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Quantum Machine Learning (QML): Variational Classifiers, Quantum Kernels and Hybrid Architectures

Sunish Vengathattil *

College of Business & Information Systems, Dakota State University, Madison, SD 57042 USA.

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Abstract

Quantum machine learning (QML) is an emerging interdisciplinary field which incorporates some features of quantum computing with machine learning. Quantum hardware development has sparked research interest for AI scientists because it gives capabilities in high-dimensional data processing and simultaneous operation execution. The investigation within this paper traces the main features of QML by reviewing variational quantum classifiers (VQCs) as well as quantum kernels and hybrid quantum-classical models. VQCs serve as quantum parameterized circuits whose optimization process with classical feedback achieves quantum superiority for classification applications. Quantum kernels expand Hilbert space features to improve traditional kernel methods, thus proving their functionality in quantum feature space. Hybrid approaches unite NISQ hardware with classical systems, which makes QML applicable to real-world applications right now. (Rietsche et al., 2022; Tychola et al., 2023) An analysis explores separate functions and combined effects of these components, which enhance model performance, extend generalization, and boost computational efficiency. The paper discusses necessary knowledge first, along with existing applications, before analyzing them against traditional methods. The paper reviews current QML tools while exploring their operational readiness as well as practical issues and deployment barriers for broader adoption. The paper conducts an in-depth investigation of significant limitations that include hardware noise alongside questions regarding scalability and interpretability. This paper shows how QML will transform machine learning applications through its review of obstacles that must be resolved to achieve its complete potential development. The study presents researchers and practitioners with an extensive comprehension of QML developments and emerging paths for this revolutionary field.

Keywords: Quantum Computing; Machine Learning; Quantum Machine Learning; Variational Quantum Classifiers; Hybrid Quantum-Classical Models

1. Introduction

Breakthroughs have been achieved by classical ML across fields like image recognition, natural language processing, etc. Using huge information and improved PCs like neural systems help vector machines, and pack strategies, ML frameworks are great at example acknowledgment and prediction (Ian Jamesiasch, Patrick Zschech, and Lars Heinrich, 2021). As datasets and model complexities grow exponentially, classical resources have too much of a challenge. Training deep models (as high dimensional parameters) and processing the massive dataset within reasonable time limits are bottlenecks (Paleyes, Urma, & Lawrence, 2022). As a result of these computational limitations, researchers have pursued alternatives with the hope of providing exponential speedups and solving intractable problems on classical systems.

Quantum computing (QC) is a rapidly developing area in which the way of computation is fundamentally different. Classical bits are used to represent the '0 or 1' type of values, but quantum bits (qubits) can exist in the superposition

* Corresponding author: Sunish Vengathattil

of both states at the same time. Quantum entanglement, which is an intrinsic correlation between the qubits and quantum interference, allows for a unique form of parallelism, and with the help of some algorithms, one can solve the problem faster than one's classical counterpart (Hassija et al., 2020). The quantum advantage in factoring and searching has been proved in theory by notable quantum algorithms, such as Shor's and Grover's. Taking these principles further, there has been substantial interest in marrying quantum computing with ML, which has become a very promising frontier of research. The area at the junction of quantum computing and artificial intelligence is thus known as Quantum Machine Learning (QML). The goal is to take advantage of quantum hardware and quantum algorithms for greater efficiency and expressiveness of machine learning models as well as better performance in prediction. Some variational quantum classifiers are found (Blance & Spannowsky, 2021), quantum kernels to be used as support vector machines (Jäger & Krems, 2023), and hybrid quantum/classical models that stack quantum subroutines on top of classical processing (Brunken & Reiher, 2021; He et al., 2023a).

The motivation for QML lies in both theoretical promise and the increasing availability of quantum hardware. This shift follows the introduction of Noisy Intermediate-Scale Quantum (NISQ) devices; three orders of magnitude that promise 50 ~ 100 qubits yet still suffer from noise, and emphasize near-term applications that can tolerate noise (Claudino, 2022). Such developments are already being realized in QML, with early theoretical explorations anticipating that these topics should reveal themselves once NISQ systems can be operated, and yet it is the appearance of NISQ systems that takes QML from a theoretical concept to an experimentally testable area (Motta & Rice, 2022; Lubinski et al., 2023). We also discuss the challenges in scaling a quantum model (Kottahachchi Kankanamge Don et al., 2024; Metawei et al., 2023), generalizing the model, and deploying the model.

QML is the main perspective that lies at the intersection of two computational trends: the quantum processor (QP) brings new computational strengths, and the amplitude of ML is imbued with data dependency, both of which together may redefine how we do learning from data, an approach that is more data driven, and, therefore more computation than intelligent.

2. Quantum computing fundamentals for qml

An entirely new information processing paradigm is introduced by quantum computing through the use of principles of quantum mechanics for the representation and manipulation of data that classical computers cannot access. In the case of Quantum Machine Learning (QML), to understand the mechanisms supporting QML, it is necessary to understand more deeply how quantum systems, e.g., quantum gates, circuits, and their computational peculiarities, behave. These concepts provide new ways of improving the properties of learning models, increasing computational capacity, and addressing problems previously thought to be intractable to classical methods.

2.1. Quantum Gates, Circuits, and Measurement

Classical bits, physical bits that are 0 or 1, can exist in a superposition between themselves – e.g., 0 and 1 simultaneously. Quantum gates implement reversible unitary transformations (such operation) to achieve and manipulate this characteristic. The Hadamard gate, analogous to the Z gate, creates an equal superposition, the Pauli X gate (a NOT gate counterpart) and the CNOT gate (or controlled-NOT gate) that entangles two states.

Quantum operations are performed on a qubit register in a sequence, which is represented by a combination of such gates in quantum circuits. These circuits, especially variational quantum circuits (VQCs) are the basis of many models including variational quantum classifiers (Blance & Spannowsky, 2021), the success of quantum algorithms; in particular, QML. Measurement is the final operation in a circuit collapsing the qubit state to the classical value (either 0 or 1) (the probability of which is dependent on the amplitude of the qubit before measurement) (Bardin, Slichter, & Reilly, 2021).

Table 1 Common Quantum Gates and Their Functions

Gate	Symbol	Function	Example Use
Hadamard	H	Creates superposition	Initializes qubits
Pauli-X	X	Bit-flip	Acts like NOT gate
CNOT	CX	Entangles qubits	Used in quantum circuits

2.2. Quantum Circuit Complexity and Computational Advantage

Depth (number of gate layers) and width (number of qubits used) are the means for evaluating quantum circuits. The computational complexity of the algorithm and its feasibility in being implemented on current quantum hardware depends on these parameters. Although there are many examples where quantum circuits provide a computational advantage over equivalent classical circuits, e.g., when the output state is specified by an NP-complete problem, a primary motivation for using quantum circuits for machine learning tasks is a possibly forthcoming point in time, quantum advantage, where the quantum algorithm outperforms any (known) classical algorithm in terms of, perhaps computational or communication runtime, or resource efficiency.

Similarly, theoretical speedups in QML have also been derived from algorithms such as Shor's algorithm for factorization and Grover's search algorithm (Lubinski et al., 2023). Variational quantum models execute a parameterized quantum circuit combined with classical gradient descent or other similar optimization techniques (Miyahara & Roychowdhury, 2022). In so doing, this hybrid approach makes better function approximation than deep neural networks with fewer parameters.

2.3. Quantum Parallelism and Interference: Implications for ML

Superposition allows a quantum computer to execute a quantum parallelism and process an immense number of input states at the same time. In the case of a VQC, a qubit can represent many states at the time of initialization, so quantum gates act on these states from exponentially large Hilbert space. This allows quantum models to be supplied access to features and patterns that are invisible or too costly to calculate classically (Jäger & Krems, 2023).

Quantum interference also guarantees that desirable computational paths support each other and that erroneous paths are wiped out. This is crucial for amplifying correct classifications in quantum models, such as support vector machines and neural networks with quantum enhancements (Gupta et al., 2023). Parallelism and interference, together, constitute the source of the expressive power of quantum models and their ability (in principle) to outperform their classical counterparts in problems with high dimensional and structured data.

2.4. Challenges in Quantum Computation

Theoretical benefits are substantial, but quantum computing is far from easy to practice. Related problems that are chief among them include decoherence the loss of quantum properties of a quantum system due to interaction with the environment. However, the slightest noise can collapse a qubit's state early, which is extremely hard to overcome when keeping computations along long circuits (Hassija et al., 2020). Therefore, there is a need for quantum error correction (QEC), which encodes the logical qubits into several physical qubits for noise protection. However, the use of QEC brings substantial overhead. Due to short coherence windows and shallow circuits, most of quantum algorithms (including QML models), must be implemented on today's noisy intermediate scale quantum (NISQ) devices within short coherence windows and use shallow circuits (Brunken & Reiher, 2021; He et al., 2023b).

Therefore, hybrid quantum-classical models are currently the most accessible ones. The models referred to these as quantum circuits for parts of the computation (e.g., feature encoding, kernel evaluation, or sampling) and classical processors for optimization and decision (Metawei et al., 2023).

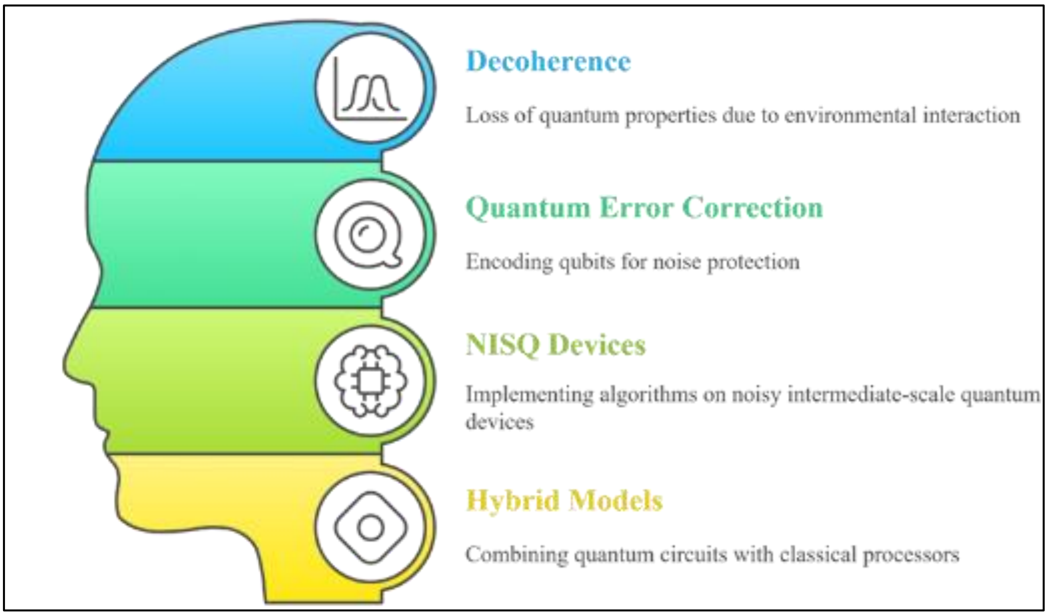

Figure 1 Overcoming Challenges in Quantum Computing

2.5. The Quantum Software and Hardware Ecosystem

In recent years, the quantum computing ecosystem has seen great advances across hardware and software platforms to aid the research and deployment of QML in the real world. Major players include:

- Quantum programming on superconducting qubit-based machines provided by IBM Q
- Forest SDK and quantum hardware will be provided by Rigetti Computing through the cloud.
- Their use of trapped ion technologies that should have longer coherence times;
- Xanadu is focused on photonic quantum computing, with its specific aim being to develop and supply the PennyLane library, which focuses on quantum machine learning (Claudino, 2022; Chen & Yoo, 2021).

Some of these tools enable the development of VQCs, quantum kernels, quantum neural networks, and integrate with classical ML libraries such as TensorFlow and PyTorch. In particular, gradient based optimization on quantum circuits is available directly in PennyLane, making it well suited for training variational models in QML.

Table 2 Quantum Data Encoding Strategies

Encoding Method	Description	Qubits Required	Advantages	Limitations
Angle Encoding	Maps features to qubit rotation	O(n)	Simple and hardware-friendly	Limited feature entanglement
Amplitude Encoding	Encodes data in state amplitudes	O(log n)	Efficient representation	Complex state preparation
Basis Encoding	Direct binary mapping to qubit state	O(n)	Intuitive interpretation	Low information density per qubit

3. Core QML techniques: VQCS and quantum kernels

3.1. Variational Quantum Classifiers (VQCs)

Variational Quantum Classifiers (VQCs) are a prominent class of hybrid algorithms at the heart of quantum machine learning, which requires quantum computing to solve a problem that can be assisted by classical optimization. Parametrized quantum circuits (PQCs) are parametrized by tunable parameters of quantum gates. A classical feedback loop optimizes these parameters to minimize a task-specific cost function (Miyahara & Roychowdhury, 2022).

Encodings of classical input data into quantum states using a data embedding scheme (generally amplitude or angle encoding) form part of the general workflow of a VQC. The second part of this thesis involves the application of a parametrized quantum circuit to transform the encoded input into a representation that separates the data classes. Based on the measured output, the probabilities are used to compute a cost function, which will usually be cross-entropy or mean squared error and minimized using gradient-based or gradient-free optimizers (Tanwar, 2024) (Maheshwari et al., 2022).

Table 3 Comparison of VQCs vs Classical Classifiers

Feature	VQC (Quantum)	Classical Classifiers
Model Type	Parametrized quantum circuit	SVM, Logistic Regression, etc.
Data Encoding	Quantum feature maps (angle, etc.)	Vectorized feature arrays
Optimization Process	Hybrid quantum-classical loop	Gradient descent or similar
Computational Demand	Requires quantum simulator/hardware	Fully classical
Expressiveness	Potentially exponential	Depends on kernel/architecture

Barren plateaus regions of vanishing gradients are prevalent in the training process of VQCs (Miyahara & Roychowdhury, 2022). Recently, attempts have been made to address this problem with better circuit architectures and initialization schemes (Kottahachchi Kankanamge Don, Khalil, & Atiquzzaman, 2024). Furthermore, the approach of measurement strategy and cost function for modeling indoor navigation also affects the convergence and generalization of the model (Maheshwari, Sierra-Sosa, & Garcia Zapirain, 2022).

VQCs have promise from the performance standpoint, which has been demonstrated in tasks on synthetic datasets and domain-specific applications. For example, Maheshwari, Garcia Zapirain, and Sierra Sosa (2022) conducted a systematic review and concluded that some VQCs outperformed certain classical relatives in small data sets. Rather similarly, variational classifiers have been used in high energy physics for event classification tasks, obtaining similar accuracy to more classical models at the price of working in a smaller, more compact representation of the features (Blance & Spannowsky, 2021). One particularly relevant case study is implementing a VQC to distinguish real and synthetic datasets. Here, the classifier was trained to generalize across data distribution using fewer training samples than a classical model would need and driven by the expressiveness of the quantum circuit (Maheshwari, SierraSosa, and GarciaZapirain, 2022). Moreover, VQCs are inherently quantum objects that work with exponentially large Hilbert spaces and can project the inputs onto higher dimensional spaces more efficiently than classical deep networks (Jäger & Krems, 2023).

However, implementation of VQCs in real world is still limited by the hardware limitations (qubit decoherence and also noise). These factors limit the depth and expressivity of circuits which may be run on present NISQ devices (Lubinski et al., 2023). Therefore, the research direction of developing the error resilient VQC architectures still remains critical.

3.2. Quantum Kernels and Feature Space Expansion

Kernel methods are the foundation of classical machine learning and are present in such well-known algorithms as the Support Vector Machines (SVMs), which make use of implicitly mapping the input space to higher dimensionality feature space. The kernel function itself computes the inner product between data points after being transformed by said function, which is the so-called kernel trick.

Quantum-enhanced kernels push this idea further by using quantum circuits to accomplish the mapping. In particular, input vectors are encoded into quantum states, and a quantum feature map is used. The quantum kernel is the fidelity between quantum states, which is the inner product between the quantum states (Jäger & Krems, 2023). It enables the computation of similarities in exponentially large Hilbert spaces, with a potential quantum advantage, for separating complex data distributions.

The kernel matrix is constructed by estimating fidelities between all pairs of inputs through a Quantum Kernel Estimation (QKE) protocol, and hence, quantum kernels are typically evaluated this way. Then these matrices are fed to classical kernel-based classifiers (SVMs, Blance & Spannowsky, 2021). The authors Jäger and Krems (2023) demonstrated that quantum kernels can achieve universality in which they can represent a variety of decision borders with a shallow quantum circuit. However, in the past, quantum kernel methods have been investigated in the case of high-energy physics, where traditional feature engineering is computationally expensive. However, the work of Guan et al. (2021) has shown that a process similar to this could be automated with the assistance of QML techniques, such as quantum kernels, to improve classification performance in particle ID tasks. The same is the case for quantum kernel methods in the biomedical domain using binary classification problems with small to medium data sets (Maheshwari, Garcia-Zapirain, & Sierra-Sosa, 2022).

Furthermore, similarity matrices are also central to unsupervised learning tasks, and quantum kernels have the potential in such tasks, e.g., clustering. The less explored notion is that early stage research shows how quantum enhanced similarity metrics can improve clustering algorithms with a better representation of complex dataset latent structure (Metawei et al., 2023). Although these have the advantage, there are also some limitations to be recognized. Quantum kernel methods are not scalable in large datasets, all pairwise fidelities are impossible to estimate in reasonable time due to exponential growth in the computations, as well as the limited coherence time of quantum computers (Lubinski et al., 2023). Additionally, quantum feature maps are not very interpretable. Since quantum kernels act in somewhat abstract spaces, it is hard to have intuition with regard to the model behavior, unlike classical kernels that have custom basis functions (RBF and polynomial kernels) (Roscher et al., 2020; Rudin et al., 2022) (Paleyes, Urma, & Lawrence, 2022).

In order to counter these issues, hybrid strategies are being designed based on complementarity between quantum feature extractors and classical post-processing. These achieve partial quantum advantage with proxy use of classical resources for kernel PCA or model explanation (Brunken & Reiher, 2021). On the other hand, the use of parameterized quantum feature maps (which are in this form reminiscent of the VQCs) is receiving attention as a tool that can be used in different problem domains.

Thus, VQCs and quantum kernels are two of the most mature and theory-backed approaches in quantum machine learning today. Quantum kernels utilize data embedding into a rich, high-dimensional space with the goal of exploiting structural differences, while VQCs train quantum circuits as trainable models with classical techniques. The merits of both approaches demonstrate that the future of QML lies in hybrid quantum-classical architectures and shows the promise of future QML use cases to solve intractable problems on classical methods and, in particular, problems of low data and high complexity.

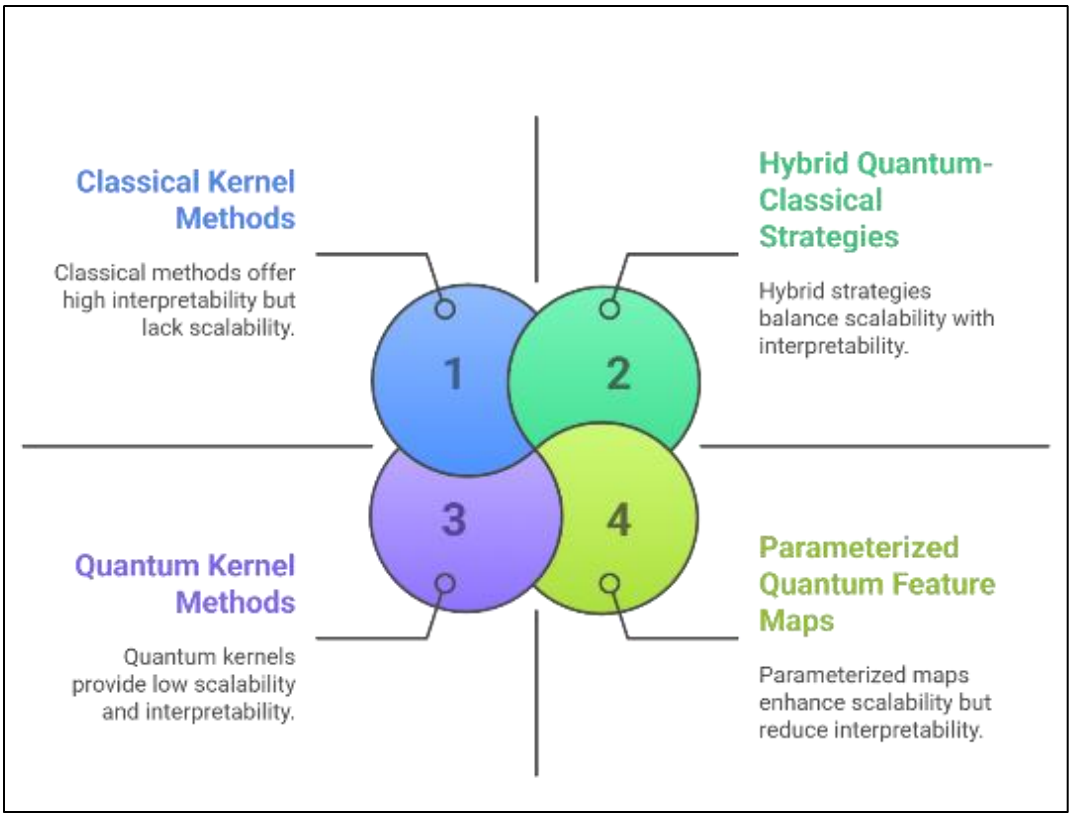

Figure 2 Quantum Kernel Methods in Machine Learning

4. Hybrid quantum-classical architectures

With the onset of the Noisy Intermediate-Scale Quantum (NISQ) era of quantum computing, where it suffers from limited qubit counts and imperfect quantum gates, hybrid quantum-classical architectures are emerging as an agile approach to benefit quantum advantage with the constrained hardware (Burić et al., 2013; Brunken & Reiher, 2021). They consist of quantum computing subroutines located strategically within classical workflows so that tasks like learning, optimization, and simulations can be carried out for quantum system design without fault-tolerant quantum systems.

4.1. Architectural Design: Embedding Quantum Layers

In the hybrid architectures, quantum layers appear as part of the classical neural network models. Parameterized quantum circuits (PQCs) can be constructed to act as parameterized trainable modules that can be used as quantum layers. In training, classical optimization algorithms are used to optimize (i.e., adjust) the parameters of the quantum circuit using gradients (or loss feedback). This is another variational quantum algorithm (VQA) (Miyahara & Roychowdhury, 2022; Kottahachchi Kankanamge Don et al., 2024).

An example of such approach is Quantum Neural Networks (QNNs). Quantum circuits are sandwiched between classical pre-processing and post-processing stages in order to build them. It has been shown that a subclass of QNNs, notably the variational quantum classifier (VQC), is promising in classification task by optimizing a cost function defined over quantum measurements (Blance & Spannowsky, 2021; Maheshwari et al., 2022).

The other important approach is the Quantum Approximate Optimization Algorithm (QAOA), which solves combinatorial optimization problems by combining quantum evolution with classical parameter updates. However, QAOA is most applicable for optimization problems in which classical heuristics are not scalable or sufficiently accurate (Lubinski et al., 2023).

4.2. Real-World Applications

Hybrid quantum-classical systems have already been applied to several domains. QNNs have been applied to image recognition where low dimensional images e.g., MNIST digits have been classified with very good accuracy, yet they are able to capture data structure that classical models may miss (Senokosov et al., 2024) (He et al., 2023a). To encode textual data into quantum state (quantum encodings), natural language processing (NLP) has explored hybrid models that operate the semantic PQC based transformations (Metawei et al., 2023).

Of all the hybrid methods, none have had more impact on quantum chemistry. Hybrid quantum classical treatment of lithium ion transfer reactions at graphite electrolyte interface has provided new insights at the atomic level to the battery performance (He et al., 2023b). Likewise, the electrostatic effects simulations conducted in quantum dots using hybrid models have resulted in higher accuracy than what purely classical models have obtained (Liu et al., 2017).

There has also been potential in quantum–classical fusion for healthcare. Consequently, in these studies, Gupta et al. (2023) argue that hybrid quantum models could drastically improve diagnostic accuracy and efficiency in the post-COVID-19 healthcare ecosystem by accelerating the computational complexity of complex pattern recognition tasks that overwhelm current classical systems.

4.3. Tools and Frameworks

Several open-source frameworks have appeared to support research and development in QML. Qiskit Machine Learning (IBM developed) provides a means to construct and run quantum circuits within scikit learn pipelines. The Xanadu created PennyLane is an API that allows quantum layers to work with classical machine learning toolkits such as PyTorch and TensorFlow. Automatic differentiation is required for training hybrid models, and it supports that (Brunken & Reiher, 2021).

Google develops TensorFlow Quantum (TFQ), which brings quantum computing to the TensorFlow ecosystem and empowers researchers to compose quantum enhanced machine learning applications quite easily. This abstracts much of the difficulty of quantum circuit design so that a broader range of quantum design participants from the classical ML community can participate (Claudino, 2022).

4.4. Benchmarking Against Classical Models

Performance benchmarking is, without a doubt, one of the critical concerns in the hybrid QML landscape. Tasks of classification, regression, and clustering have been performed using classical deep-learning counterparts and compared to QML models in comparative studies. Although, at the current quantum scales, hybrid models do not generally outperform classical models, it is shown that they generalize well on specific synthetic datasets and have potential advantages in learning entangled data distributions (Maheshwari et al., 2022; Jäger & Krems, 2023).

Lubinski et al. (2023) proposed application-oriented benchmarks that factor in both quantum hardware limitations and end-task performance. The importance of utilizing practical evaluation metrics for comparing quantum and classical models is emphasized, due to such metrics being defined by metrics such as accuracy-per-runtime and parameter efficiency.

Hybrid models are close to the hardware bottlenecks, and are attempting to push the modern boundaries. With increasing capabilities of quantum hardware, these hybrid frameworks are on their way to leap from experimental tools to practical solutions for any field from drug discovery to logistics to finance.

5. Current limitations and future directions

Yet, as QML have been rapidly progressing, many technical and theoretical barriers stand in the way of practical deployment. Three major classes contributing to these problems are hardware limitations, algorithmic constraints, and societal issues that have not been fully addressed. Still, there is emerging research that provides directions to achieve scalable and impactful learning with quantum enhancement.

5.1. Practical Barriers

The primary limitation of QML is the existing QML hardware. Currently, most quantum devices are in the Noisy Intermediate Scale Quantum (NISQ) era, with very few qubits and lots of gate noise (Hassija et al., 2020). Are variational quantum classifiers (VQCs) potential in the small dataset? However, variational quanta classifiers (VQCs) are generally restricted by decoherence and circuit depth limitations inhibiting scalability (Ur Rasool et al., 2023) (Blance & Spannowsky, 2021; Miyahara & Roychowdhury, 2022). Encoding classical data into quantum states—namely quantum feature mapping—is computationally expensive and can even be unfavorable if not optimized properly (Jäger & Krems, 2023).

A workaround to hardware limitations has been to delegate part of the computation to classical processors via hybrid quantum classical models. Nevertheless, these systems also exhibit bottlenecks when it comes to data transfer latency and circuit training overhead (He et al., 2023) a, Brunken and Reiher, 2021). Finally, the classical interface presents itself as an expensive, complex to scale object. (Verbraeken et al., 2020)

5.2. Algorithmic Limitations

QML is very much in its infancy algorithmically. While quantum models are typically highly problem-specific, classical machine learning is a developed research area with tens of years of development time and an assortment of general-purpose algorithms that can be readily repurposed as needed by any problem. Despite their popularity, variational methods are heuristic and have heuristic guarantees of convergence and generalization (Maheshwari et al., 2022; Lubinski et al., 2023). Furthermore, there are no standard benchmarks to evaluate quantum learning models between tasks (Lubinski et al., 2023).

In addition, while QML algorithms are complex to trust, most of them are still not very robust to noise and variation of input data (Chen & Yoo, 2021; Bardin et al., 2021). Thus, these algorithms are complex to adapt to in mission-critical domains like finance or even healthcare without further theoretical validation.

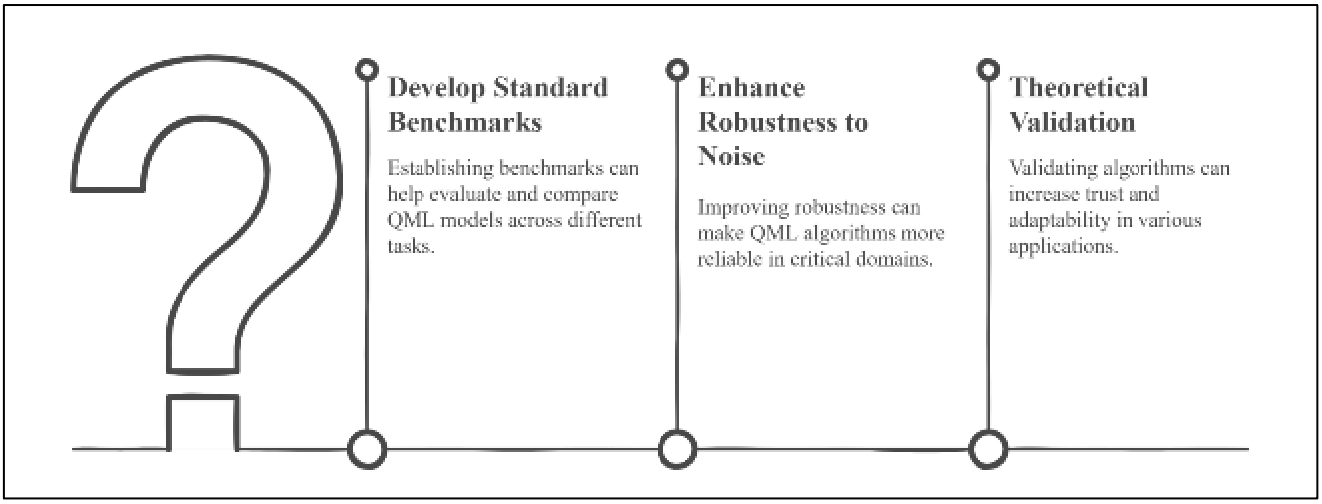

Figure 3 How to address the limitations of QML algorithms?

5.3. Emerging Research and Theoretical Opportunities

Despite these, research has been speedy. Lastly, there are new studies that proposed noise-resilient quantum circuits and adaptive learning algorithms that promote accuracy in the presence of noise (Metawei et al., 2023). The quantum advantage threshold, i.e., the point where the QML algorithm is more beneficial in practice than its classical counterpart (Kottahachchi Kankanamge Don et al., 2024), is also under active investigation. Co-design approaches to hybrid quantum-classical architectures that jointly optimize their quantum and classical components for better performance are becoming more complex (He et al., 2023b).

QML could look forward transform fields of large scale computations like drug discovery, materials science or cryptography. Such as, quantum enhanced models can perform molecular interaction models with greater precision than classical counterparts (e.g. Motta & Rice, 2022; Claudino, 2022). Hybrids could fill a gap between data driven inference at real time and numerical simulation in scientific computing (Liu et al., 2017).

5.4. Societal Implications

The deployment of QML also raises significant societal questions. Now that quantum systems have started to be used in AI workflows, data privacy, algorithmic transparency, and equitable access to technology have become related matters of immediate importance. One way to obtain better privacy while still performing well at learning is to change how data processing is performed by moving it to the edge where data is generated (federated quantum learning), such as in Chen and Yoo (2021). Next, access to these quantum computing resources is currently limited but only accessible to elite institutions and corporations, which widens the technological divide (Gupta et al., 2023).

The ethical use of powerful quantum-enhanced AI requires a large degree of prudence in avoiding unintended consequences of the AI and a preemptive resolution towards algorithmic bias and the governance of autonomous systems.

Table 4 Challenges in Quantum Machine Learning and Potential Solutions

Challenge	Description	Impact	Possible Solutions
Hardware Noise	Qubit decoherence	Reduces accuracy	Error correction
Scalability	Limited qubit count	Affects model size	Modular hardware
Interpretability	Hard to decode quantum decisions	Trust issues	Hybrid models for transparency

6. Conclusion

At the core of Quantum Machine Learning (QML) there are pivotal components such as variational quantum classifiers (VQCs), quantum kernels, and hybrid quantum-classical architectures. In tasks of high dimensional data as well as complex pattern recognition tasks, these models are potentially superior compared to classical algorithms (Jäger & Krems, 2023; Miyahara & Roychowdhury, 2022; Brunken & Reiher, 2021). Specifically, VQCs are promising since they are feasible with near-term quantum devices and also can be optimized with classical feedback communication loops. The theoretical underpinnings of QML are very compelling, but learning QML is a complex problem. However, scalability and error correction are limited by current qubit counts, gate fidelity, and decoherence times (Lubinski et al., 2023; Hassija et al., 2020). Despite the above, QML is starting to show some promising demonstrations in specific use cases during the NISQ era, such as particle physics (Blance & Spannowsky, 2021), quantum chemistry (Motta & Rice, 2022), and biomedical applications (Maheshwari, Garcia-Zapirain, & Sierra-Sosa, 2022).

Interdisciplinary collaboration plays a very crucial role in the advancement of QML (Paleyes, Urma, & Lawrence, 2022). Collaboration on these efforts is crucial to guide the use of quantum feature encodings to optimality, enhance model interpretability, and remove engineering constraints. Despite the fact that QML is a maturing program, its path towards quantum advantage in machine learning is still plausible. Using prolonged innovation, QML can realize prodigious theoretical breakthroughs and hone efforts in cross disciplinary engagement in order to break the intellectual boundaries to what we can accomplish using intelligent systems.

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