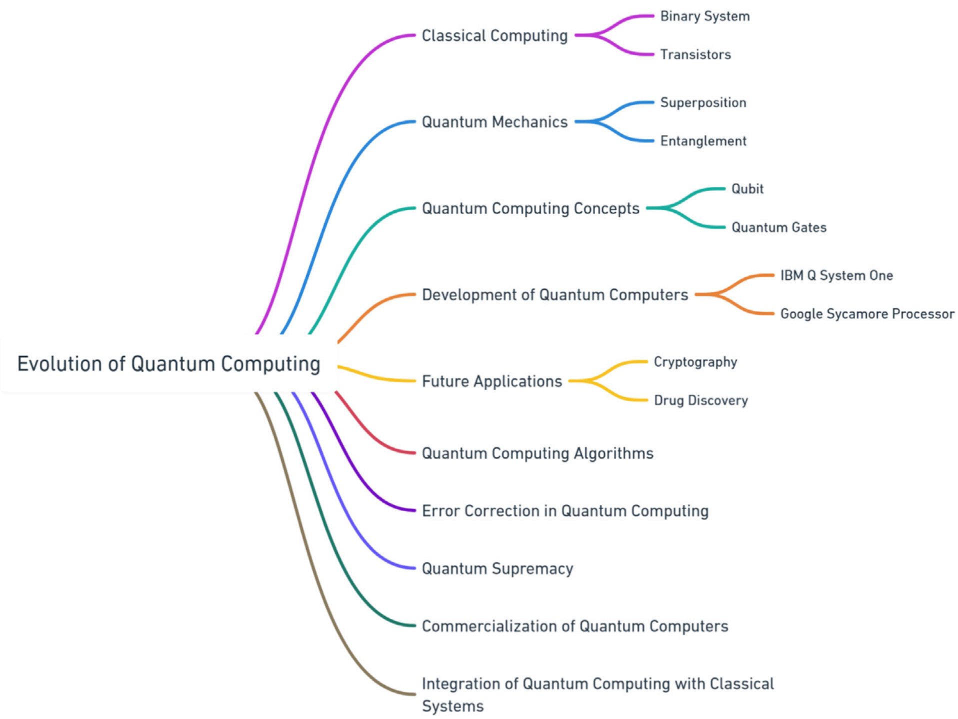

Fig. 1. Quantum computing evolution.

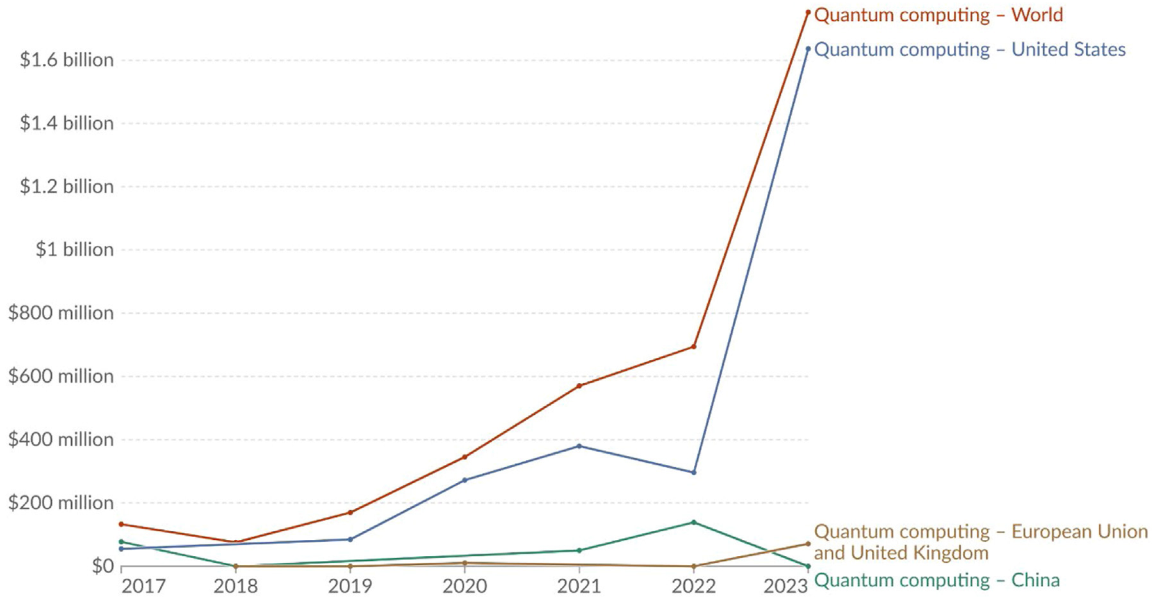

Fig. 2. Annual private investments in Quantum computing (Source: Quid via AI Index,U.S. Bureau of Labor Statistics (2024)).

The development of quantum computing has been marked by technological breakthroughs, such as IBM Q System One and Google's Sycamore Processor. IBM Q System One represents one of the first commercial quantum computers, showcasing advancements in practical quantum systems. Google's Sycamore Processor achieved quantum supremacy by solving computations in seconds that would take classical supercomputers millennia to complete. These developments highlight quantum computing's potential for solving real-world problems, particularly in fields like cryptography and drug discovery [8]. Fig. 2 shows annual private investments in Quantum Computing across regions, with global investments peaking in 2023 at over $1.6 billion. The United States leads in investments, while the EU, UK, and China lag significantly behind.

Quantum systems can break traditional encryption through algorithms such as Shor's, which factorize large integers efficiently, while quantum simulation enables accurate modeling of molecular structures to accelerate drug design and medical innovations [9].

Quantum computing algorithms further exemplify the power of these systems, with notable examples including Shor's algorithm for cryptographic applications and Grover's algorithm, which optimizes database search operations [10]. Despite these advances, error correction remains a major challenge, as quantum systems are highly sensitive to environmental disturbances that cause errors. Techniques like surface codes and fault-tolerant methods are being developed to mitigate these errors and maintain qubit integrity in noisy environments [11]. Quantum supremacy [12], a milestone where quantum systems outperform classical computers for specific tasks, signifies the vast computational potential of this technology, as demonstrated by Google's Sycamore.

The commercialization of quantum computers is another key development, with major corporations such as IBM, Google, and D-Wave leading efforts to make quantum systems scalable and accessible [13]. These efforts are driving the transition from theoretical research to practical applications across industries. The integration of quantum computing with classical systems represents the next step in this evolution, where hybrid systems optimize computational resources and bridge the gap for widespread adoption [14]. Combining classical computing's stability with quantum advantages will unlock new opportunities in artificial intelligence, cryptography, and scientific discovery [15]. Fig. 3 shows The Global Quantum Computing as a Service market size is expected to around USD 48.3 Billion by 2033, from USD 2.3 Billion in 2023, at a CAGR of 35.6 % during the forecast period from 2024 to 2033.

Two interconnected approaches outline the current state of quantum machine learning: quantum-enhanced classical machine learning and specifically native quantum machine learning algorithms. Table 1 provides a comparison of Classical Machine Learning(CML) Quantum Machine Learning(QML) models.

Quantum-enhanced models of classical models make use of a quantum system to enhance or expedite the traditional machine-learning approach, such as deep network training for neural networks and the SVM classification algorithm [22]. Native quantum machine learning algorithms—such as quantum variational classifiers or quantum Boltzmann machines—use principles of the quantum mechanical regime to completely design new representations and methods of learning data [23].

Recent studies highlight both the opportunities and challenges in this field. Researchers have demonstrated quantum supremacy in tasks such as quantum feature space encoding, allowing quantum systems to identify patterns in high-dimensional datasets that classical systems struggle to analyze [24]. However, practical challenges remain, including the need for error correction in quantum systems, limited qubit coherence times, and difficulties in interfacing classical data with quantum systems [25].

Below are the research questions framed,

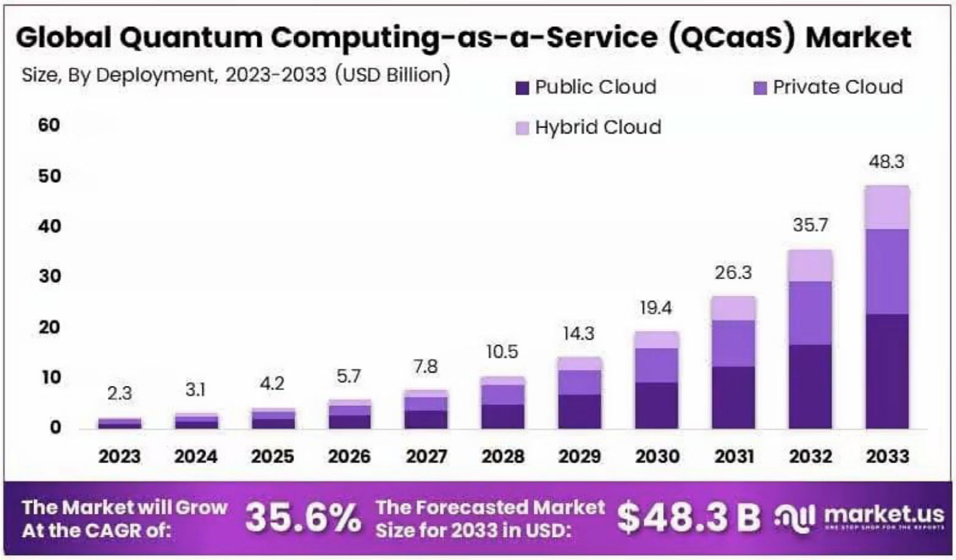

Fig. 3. QCaaS market growth (Source: market.us).

Table 1
Comparison of CML and QML models.

Criteria	Classical Machine Learning	Quantum Machine Learning
Data Representation	Data is represented in binary form (bits)	Data can be represented using quantum states (qubits) [16]
Computational Units	Classical bits (0 or 1)	Quantum bits (superposition of 0 and 1) [15]
Parallelism	Limited parallelism, achieved through multi-threading	Intrinsic quantum parallelism through superposition [17]
Processing Speed	Speed depends on classical computing resources	Exponential speed-up for certain problems (e.g., Grover's and Shor's algorithms) [18]
Scalability	Challenging for large-scale computations	Highly scalable for complex, high-dimensional problems [19]
Algorithms	Traditional algorithms (e.g., Decision Trees, SVMs, Neural Networks)	Quantum algorithms (e.g., Variational Quantum Eigensolver, Quantum SVM) [20]
Applications	Applications in image recognition, NLP, and structured data analysis	Applications in optimization, cryptography, and quantum chemistry simulations [21]

1) How do fundamental quantum principles, such as qubit representation, superposition, entanglement, and unitary evolution, contribute to the computational advantages of quantum algorithms in machine learning and optimization?
2) What are the Application Area, Mathematical Contributions, Key Findings and Limitations of previous studies on Quantum integrated with SVMs
3) What are the Application Area, Mathematical Contributions, Key Findings and Limitations of previous studies on Quantum integrated with KNN.
4) What are the Application Area, Mathematical Contributions, Key Findings and Limitations of previous studies on Quantum integrated with neural network.

Method details

Question 1: How do fundamental quantum principles, such as qubit representation, superposition, entanglement, and unitary evolution, contribute to the computational advantages of quantum algorithms in machine learning and optimization?

State of a qubit

Represents the quantum state as a linear combination of basis states $|0\rangle$ and $|1\rangle$, with normalized coefficients [26].

$$|\psi\rangle = a|0\rangle + b|1\rangle, \quad \text{where } |a|^2 + |b|^2 = 1 \tag{1}$$

The principles of quantum mechanics serve as the backbone of quantum computing and quantum machine learning. The Schrödinger Equation governs the evolution of quantum states, while measurement probabilities are determined by the Born Rule. Fig. 4 shows the Bloch Sphere representation, which visualizes a qubit's state as a point on a sphere defined by angles θ and ϕ.

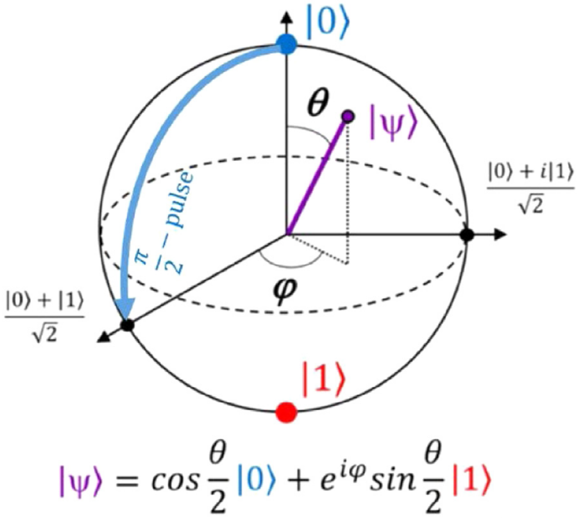

Fig. 4. Visualization of a qubit state on the Bloch Sphere using angles θ and ϕ [27].

Schrödinger equation

The time-dependent Schrödinger equation is the fundamental equation describing the dynamics of a quantum system [28]:

$$i\hbar\frac{\partial}{\partial t}|\phi(t)\rangle = \hat{G}|\phi(t) \tag{2}$$

This equation describes the time evolution of a quantum state $|\ \phi(t)\rangle$ under the Hamiltonian operator $\hat{G}$.

Born rule

The probability of observing a specific outcome when measuring a quantum state is given by [29]:

$$P\left(b_j\right) = \left|\left\langle b_j|\chi\right\rangle\right|^2 \tag{3}$$

This expresses the probability P(bj) of observing an outcome associated with the basis state |bj⟩, given the quantum state $|\ \chi\rangle$.

A quantum state can exist in superposition and become entangled when interacting with other states. These principles are central to quantum computation

Superposition

The general state of a qubit is expressed as [30]:

$$|\psi\rangle = \gamma|0\rangle + \delta|1\rangle, \quad |\gamma|^2 + |\delta|^2 = 1 \tag{4}$$

This equation represents the general superposition state of a qubit, where γ and δ are complex coefficients.

Entanglement

For two qubits, the maximally entangled Bell state is [31]

$$|\Psi\rangle = \alpha|00\rangle + \beta|01\rangle + \gamma|10\rangle + \delta|11\rangle \tag{5}$$

Where,

α, β, γ, δ: Complex coefficients that determine the amplitude of each state. $|00\rangle$, $|01\rangle$, $|10\rangle$, $|11\rangle$: The basis states for two qubits. The transformation of quantum states is governed by unitary operations and key algorithms such as the Quantum Fourier Transform (QFT).

Unitary evolution

The evolution of a quantum state is defined by a unitary operator $U(t, t_0)$ [32]:

$$|\phi(t)\rangle = V\left(t, t_0\right)\left|\phi\left(t_0\right)\right\rangle \tag{6}$$

Here,

$|\phi(t)\rangle$ evolves under the unitary operator $V(t,t_0)$, describing its transformation between times t_0 and t.

Quantum Fourier transform (QFT)

The quantum Fourier transform of a single qubit state $|\psi\rangle=\alpha|0\rangle+\beta|1\rangle$ is given by the following equation [33]:

$$|QFT(\psi)\rangle = \frac{1}{\sqrt{2}}(\alpha + \beta)|0\rangle + \frac{1}{\sqrt{2}}(\alpha - \beta)|1\rangle \tag{7}$$

Quantum machine learning leverages quantum principles for computational advantages. Two key mathematical concepts are the Fidelity of Quantum States and Quantum Kernels used in support vector machines. The quantum Fourier transform (QFT) plays a critical role in quantum algorithms like Shor's, but it generates only a constant amount of entanglement, despite its initial appearance of high entangling power. This entanglement behavior, linked to the bit reversal in QFT, allows for efficient classical simulations, demonstrating a potential speedup over the classical fast Fourier transform [34].

Quantum fidelity

The Quantum Fidelity measures the closeness between two quantum states, often denoted as $|\psi\rangle$ and $|\phi\rangle$ [35]. For pure states, it is defined as:

$$F(\psi, \phi) = |\langle\psi|\phi\rangle|^2 \tag{8}$$

For mixed states, where the density matrices of the states are ρ and σ, the fidelity is defined as:

$$F(\rho, \sigma) = \left(\mathrm{Tr}\left(\sqrt{\sqrt{\rho}\,\sigma\,\sqrt{\rho}}\right)\right)^2 \tag{9}$$

For pure states $|\psi\rangle$ and $|\phi\rangle$, the fidelity is the squared magnitude of their inner product, representing how similar the two states are.

For mixed states ρ and σ, the fidelity involves the trace of matrix operations involving the density matrices.

Quantum support vector machine (QSVM) kernel

The Quantum Support Vector Machine (QSVM) leverages quantum kernels for efficient data classification in high-dimensional feature spaces [36]. The kernel function in QSVM can be expressed as follows:

$$K\left(x_i, x_j\right) = \left|\left\langle\phi\left(x_i\right)|\phi\left(x_j\right)\right\rangle\right|^2 \tag{10}$$

Where:

- $\phi(x)$ represents a quantum feature map that encodes the classical data x into a quantum Hilbert space.
- $\phi(x_i)|\phi\ (x_j)\rangle$ is the inner product between the quantum states corresponding to x_i and x_j.
- The squared magnitude of this inner product represents the kernel similarity.

The classical Support Vector Machine maps the data into a larger or much larger space to perform its separations using a kernel matrix [37]. On the other side, Quantum Support Vector Machine maps the data into some suitable quantum states using a quantum circuit and then performs a separation in a quantum-enriched space by some measurements of inner products as shown in Fig. 5.

Table 2 compares classical Support Vector Machines (SVMs) and Quantum Support Vector Machines (QSVMs) across critical aspects like data representation, kernel computation, and performance. While SVMs rely on mapping data to higher-dimensional feature spaces, QSVMs encode data into quantum states, leveraging the exponential scalability of quantum Hilbert spaces. QSVMs hold the potential for improved performance and speedup on quantum hardware, particularly for large-scale problems.

Table 2
Comparison of SVM and QSVM.

Feature	Classical SVM	Quantum SVM (QSVM)
Data Encoding	Encodes data into a higher-dimensional classical space [38]	Encodes data into quantum states via quantum circuits [39]
Kernel Computation	Uses classical kernels to compute inner products.	Inner product measured between quantum states [40]
Computational Complexity	Scales polynomially with data size and dimensions.	Leverages quantum computing for potential exponential speedup [41]
Dimensional Space	Higher-dimensional classical feature space.	Quantum-enhanced Hilbert space [42]
Key Limitation	Limited by classical computational resources.	Requires quantum hardware; limited by NISQ era.
Applications	Traditional classification and regression tasks.	Enhanced classification tasks; QML applications.
Training Complexity	Polynomial time for linearly separable data.	Complexity depends on quantum circuit depth and quantum measurements [43]
Execution Hardware	Runs on classical computers.	Requires quantum processors (NISQ devices) [44]

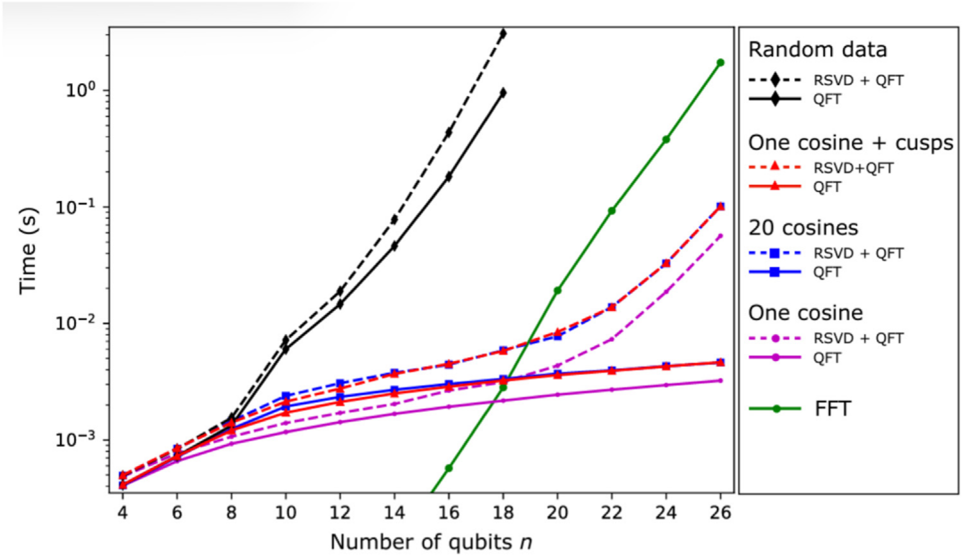

Fig. 5. Comparison of quantum algorithms (RSVD + QFT, QFT) and FFT performance across input types and qubit counts [34].

Quantum neural network (QNN)

A QNN is a computation model that applies the principles of quantum mechanics, superposition, entanglement, and unitary transformation to process quantum data, to solve machine learning problems [45]. QNNs are engineered by parameterizing quantum circuits with tunable parameters. They are optimized using either classical or hybrid quantum-classical algorithms for performing classifications, regressions, or any other kind of pattern recognition tasks efficiently within a quantum system.

QNN forward pass is given as

$$|\psi out\rangle = U(\theta)|\psi_{in}\rangle \tag{11}$$

Here,

$|\psi\text{in}\rangle$: Input quantum state.

U(θ): Parameterized quantum unitary operation (quantum circuit) with learnable parameters θ.

$|\psi\text{out}\rangle$: Output quantum state after applying the quantum circuit.

Parameterized Quantum Neural Networks use quantum gates with tunable parameters (angles of rotation) to act on qubits [46]. In the context of quantum neural networks, the cost function can often be defined as the expected value of an observable related to the quantum state [47]. A common formulation for the cost function in this setting is given by:

$$C(\theta) = \langle \psi(\theta) \mid O \mid \psi(\theta) \rangle \tag{12}$$

Where:

- $C(\vartheta)$ is the cost function dependent on the parameters ϑ.
- $|\psi(\vartheta)\rangle$ is the quantum state produced by the neural network, parameterized by ϑ.
- is the observable that we are measuring, which could represent some physical quantity or a problem-specific metric.

For a more specific case, such as when using a mean squared error approach, the cost function can also be expressed as:

$$C(w,b) = \frac{1}{2m}\sum_{j=1}^{m}\left(f\left(x_j;w,b\right) - y_j\right)^2 \tag{13}$$

Where:

w denotes the weights of the network.

b represents biases.

$f(xj;w,b)$ is the output of the quantum neural network for input xjxj.

y_j is the target value corresponding to input xj.

m is the total number of training examples.

In one of the past work authors introduced a novel Quantum variational algorithm for a single-layer perceptron, expanding the possibilities for Quantum Artificial Intelligence (QAI). By leveraging quantum circuits, the model performs computations that scale exponentially with qubits, enabling the approximation of any function as shown in Fig. 6. This approach combines quantum processing with classical optimization to refine model parameters, aligning with the concept of QNNs. The integration of quantum and classical components enhances the expressive power of QNNs, particularly for tasks in the NISQ era like classification and regression.

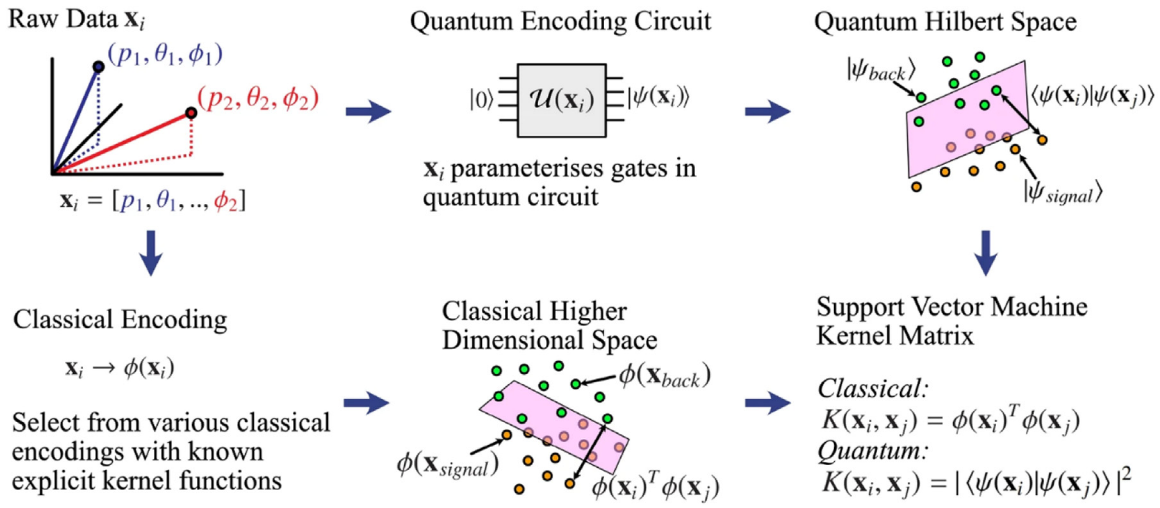

Fig. 6. Comparison between classical SVM and QSVM data points [37].

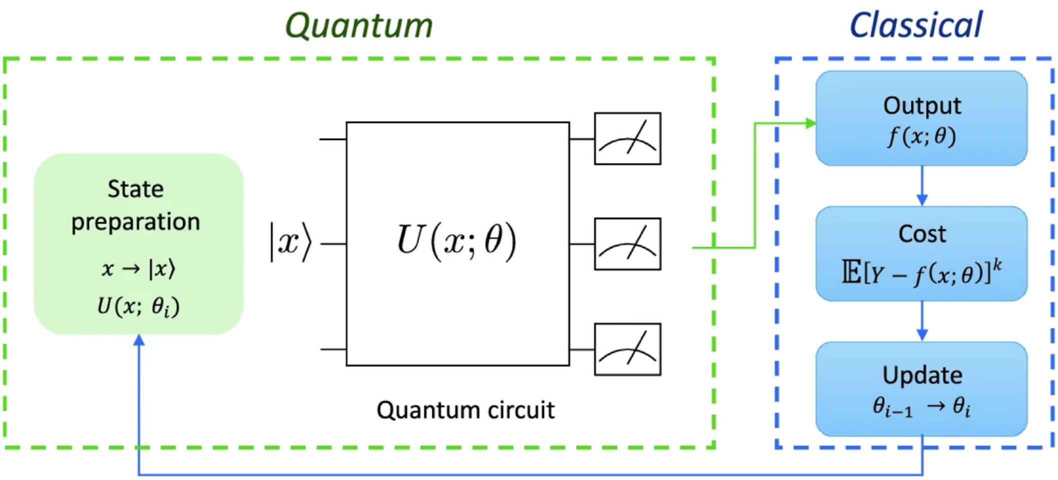

Fig. 7. Quantum-Classical approach for QNN with quantum circuits for computation and classical optimization for parameter updates [48].

General architecture of a discrete-variable quantum neural network. Like the classical neural network, the deep QNN contains an input, output and L hidden layers as shown in Fig. 7. The quantum states are communicated from the classical computer to the quantum neural network and the output distribution resulting from the quantum neural network is sampled.

Next, we begin by giving the number of publications that happened in IEEE Explore and Springer databases. Fig. 8 displays number of publications in IEEE Explore. Fig. 9 illustrates number of publications in Springer database for last 5 years.

Question 2: What are the Application Area, Mathematical Contributions, Key Findings and Limitations of previous studies on Quantum integrated with SVMs.

Table 3 discusses studies which employed Quantum integrated with SVMs.

Fig. 10. compares the accuracy of Quantum Support Vector Machines (QSVM) across various application domains, such as healthcare, environmental science, and finance. It highlights the highest performance in breast cancer diagnosis (95 %) and relatively low accuracy in medical data analysis (81 %). Fig. 11 illustrates a few challenges faced by Quantum SVM with the impact severity level from 1 to 10.

Fig. 11 depicts the severity impact of various challenges associated with Quantum SVM applications. Hardware constraints and scalability pose the most significant challenges, while generalization and dataset limitations also have considerable impact. Fig. 12 represents QSVM contributions by application areas.

Fig. 12 illustrates the distribution of key contributions of QSVM across different fields. Healthcare leads with 25 %, followed by significant contributions in weather modeling and finance, showcasing the diverse applicability of QSVMs in critical areas.

Question 3: What are the Application Area, Mathematical Contributions, Key Findings and Limitations of previous studies on Quantum integrated with KNN.

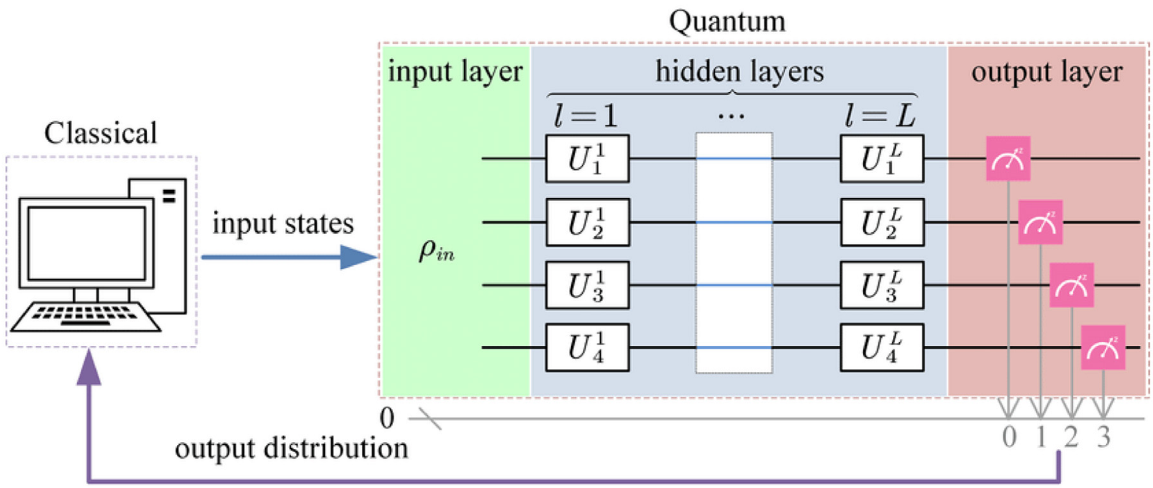

Fig. 8. Deep QNN [49].

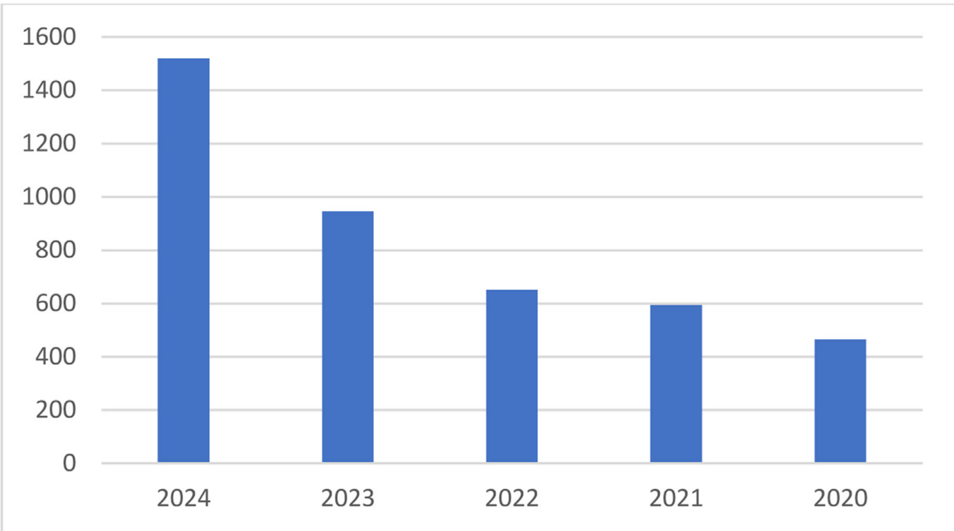

Fig. 9. Number of publications in IEEE Explore.

Table 4 discusses studies which employed Quantum integrated with KNN algorithm.

The steady increase, especially in recent years like 2023 and 2024, highlights growing advancements in quantum KNN methodologies, with higher gains reflecting improved techniques and optimizations as per Fig. 13.

Fig 14. Shows the mathematical contributions made in Quantum KNN studies. Distance metrics and circuit design are the most prevalent, indicating their foundational role in quantum KNN. Other innovations, such as quantum search and divide-and-conquer strategies, are also prominent (Fig. 15).

Question 4: What are the Application Area, Mathematical Contributions, Key Findings and Limitations of previous studies on Quantum integrated with neural network.

Table 5 discusses studies which employed Quantum integrated with neural network.

Research gaps

The dependency on quantum hardware and the scalability of these systems presents a major challenge. Research work, such as Landman et al. (2022) and J et al. (2022), indicate the presence of remarkable drops in performance for QNNs when they are run on currently available quantum hardware. Such limitations combined with scalability issues have limited the scope of applying QNNs on larger datasets and complex real-world problems. Furthermore, noise sensitivity continues to hinder the robustness and accuracy of these models, as has been recently discussed by Nguyen and Kukliansky et al. Without robust strategies for noise mitigation, it hinders their practical implementation, particularly in high-sensitivity domains such as medical imaging and satellite-ground systems.

Table 3
Quantum studies on SVM.

Author/Year	Application Area	Mathematical Contributions	Key Findings	Limitations
P, J., Hariharan, S., Madhivanan, V., N, S., Krisnamoorthy, M., & Cherukuri, A.K. (2024) [50]	Breast cancer diagnosis	Combining quantum support vector machines (QSVMs) with elitist non-dominated sorting genetic optimization (ENSGA)	Addresses the binary classification problem for malignant breast cancer, outperforming traditional methods, High accuracy	Challenges in terms of accessibility and implementation in standard healthcare practices, given the current state of quantum technology
Jaderberg, B., Gentile, A.A., Ghosh, A., Elfving, V.E., Jones, C., Vodola, D., Manobianco, J., & Weiss, H. (2024) [51]	weather modeling	Barotropic Vorticity Equation (BVE),	Effectively tackle weather modeling challenges, advancements in solving complex partial differential equations (PDEs) with quantum machine learning techniques	Does not address all aspects of atmospheric dynamics, suggesting a need for broader exploration in future work
Farooq, O., Shahid, M., Arshad, S., Altaf, A., Iqbal, F., Vera, Y.A., Flores, M.A., & Ashraf, I. (2024) [52]	Air quality prediction,	Complex dataset handling using a mathematical framework	With higher accuracy in air quality prediction, quantum computing can outperform classical methods in complex classification tasks	scalability of quantum SVMs for huge datasets, limited discussion on computational resources
Suzuki, T., Hasebe, T., & Miyazaki, T. (2023) [53]	Fraud Detection, Image Recognition, Financial Predictions	Support Vector Classification, Regularization Parameter, Root Mean Square Error (RMSE)	Performance Comparison, Noise Mitigation, Alignment Measurement	shallow quantum circuits limits expressibility, posing challenges for scalability, Approximation of Real Errors
Aksoy, G., Cattan, G., Chakraborty, S., & Karabatak, M. (2024) [54]	Mental Health Diagnosis, Healthcare Technology, Quantum Computing in Medicine	Principal Component Analysis (PCA), Quantum Feature Mapping	High Accuracy, Effectiveness of Quantum Algorithms, Dimensionality Reduction	Not suitable for real world environment, limit generalizability, Complexity of Quantum Systems
Egginger, S., Sakhnenko, A., & Lorenz, J.M. (2023) [55]	Healthcare, Data Pre-screening	Geometric Difference Metric, Hyperparameter Analysis, Empirical Performance Metrics	Hyperparameter Impact, Dataset Analysis	Empirical Focus, Generalization of Findings
Delilbasic, A., Saux, B.L., Riedel, M., Michielsen, K., & Cavallaro, G. (2023) [56]	Remote Sensing, Quantum Machine Learning	Quadratic Unconstrained Binary Optimization, Direct Multiclass Classification	Accuracy Comparison, Feasibility of Quantum Approaches	limit its applicability in larger datasets, Current Hardware Constraints
Akpinar, E., Islam, S.M., & Oduncuoglu, M. (2024) [57]	Medical Data Analysis, Classification Problems,	Feature Mapping Techniques, Quantum Kernel Matrices	Impact of Feature Mapping, Best Performance Achieved	Limited Dataset Variety, Quantum Resource Constraints

From the analysis accuracy of accuracy of Quantum SVM across various domains was found as depicted in Fig. 10.

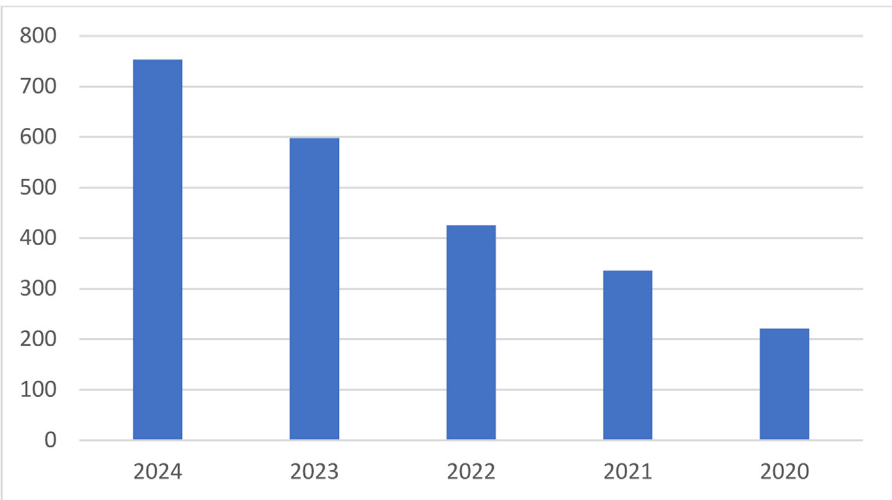

Fig. 10. Number of publications in Springer.

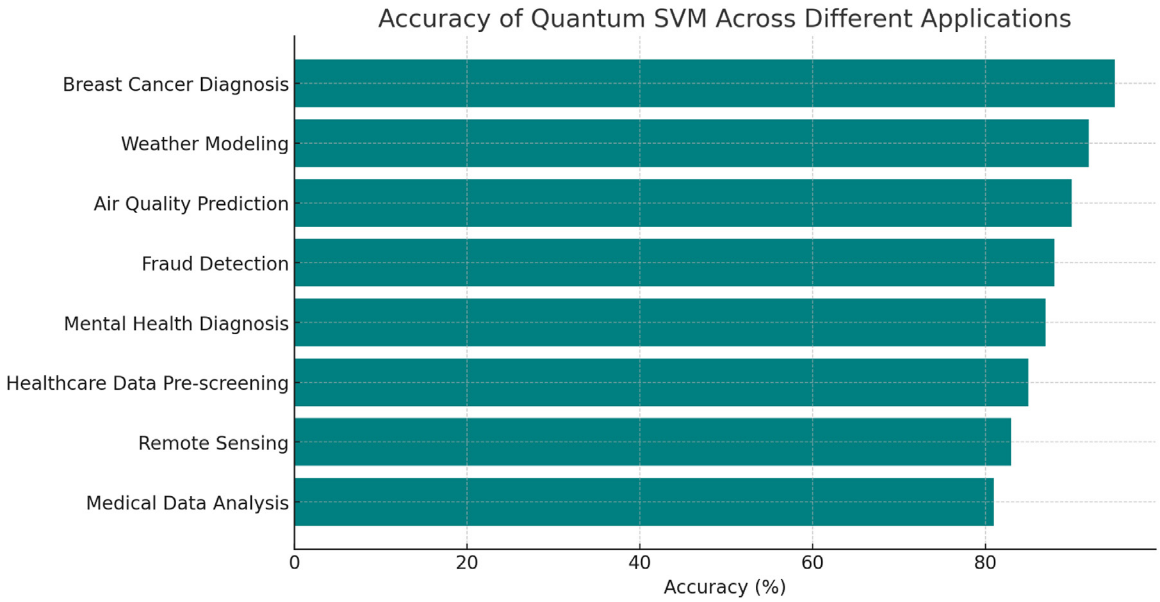

Fig. 11. Accuracy of Quantum SVM across various applications.

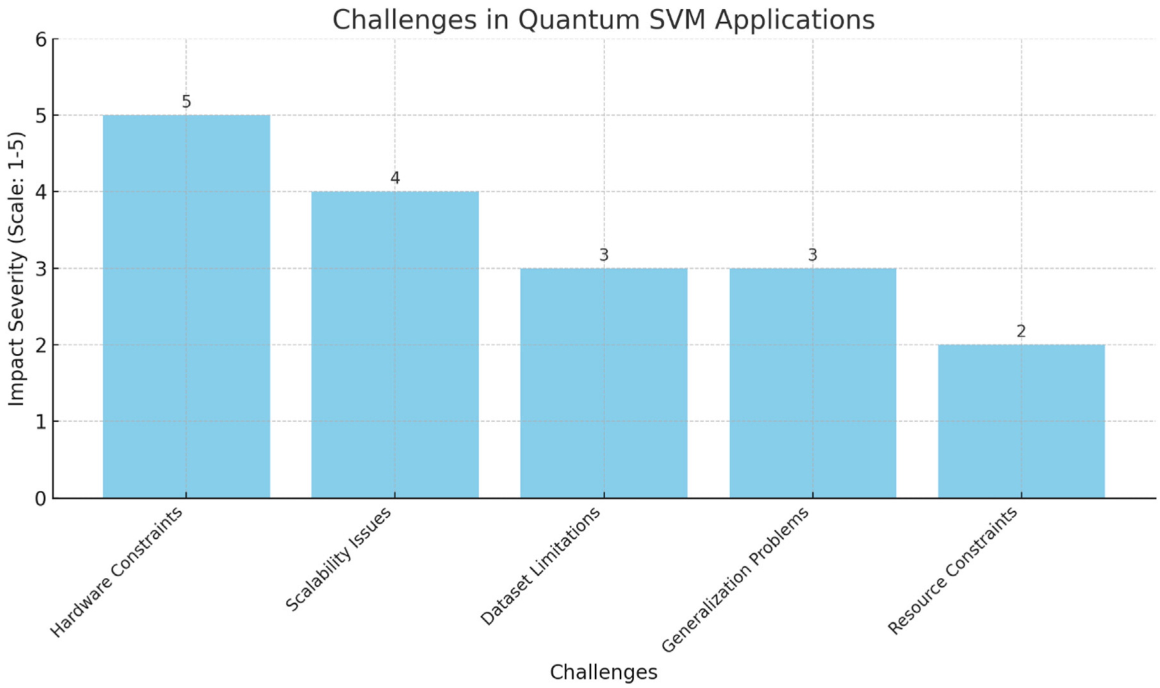

Fig. 12. Challenges in Quantum SVM applications.

The other major gap that has come forward is training complexity and resource usage of quantum-enhanced models. For instance, the hybrid models postulated by Senokosov et al. in 2023 and Bai & Hu in 2024 call for considerable computational power with training times also slower than classical models. In the case of state preparation and computation of quantum gradients reported by Smaldone et al., are bottlenecks that need improvement to make this model a strong contender. More importantly, the studies lack generalization to a broad variety of datasets and applications. Most studies focus on restricted MNIST datasets while more comprehensive datasets are largely untouched and far more complicated applications remain under-examined. Finally, there exist some models which are built only based on the simulations and even evaluated solely through simulation by Rousselot & Spannowsky.

Table 4
Quantum studies on KNN.

Author/Year	Application Area	Mathematical Contributions	Key Findings	Limitations
Zardini, E., Blanzieri, E., & Pastorello, D. (2023) [58]	Healthcare	Data Representation, Distance Metric	increasing the number of measurements can enhance performance, suggesting potential avenues for optimization in real-world applications.	increased computational complexity and errors in classification, require significant computational resources
Gao, L., Lu, C., Guo, G., Zhang, X., & Lin, S. (2022) [59]	High-Dimensional Data Analysis	Mahalanobis Distance, Quantum Minimum Search Algorithm	Performance Improvement, Quadratic Speedup, Robustness Against Feature Variability	Complexity of Quantum Implementation, Scalability issues
Feng, C., Zhao, B., Zhou, X., Ding, X.T., & Shan, Z. (2023) [60]	Big Data Applications	Polar Distance Metric, Quantum Circuit Design	Comparable Accuracy, Superior Performance in QKNN	Implementation Complexity, Measurement Sensitivity
Gong, L., Ding, W., Li, Z., Wang, Y., & Zhou, N. (2024) [61]	High-Dimensional Data Analysis	Divide-and-Conquer Strategy, Quantum Circuit Design	Improved Classification Efficiency, Performance Validation	Resource Requirements, Implementation Complexity, Measurement Sensitivity
Li, J., Lin, S., Yu, K., & Guo, G. (2021) [62]	Binary Classification Tasks, Data with Discrete Features	Hamming Distance Calculation, Quantum Minimum Search Algorithm	Quadratic Speedup, Parallel Processing Capability	Quantum Hardware Dependence, Measurement Challenges
Zhou, N., Liu, X., Chen, Y., & Du, N. (2021) [63]	Image Classification, High-Dimensional Data Analysis	K-L Transform, Quantum Distance Calculation	Enhanced Classification Accuracy, Efficiency Gains	Quantum Hardware Constraints, Measurement Sensitivity
Zeguendry, A., Jarir, Z., & Quafafou, M. (2024) [64]	Text Classification, Natural Language Processing (NLP)	Hybrid Approach, Unified Circuit Design, Distance Metric Optimization	Improved Classification Performance, Efficiency Gains	Quantum Hardware Dependence, Measurement Challenges
Ma, Y., Song, H., & Zhang, J. (2021) [65]	Supervised Learning, High-Dimensional Data Analysis	Categorical Tensor Network States, Distance Calculation Framework	Improved Classification Efficiency, Robustness Against Noise	Complexity of Implementation, Specificity to Categorical Data
Maldonado-Romo, A., Montiel-Pérez, J.Y., Onofre, V., Maldonado-Romo , J., & Sossa-Azuela , J.H. (2024) [66]	Supervised Learning, High-Dimensional Data Analysis	Integration of QRAM, SWAP-Test Technique	Enhanced Performance, speedups in processing time	Quantum Hardware Constraints, Complexity of Implementation
Wang, Y., Wang, R., Li, D., Adu-Gyamfi, D., Tian, K., & Zhu, Y. (2019) [67]	Handwritten Digit Recognition, Image Processing	Quantum KNN Framework, Distance Calculation Optimization	Improved Recognition Accuracy, Efficiency Gains	Specificity to Handwritten Digits, Quantum Hardware Constraints

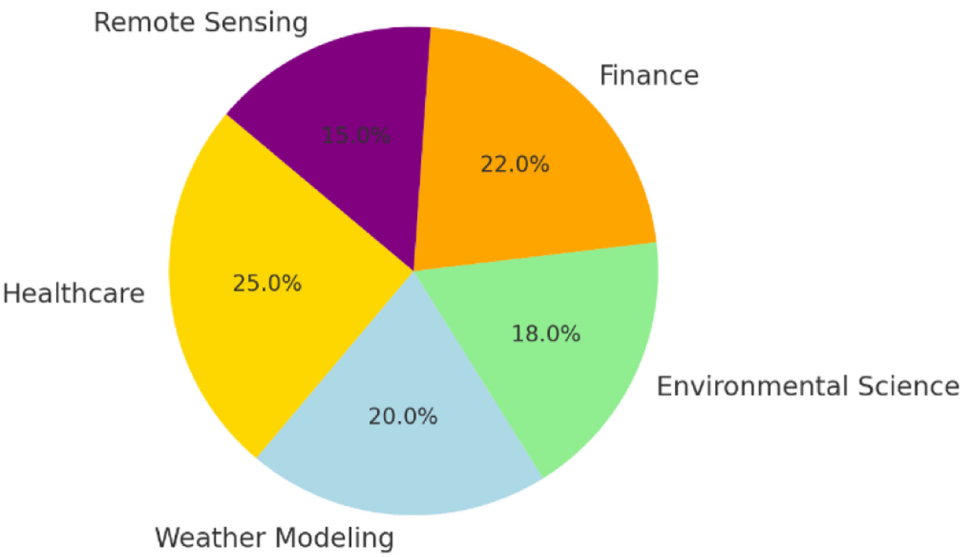

Fig. 13. Quantum SVM contributions across different applications.

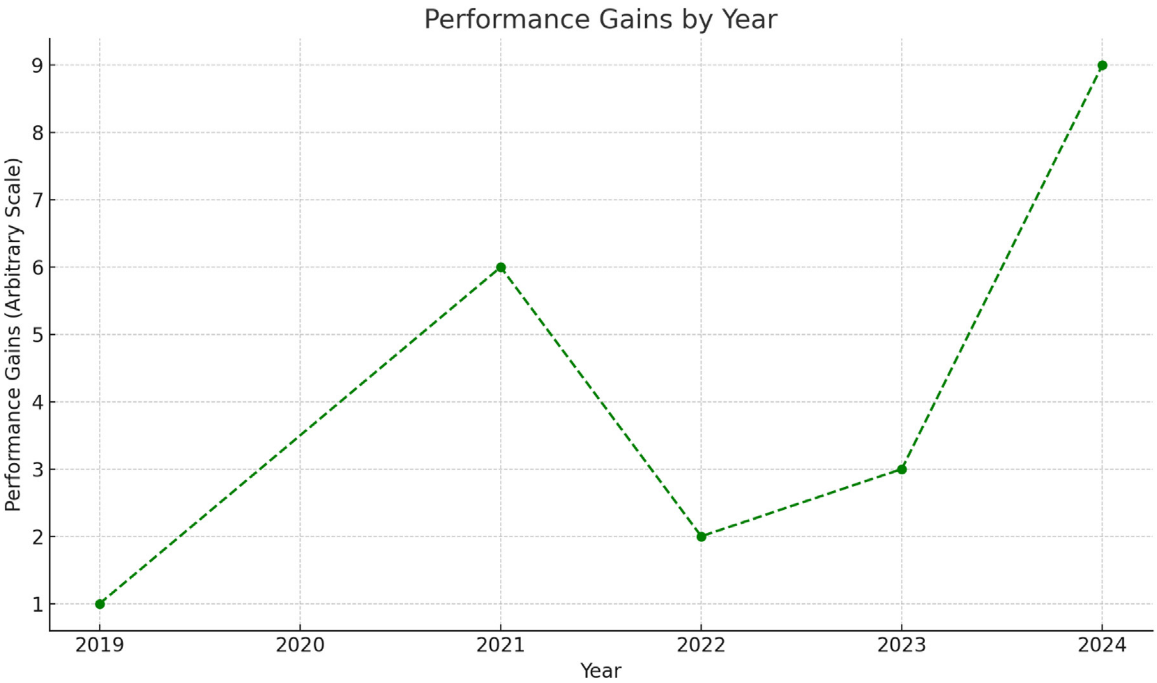

Fig. 14. Performance gains by year.

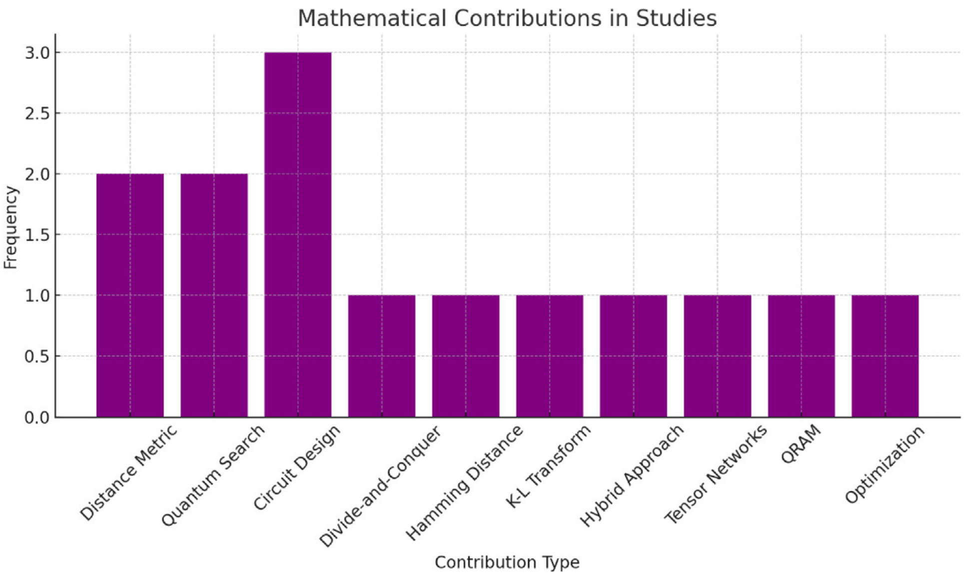

Fig. 15. Mathematical contributions in Quantum KNN.

Future research directions

To fill these gaps, several directions for future research are recommended. First, the development of scalable, noise-resistant quantum hardware is key. Innovation in error correction mechanisms could mitigate noise effects and ensure more reliable computation. Simultaneously, better algorithms for training the hybrid quantum-classical systems would be required, reducing computational complexity and making these systems more efficient. Quantum-inspired techniques may further help to achieve better state preparation and gradient computation, which would overcome current bottlenecks.

Another important direction is to generalize the scope of quantum neural networks to various datasets and real-world applications. Fields such as multi-LEO satellite systems and cancer biomarker analysis are promising yet underexplored opportunities. Interdisciplinary approaches combining quantum AI with domains like climate science, robotics, and cybersecurity can further ex-

Table 5
Quantum studies on Neural networks.

Author Year	Applications	Mathematical contributions	Findings	Limitations
(Senokosov et al., 2023) [68]	Image classification	quanvolutional layer is introduced as a part of hybrid quantum neural network.	Hybrid quantum neural network with parallel quantum circuits, with high accuracy (99.21 % on MNIST and over 99 % on Medical MNIST).	1. The training of quantum layers is more complex. 2. The feasibility of the proposed models is dependent on the existence of efficient quantum hardware. 3. Hybrid quantum models are trained slower than their classical counterparts.
(Landman et al., 2022) [69]	Medical image classification	Encompasses quantum orthogonal neural networks and quantum-assisted neural network.	The quantum-assisted neural networks achieved comparable accuracy to that of the classical neural networks for medical image classification tasks. The quantum orthogonal neural networks showed promising results, but there was a noted drop in performance when both training and inference were performed on quantum hardware.	1. Performance drop can happen in complex tasks based on the qubits. 2. Noise can lead to a drop in accuracy 3. Unstable results 4. Scalability issue
(Smaldone et al., 2024) [70]	Drug discovery	Quantum neural networks	Fast and accurate predictions in drug discovery	1.Performance for test data is not guaranteed 2.State Preparation Challenges 3. quantum gradient computation
(Park et al., 2024) [71]	Satellite-Ground Integerated Systems	Proposes slimmable quantum federated learning (SQFL) and slimmable quantum neural networks (sQNN)	The proposed approach acquired relatively high accuracy in comparison with Quantam Federated learning and classical slimmable federated learning	1. For multi-LEO scenarios, the approach has not been tested. 2. Optimal power allocation for superposition coding is not calculated
(Nguyen, 2024) [72]	Genetic biomarkers for cancer treatment	Combines CTLA4-activation pathways and Quantum Neural Networks	The concept is demonstrated in four targeted pathways associated CTLA4 and the results show that QNN proved to be a relevant approach for cancer treatment	The effect of noise is not addressed for evaluating the efficiency
(Bai & Hu, 2024) [73]	Image classification	superposition-enhanced quantum neural network	The principles of quantum superposition and entanglement are combined and achieve superior performance in terms of accuracy and efficiency on three bench mark datatsets	Quantam-enhanced binary classifiers can lead to the misclassification of samples
(Kukliansky et al., 2024) [74]	Intrusion detection	Quantum Neural Networks are utilized to detect the attacks using IonQ's Aria-1 quantum computer	The proposed methodology achieves a notable F1 score of 0.86 and introduced a certainty factor	Impact of noise can degrade the performance
(Rousselot & Spannowsky, 2024) [75]	jet-associated production of a Z-boson that decays into leptons	Quantum Invertible Neural Network	Hybrid QINN can be compatible with larger classical Invertible Neural Network (INN) in learning and generating complex data.	The evaluation is done based on simulations
(J et al., 2022) [76]	Image classification	Developed a QNN using the Projected Quantum Kernel feature to classify the image.	QNN model achieved a significant accuracy of 98.6 % which is superior to QNN.	1. Resource utilization is high 2.Scalability issues
(Khatoniar et al., 2024) [77]	Medical image classification	Quantum Convolutional Neural Networks (QCNNs) are investigated with regard to image classification problems.	The QCNN model is robust and scalable in classifying normal and pneumonia data with limited number of features and achieved remarkable results.	Limited scope of data

tend the impact of QNNs. Additionally, robust noise-mitigation strategies must be developed to ensure model stability and accuracy in noisy environments. Quantum-enhanced robustness metrics could represent standardized tools to evaluate model efficiency in such conditions.

Optimizing resource utilization is another key area of improvement. Optimized quantum circuit design can help decrease the use of resources and increase scalability in big data. Tensor networks or divide-and-conquer strategies might be more viable alternatives for applications with limited resources. Finally, hybrid approaches integrating QNNs with classical models can leverage the strengths of both paradigms to ensure consistency in performance and innovation. By closing the cited research gaps and following the proposed directions, quantum neural networks may become a backbone of future machine learning, filling in the gap between theoretical promises and practical application.

Conclusion

This all-encompassing research has delved into the multi-faceted advancements in quantum machine learning, with a special focus on quantum-enhanced K-Nearest Neighbors and Quantum Neural Networks. This research points out the transformative potential of quantum machine learning across diverse domains such as healthcare, image classification, drug discovery, and natural language processing. Quantum-enhanced methods, including advanced distance metrics, hybrid architectures, and quantum circuit designs, have shown superior accuracy, efficiency, and robustness compared to classical approaches. However, major challenges persist, such as dependency on quantum hardware, noise sensitivity, scalability issues, and high computational demands. Most studies remain limited to small-scale or benchmark datasets, thus requiring broader generalization and application to complex real-world problems. Advances in the fields of scalable, noise-resistant quantum hardware, efficient training algorithms, and hybrid quantum-classical models will help break through these barriers. Increasing the applicability scope and optimizing resource usage will also increase the practicality of the quantum applications. In conclusion, although significant challenges remain, the progress made in quantum machine learning underscores its potential to revolutionize machine learning, bridging theoretical innovation with practical impact

Supplementary material and/or additional information [OPTIONAL]

None

Ethics statements

No data was collected from any social media platforms.

CRediT author statement

Raghavendra M Devadas: survey of previous works, conceptualization, **Sowmya T:** editing, reviewing, diagrams.

Declaration of competing interest

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

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