Quantum circuit-based learning models: bridging quantum computing and machine learning

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Abstract
Machine Learning (ML) has been widely applied across numerous domains due to its ability to automatically identify informative patterns from data for various tasks. The availability of large-scale data and advanced computational power enables the development of sophisticated models and training strategies, leading to state-of-the-art performance, but it also introduces substantial challenges. Quantum Computing (QC), which exploits quantum mechanisms for computation, has attracted growing attention and significant global investment as it may address these challenges. Consequently, Quantum Machine Learning (QML), the integration of these two fields, has received increasing interest, with a notable rise in related studies in recent years. We are motivated to review these existing contributions regarding quantum circuit-based learning models for classical data analysis and highlight the identified potentials and challenges of this technique. Specifically, we focus not only on QML models, both kernel-based and neural network-based, but also on recent explorations of their integration with classical machine learning layers within hybrid frameworks. Moreover, we examine both theoretical analysis and empirical findings to better understand their capabilities, and we also discuss the efforts on noise-resilient and hardware-efficient QML that could enhance its practicality under current hardware limitations. In addition, we cover several emerging paradigms for advanced quantum circuit design and highlight the adaptability of QML across representative application domains. This study aims to provide an overview of the contributions made to bridge quantum computing and machine learning, offering insights and guidance to support its future development and pave the way for broader adoption in the coming years.

Keywords Quantum computing · Machine learning · Quantum circuit · Parameterized quantum circuit

Abbreviations

AE	Autoencoder
BP	Barren Plateau
CNN	Convolutional neural network
EO	Earth observation
FRQI	Flexible representation of quantum images
FQK	Fidelity quantum kernel

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GAN	Generative adversarial network
GNN	Graph neural network
GPU	Graphical processing unit
HPC	High-performance computing
Last-QGAN	Latent-style quantum generative adversarial network
MLP	Multilayer perceptron
MPS	Matrix product states
ML	Machine learning
NN	Neural network
NISQ	Noisy intermediate-scale quantum
PQC	Parameterized quantum circuit
PCA	Principal component analysis
PQK	Projected quantum kernel
QML	Quantum machine learning
QC	Quantum computing
QNN	Quantum neural network
QSVM	Quantum support vector machine
QKE	Quantum kernel estimation
QEK	Quantum embedding kernel
QCNN	Quantum convolution neural network
QGAN	Quantum generative adversarial network
QCBM	Quantum circuit born machine
QRNN	Quantum recurrent neural network
QAE	Quantum autoencoder
QGNN	Quantum graph neural network
QDNN	Quantum deep neural network
QViT	Quantum vision transformer
QDM	Quantum diffusion model
QBNN	Quantum Bayesian neural network
QNAS	Quantum neural architecture search
QFL	Quantum federated learning
RS	Remote sensing
RNN	Recurrent neural network
SVM	Support vector machine
ViT	Vision transformer
VQE	Variational quantum eigensolver
VQA	Variational quantum algorithm

1 Introduction

Machine Learning (ML), a field of artificial intelligence, focuses on algorithms that can learn patterns from data to perform different tasks. Deep learning, a subfield of machine learning, enables models to automatically identify patterns and relationships within complex data, thereby reducing or eliminating the need for manual feature engineering across various tasks. To date, by leveraging advances in computational power and the availability of large datasets, this technology has been applied to numerous scientific fields and transformed real-world applications across diverse domains, as reviewed in earth observation (Zhu et al. 2017), finance (Ozbayoglu et al. 2020), and healthcare (Esteva et al. 2019). The large amount of available data and the rapid growth of computational capacity offer great opportunities to develop sophisticated models that achieve state-of-the-art performance. However, they also pose substantial challenges and have attracted increasing attention from both scientists and information technology experts (Najafabadi et al. 2015; Hu et al. 2021), as such models often demand considerable computational resources. The study by Thompson et al. (2020) concluded that the gain in computing power is actually central to performance improvements, which has historically been driven by the dimensional scaling of silicon-based transistors. However, as transistors approach their physical and technological limits, this trend has begun to decelerate (Waldrop 2016). To compensate for the weakening growth of computing resources over time, High-Performance Computing (HPC) is increasingly moving towards heterogeneous hardware, including Graphical Processing Units (GPUs), among others. This has, in turn, accelerated the convergence of HPC and ML workflows, and has also fostered the exploration of new classes of accelerators, including quantum.

Quantum Computing (QC), an emerging field, has received growing attention for its potential to accelerate certain computational tasks according to computational complexity theorems, as discussed in Arora and Barak (2009). This computation paradigm leverages quantum mechanisms, such as superposition and entanglement, to process information in fundamentally different ways from classical computing, which could offer benefits in various fields, including machine learning tasks. Specifically, there are two major models for quantum computation: quantum gate computing and adiabatic quantum computing. The former, known as the basis of universal quantum computing, relies on the quantum circuit model, performing computation through a sequence of quantum gates, whereas the latter, primarily applied for optimization, is based on the adiabatic theorem to carry out computation. However, current quantum devices face several constraints, such as limited available qubits and noise effects, which introduce significant challenges to their practical implementation. Nevertheless, note that the development of quantum computing, encompassing technologies from hardware infrastructures to software algorithms, has attracted significant global investment from governments, organizations, and private investors, as discussed in Otgonbaatar et al. (2023).

Quantum Machine Learning (QML), the integration of quantum computing and machine learning, has garnered increasing interest in addressing the aforementioned challenges, with a notable rise in studies in recent years, as techniques from one field offer the potential to overcome limitations in the other. In this study, we mainly focus on the benefits and limitations of using quantum computing for machine learning tasks. Nevertheless, for completeness, it is worth noting that numerous valuable studies have explored the converse direction, leveraging machine learning techniques to advance quantum computing, such as Zlokapa and Gheorghiu (2020); Muqeet et al. (2024a, 2024b); Quetschlich et al. (2025). Instead of covering all quantum computing models and QML algorithms, we focus on quantum gate computing, and our aim is to deepen the understanding of its potential and limitations for machine learning tasks on classical data by examining existing research and to provide insights and guidance on QML applications both in the near term and when fault-tolerant, large-scale quantum computers become available in the future.

For quantum circuit-based machine learning, a hybrid framework known as Parameterized Quantum Circuit (PQC) is widely adopted, consisting of a sequence of quantum gates with trainable parameters optimized during training using classical algorithms. One of the motivations for introducing PQC is its use within the he Variational Quantum Algorithm (VQA), which in turn is necessary as a tool to exploit present-day quantum devices and keep quantum circuits shallow (see Qi et al. (2024) for a recent review). The interplay between the classical and quantum components in the variational algorithms is also at the core of the integration efforts of quantum computing within heterogeneous HPC (Schulz et al. 2021).

Thus, the design of the PQC plays a crucial role in determining both its efficiency and effectiveness in machine learning tasks. To date, there are two fundamental types of QML: kernel-based and neural network-based approaches. The former aims to map the data into a high-dimensional Hilbert space using PQCs to uncover complex relationships within the data for further analysis, whereas the latter is expected to automatically extract informative features with PQCs for target tasks. Numerous QML models, along with several variants, have been developed in both categories. In addition to the discussion of quantum circuit design for data analysis, we also explore the use of quantum circuits to represent various types of classical data, since the choice of quantum circuits for data embedding not only affects the validity of the subsequent feature extraction but also influences the overall complexity of QML models. As widely observed, most proposed QML models employ a hybrid framework that generally integrates quantum and classical layers, potentially leveraging their complementary strengths while addressing the limitations of current quantum devices. In this study, we discuss and summarize existing hybrid architectures from different perspectives: the contribution of the quantum component within QML models, the scale of its input, and its position in the overall processing pipeline, with which we aim to structurally demonstrate the current exploration of hybrid QML structures and provide insights for the development of more effective integration strategies.

Additionally, we also collect the studies revealing the capabilities of circuit-based learning models, including expressivity, learnability, and generalizability, aiming to summarize existing theoretical analyses of QML model performance and highlight factors that may influence these capabilities. The observed advantages of QML based on empirical evaluations using simulators or real quantum devices with real or synthetic data are also provided as complementary. To assess the near-term practicality of QML, we examine studies addressing the current constraints of quantum devices. In particular, we discuss contributions to noise-resilient QML and hardware-efficient QML, which offer guidance for its practical applications in the near future. Moreover, we also cover several emerging paradigms for advanced quantum circuit design, such as circuit interpretability, circuit structure optimization, and circuit distribution.

To further understand the potential of QML and its adaptability across various domains, we highlight investigations in three representative domains: earth observation, healthcare, and finance, demonstrating the application of QML. Finally, building on insights from existing contributions, we propose research directions that could deepen our understanding of QML models and offer feasible solutions across a wide range of applications in the Noisy Intermediate-Scale Quantum (NISQ) era.

Several existing surveys have reviewed recent developments in QML from different perspectives (Cerezo et al. 2022; Wang and Liu 2024; Zaman et al. 2023; Peral-García et al. 2024; Lamichhane and Rawat 2025). However, recent progress in quantum circuit-based learning, particularly in learning capacity analyses, model design principles, emerging design paradigms, and practical deployment considerations, has received comparatively less attention. Motivated by this, we review existing contributions to quantum circuit-based learning models, synthesize their design principles, discuss their reported benefits and remaining challenges, aiming to provide insights and guidance for future studies and to pave the way for broader adoption both in the near term and longer term when large-scale, fault-tolerant quantum devices become available. This paper is organized as follows:

- Sect. 2 introduces the basic principles of quantum computing, core concepts of circuit-based learning, and an overview of available quantum devices and software.
- Sect. 3 presents existing quantum circuit structures for learning tasks, including circuits for encoding different types of data as well as circuits for kernel-based learning and neural network-based learning purposes.
- Sect. 4 particularly focuses on hybrid QML models and summarizes its design patterns from three different perspectives.
- Sect. 5 discusses and highlights the capabilities, limitations, and practicality of quantum-circuit learning models.
- Sect. 6 introduces some emerging paradigms in quantum circuit design, covering interpretability, circuit optimization, and distributed circuit design.
- Section 7 summarizes the design guidelines for quantum circuit-based learning.
- Section 8 covers the applications of QML in six representative domains.
- Sect. 9 provides an outlook on future work.

2 Background

2.1 Quantum computing

Quantum computing is a computational paradigm that harnesses principles of quantum mechanics to process information in fundamentally different ways than classical computing. Its basic unit, the quantum bit (qubit), exhibits special phenomena such as superposition and entanglement, enabling novel computational capabilities. These properties have the potential to provide computational advantages in solving certain problems with respect to the corresponding classical algorithms, particularly in areas like optimization and machine learning.

2.1.1 Qubits and their properties

The qubit, analogous to a classical bit, also has two distinguished basis states (e.g., $|0\rangle$ and $|1\rangle$), which are orthonormal and hence are linearly independent, as represented in Eq. (1).

$$|0\rangle = \begin{bmatrix}1\\0\end{bmatrix} \quad and \quad |1\rangle = \begin{bmatrix}0\\1\end{bmatrix} \tag{1}$$

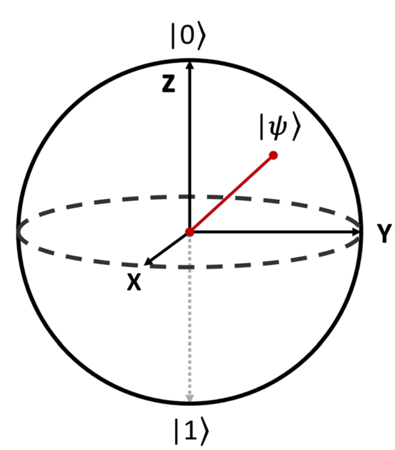
The state of a qubit exists in a two-dimensional Hilbert space and can be expressed as a linear combination of its basis states (phenomenon known as superposition), as described in Eq. (2), where the coefficients α and β are complex numbers that represent the amplitudes of the quantum state, and must satisfy the normalization condition.

$$\begin{aligned}&|\psi\rangle = \alpha\,|0\rangle + \beta\,|1\rangle = \begin{bmatrix}\alpha\\\beta\end{bmatrix}\\&|\alpha|^2 + |\beta|^2 = 1; \quad \alpha, \beta \in \mathbb{C}\end{aligned} \tag{2}$$

The state of a single qubit can be visualized within the Bloch sphere as shown in Fig. 1. When measuring a qubit in the computational basis, it will collapse either to the state $|0\rangle$ or $|1\rangle$.

Multiple qubits can be combined to form a quantum register, and a quantum register with n qubits exists in a superposition of 2^n computational basis states, indicating that the dimension of the Hilbert space, where quantum states are represented as vectors, grows exponentially with the number of qubits. For instance, given two independent qubits, $|\psi_1\rangle = \alpha_1\,|0\rangle + \beta_1\,|1\rangle$ and $|\psi_2\rangle = \alpha_2\,|0\rangle + \beta_2\,|1\rangle$, the corresponding state of the quantum system is expressed as the tensor product of their individual states, as shown in Eq. (3), and measuring one qubit will not have any effect on the state of the other qubit.

Fig. 1 Bloch sphere representation of a qubit



$$|\psi_1\rangle \otimes |\psi_2\rangle = \alpha_1\alpha_2 |00\rangle + \alpha_1\beta_2 |01\rangle + \beta_1\alpha_2 |10\rangle + \beta_1\beta_2 |11\rangle \tag{3}$$

However, entanglement introduces a fundamental difference. When qubits are entangled, their states become correlated such that the state of the system cannot be expressed as the tensor product of individual qubit states. An important example of a two-qubit entangled state is a Bell state. As shown in Eq. (4), these two qubits exhibit quantum correlations: although each qubit individually is in a mixed state, measurements performed on them are strongly correlated.

$$|\psi_{Bell}\rangle = \frac{1}{\sqrt{2}} |00\rangle + \frac{1}{\sqrt{2}} |11\rangle \tag{4}$$

The temporal evolution of a closed quantum system is governed by the Hamiltonian operator according to the Schrödinger Eq. (5), in which $\mathcal{H}$ is the Hamiltonian operator. Unlike classical systems, the evolution of a quantum state in a closed system follows a unitary transformation, which preserves the state's normalization and ensures reversibility. Thus, the operations we perform on qubits must be unitary.

$$i\frac{d|\psi\rangle}{dt} = \mathcal{H}|\psi\rangle \tag{5}$$

To extract information from the quantum system, we perform quantum measurements, which are described by a set of measurement operators indicated by $M = M_m^\dagger M_m$. When measuring a quantum state $|\psi\rangle$, the probability to get the output m is given by Eq. (6a), and upon measurement, the state collapses to the one indicated by Eq. (6b)

$$\langle\psi| M_m^\dagger M_m |\psi\rangle \tag{6a}$$

$$\frac{M_m|\psi\rangle}{\sqrt{\langle\psi| M_m^\dagger M_m |\psi\rangle}} \tag{6b}$$

Measuring a qubit in the computational basis is a fundamental case. For instance, given a qubit in the state $|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$, a computational basis measurement with $M_0 = |0\rangle\langle 0|$ and $M_1 = |1\rangle\langle 1|$ yields the states $|0\rangle$ or $|1\rangle$, with the probability $|\alpha|^2$ and $|\beta|^2$, respectively, as described by Eq. (6). Theoretically, to obtain different information, the state $|\psi\rangle$ can be measured on any orthonormal basis.

2.1.2 Quantum circuits for computing

Quantum Gate Computing is one of the two major models of quantum computation, which is based on the quantum circuit model, analogous to classical digital circuits. A quantum circuit consists of a sequence of quantum gates, each applying a specific transformation to the quantum state. A fundamental distinction from classical computation is that every quantum gate must be unitary to ensure the reversibility of quantum operations and the normalization of the quantum system. Mathematically, a quantum gate is represented by a unitary matrix U, thus satisfying the condition $U^\dagger U = I$, where $U^\dagger$ is the Hermitian adjoint of U and I is the identity matrix. Thus, quantum gates play a crucial role in quantum circuits, enabling the transformation of quantum states for information processing. We introduce some elementary gates in the following:

For single-qubit gates, the Pauli definition in matrix form for the X gate, Y gate, and Z gate is given by Eq. (7). They can be described as a rotation by π radians of the qubit around respectively the x-axis, y-axis, and z-axis of the Bloch sphere.

$$X = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \quad Y = \begin{bmatrix} 0 & -i \\ i & 0 \end{bmatrix} \quad Z = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \tag{7}$$

When rotating around the x-axis, y-axis, and z-axis with an arbitrary degree θ, the corresponding gates are given by Eq. (8).

Fig. 2 An example of a quantum circuit with two qubits: H stands for Hadamard gates and $\oplus$ stands for X gate

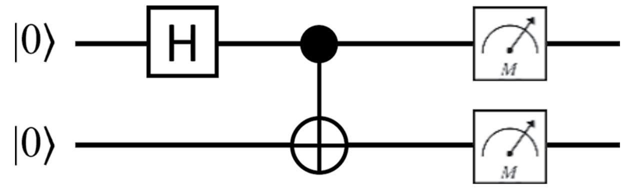
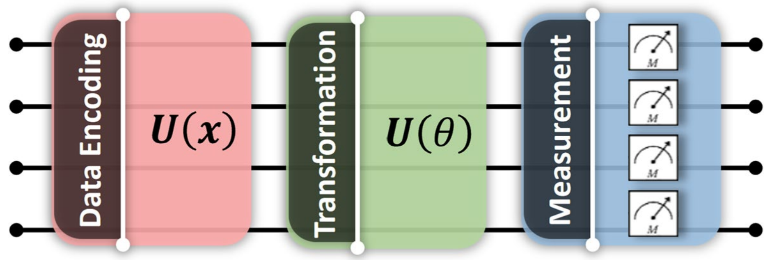


Fig. 3 Schematic of a quantum circuit for computation tasks, highlighting the sequential processes of data encoding, quantum state transformation, and measurement



$$R_x(\theta) = \begin{bmatrix} \cos\frac{\theta}{2} & -i\sin\frac{\theta}{2} \\ -i\sin\frac{\theta}{2} & \cos\frac{\theta}{2} \end{bmatrix} \quad R_y(\theta) = \begin{bmatrix} \cos\frac{\theta}{2} & -\sin\frac{\theta}{2} \\ \sin\frac{\theta}{2} & \cos\frac{\theta}{2} \end{bmatrix} \quad R_z(\theta) = \begin{bmatrix} e^{-i\frac{\theta}{2}} & 0 \\ 0 & e^{i\frac{\theta}{2}} \end{bmatrix} \tag{8}$$

A general single-qubit operation can be achieved using a $U3$ gate, which provides universal control over qubit rotations by parameterizing three angles (θ, ϕ, λ), as shown in Eq. (9).

$$U3(\theta, \phi, \lambda) = \begin{bmatrix} \cos\frac{\theta}{2} & -e^{i\lambda}\sin\frac{\theta}{2} \\ e^{i\phi}\sin\frac{\theta}{2} & e^{i(\phi+\lambda)}\cos\frac{\theta}{2} \end{bmatrix} \tag{9}$$

In addition to single-qubit gates, multi-qubit elementary gates, such as the *CNOT* gate, are also available. The *CNOT* gate operates on two qubits: a control qubit and a target qubit, and it flips the target qubit if and only if the control qubit is in the state $|1\rangle$. As a result, it entangles these two qubits. More complex multi-qubit operations can be decomposed into these elementary gates, as demonstrated in Divincenzo (1998).

A quantum circuit is constructed using quantum gates acting on qubits and can be treated as an independent module for specific computational tasks. Figure 2 illustrates a two-qubit quantum circuit consisting of a H gate followed by a *CNOT* gate, which together can generate an entangled state.

To perform quantum computing using a quantum circuit, the process generally involves three main stages, as illustrated in Fig. 3:

- *Data Encoding*: The input data are encoded into a quantum state suitable for processing with quantum algorithms.
- *Quantum State Transformation*: The encoded quantum state is transformed into the desired state by applying a sequence of quantum gates. These gates manipulate the qubits through operations such as rotations and entanglement.
- *Measurement*: At the end of the quantum circuit, the quantum state is measured, yielding classical data that encodes the solution to the computational problem.

2.2 Basic framework of circuit-based machine learning

QML is an interdisciplinary field that integrates the principles of quantum computing with machine learning techniques. In quantum circuit-based machine learning, the PQC is a fundamental concept that also typically follows the three steps, as illustrated in Fig. 4. It has been widely adopted in various QML models as a hybrid approach,

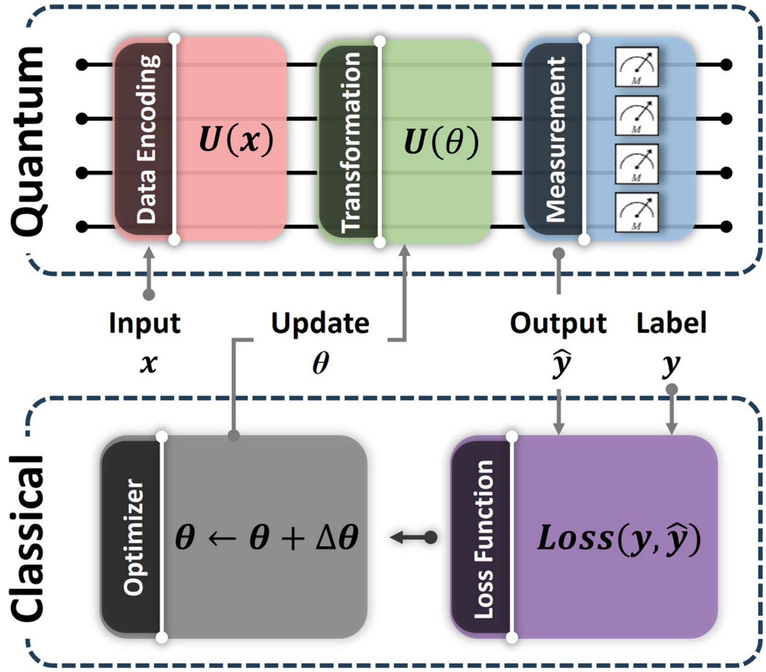


Fig. 4 Schematic of the quantum circuit-based QML model, in which the rotation angles θ of quantum gates are optimized using classical algorithms, while the evolution and measurement of quantum states are executed on a quantum device

where the rotation angles of quantum gates are optimized using classical algorithms, while the evolution and measurement of quantum states are carried out on a quantum device.

Specifically, starting from the initialized quantum state $|0\rangle$, a PQC with trainable parameters θ encodes the input data x and applies subsequent transformations, yielding the state $U(\theta)U(x)|0\rangle$. A measurement operator M is then applied to compute the output $\hat{y}$, which, together with the label y, is evaluated by a loss function $Loss(y, \hat{y})$ to guide the optimization of θ during training.

2.3 Quantum computing hardware and software

Quantum devices are currently broadly categorized based on the underlying physical systems used to realize and manipulate qubits. To date, various types of quantum devices have been explored and studied, each relying on different physical routes and exhibiting distinct advantages and limitations, as summarized in Table 1. For a more detailed introduction, interested readers may refer to the study (Cheng et al. 2023).

Besides hardware developments, several software platforms have been developed for QML as well. For instance, Bergholm et al. (2018) is an open-source framework for hybrid model development that seamlessly integrates quantum algorithms with various classical machine learning frameworks and supports different quantum hardware and simulators. TensorFlow Quantum (Broughton et al. 2020), developed by Google, is another open-source platform that extends TensorFlow (Abadi et al. 2016) to support the development of QML models. Furthermore, IBM has also developed a quantum framework, Qiskit (Javadi-Abhari et al. 2024), which offers tools for quantum algorithm development and access to different quantum devices. Additionally, other cloud-based platforms, such as Amazon Braket (Amazon Web Services 2020) and Microsoft Azure Quantum (Microsoft yyy), also provide access to quantum devices for computational tasks. For a more comprehensive overview of available QML frameworks and tools, interested readers can refer to the survey (Zaman et al. 2023).

The development of quantum computing covers a wide range of technologies from hardware systems to software frameworks and applications, as reviewed in Rodríguez-Díaz et al. (2025). Despite being in its early stages, it has attracted significant attention in recent years, with substantial investments from governments, organizations, and private investors directed toward its advancement. A comprehensive discussion is provided in Otgonbaatar et al. (2023). Consequently, these collective efforts have accelerated its progress. Following the demonstration

Table 1 Summary of different types of quantum devices and their corresponding properties. F_1 and F_2 denote the one-qubit and two-qubit gate fidelities, respectively

Device	Description	
Superconducting quantum processor	Basis	An array of artificial atoms made of Josephson junctions and capacitors, fabricated with lithography, controlled with microwave electronics
	Qubit	Individual control qubit: ~ 100
	Gate	Systems with 53 qubits: $F_1 > 99\%$; $F_2 > 99\%$
	Pros	Fast gate speed; tailored qubits; high controllability and scalability;
	Cons	Crosstalk between qubits; low temperature; supporting technology for scaling up;
Trapped ion quantum computing	Basis	Laser-cooled atomic ions held by radio-frequency electric fields in an ultra-high vacuum environment
	Qubit	Individual control qubit: $20-30$
	Gate	Systems with dozens of ions: $F_1 > 99.9\%$; $F_2 > 99\%$
	Pros	Extremely long coherence time and excellent gate operations on few ions; reconfigurable connectivity between ion qubits;
	Cons	Technically challenging in integration;
Semiconductor spin-based quantum computing	Basis	Electron or hole spins in semiconductor (silicon) quantum dot
	Qubit	Individual control qubit: 6
	Gate	Donor spin qubit: $F_1 \sim 99.99\%$; $F_2 \sim 99.5\%$ Gate-defined qubit: $F_1 \sim 99.9\%$; $F_2 \sim 99.51\%$
	Pros	Semiconductor fabrication; long coherence and fast high-fidelity gate; work at temperature $> 1K$; small footprint;
	Cons	Challenge of nanoscale fabrication
NV center quantum computing	Basis	Point defects in diamond; electron and nuclear spins with long coherence time; atom-like properties and solid-state host environment
	Qubit	Individual control qubit: 10
	Gate	$F_1 \sim 99.995\%$; $F_2 \sim 99.2\%$
	Pros	Work at room temperature; excellent quantum sensor; handy in quantum network;
	Cons	Hard to scale up
Neutral atom array quantum computing	Basis	Neutral atom arrays trapped in optical tweezers with controlled interactions based on Rydberg interactions
	Qubit	Digital quantum processors: 24 Analog quantum simulators: 289
	Gate	N/A
	Pros	Both digital and analog quantum simulations, scaling up beyond 100 qubits in programmable geometries
	Cons	Improving fidelities of two-qubit gates
NMR quantum computing	Basis	Nuclear spins in molecules
	Qubit	Individual control qubit: 12
	Gate	$F_1 \sim 99.98\%$; $F_2 \sim 99.3\%$
	Pros	Work at room temperature, long coherence time, digital quantum simulator
	Cons	Hard to scale up
Photonic quantum computing	Basis	Coherently manipulating a large number of single photons or canonically conjugate pairs of variables for electromagnetic modes to process quantum information
	Qubit	Individual control qubit: 18 Coherent control photons: 255
	Gate	$F_1 \sim 99.84\%$; $F_2 \sim 99.69\%$
	Pros	Robust against decoherence, working at room temperature, compatible with CMOS fabrication, natural interface for distributed quantum computing
	Cons	Challenge to realize deterministic photon-photon gates
Topological quantum computing	Basis	Fault-tolerant quantum computation based on non-abelian braiding of anyons
	Qubit	N/A
	Gate	N/A
	Pros	Intrinsic topological protection, few physical qubits to construct a logic qubit, promising to achieve large-scale, error-corrected computation
	Cons	Ideal materials or systems not found yet; zero topological qubit so far

Data taken from Cheng et al. (2023)

of computers with a few working qubits, quantum computing has now entered the NISQ era (Preskill 2018), in which *intermediate-scale* refers to quantum devices with approximately fifty to a few hundred qubits, enabling the first practical computations, while *noisy* highlights the limited coherence times, imperfect qubit control, and the absence of full fault tolerance. Despite these latter limitations, researchers have actively explored quantum computing's potential across a wide range of applications, offering valuable insights for its use in machine learning and paving the way for future adoption when large-scale fault-tolerant quantum devices become available.

3 Quantum circuit designs for learning

QML is an interdisciplinary field that combines the principles of quantum computing with machine learning techniques. To date, four fundamental approaches to their integration have been identified, as described in Schuld and Petruccione (2018) and illustrated in Fig. 5. These approaches are categorized based on whether the input data is classical or quantum, and whether the data processing algorithm is classical or quantum.

Specifically, *CC* refers to classical algorithms inspired by quantum principles for processing classical data; *QC* involves classical algorithms designed to analyze quantum data; *CQ* denotes quantum algorithms applied to classical data; and *QQ* represents quantum data analysis performed using quantum algorithms. As stated before, in the context of QML in this paper, we mainly focus on the CQ approach, where quantum-based algorithms are employed to analyze classical data.

3.1 Data embedding in quantum circuits

To process and analyze classical data using quantum computing, the data must first be encoded into quantum states via quantum circuits. As such, data encoding circuits play a crucial role in shaping the key properties of the resulting QML models. Thus, its design requires balancing multiple objectives, such as preserving informative features, reducing state preparation cost, and maintaining robustness to hardware noise. Since these objectives often conflict, there is no universally optimal encoding strategy, and the choice should depend on the input modality, learning task, and available quantum resources.

3.1.1 Fundamental encoding approaches

In quantum computing, various properties of quantum systems can be utilized to represent classical data. Accordingly, different encoding approaches have been proposed so far, as summarized in Ranga et al. (2024). Among

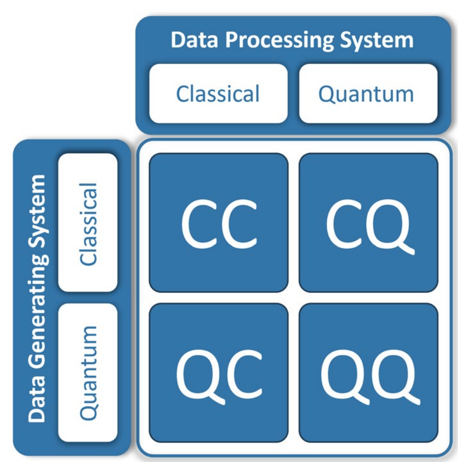


Fig. 5 Basic combinations of quantum computing and machine learning

them, computational basis encoding and amplitude encoding represent two fundamental principles for classical data encoding.

Computational Basis Encoding This method maps classical input x directly into a computational basis state. First, it is converted into a binary string form $f(x) = (b_1, b_2, \dots, b_n)$ where $b_i \in \{0, 1\}$, and it is represented by the corresponding basis state $|x\rangle$. The encoded state is then given by:

$$|x\rangle = |b_1\rangle \otimes |b_2\rangle \otimes \cdots \otimes |b_n\rangle \tag{10}$$

Given a classical vector $x = (x_1, x_2, \dots, x_N)$, the quantum system can use superposition to represent it by embedding each element into a distinct part of the quantum state. The overall encoded quantum state can then be expressed as:

$$|x\rangle = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} |x_i\rangle \tag{11}$$

Amplitude encoding In amplitude encoding, the classical data is embedded into the amplitudes of a quantum state. The input vector $x = (x_1, x_2, \dots, x_N)$ has to be normalized to $f(x_i)$ such that $\sum_{i}^{N} |f(x_i)|^2 = 1$. The normalized value $f(x_i)$ is then used as the amplitude of a quantum state, and the encoded state of the input x is indicated as:

$$|x\rangle = \sum_{i}^{N} f(x_i)\,|i\rangle \tag{12}$$

In comparison, computational basis encoding is simple to implement and requires shallow quantum circuits, but it generally requires a large number of qubits for encoding high-dimensional data. In contrast, amplitude encoding is highly qubit-efficient but generally incurs a high state preparation cost. In practice, these fundamental approaches are rarely employed directly in QML systems, and most existing models instead build upon them to develop more sophisticated encoding frameworks.

3.1.2 Standard encoding strategies

When designing quantum circuits for classical data encoding, based on whether the encoded output can faithfully retrieve the original data, there are two standard strategies: *Retrievable Encoding* and *Representation Encoding*

Retrievable encoding These methods allow for the full retrieval of the original data from the encoded quantum state. Typically, they do not require extensive classical preprocessing, and the resulting quantum states maintain a direct and interpretable correspondence with the original classical data, such as Venegas-Andraca and Bose (2003); Latorre (2005); Le et al. (2011). However, when dealing with content-rich inputs such as images, these encoding strategies demand substantial quantum resources, such as a large number of qubits and quantum gates, posing significant computational challenges, particularly in the NISQ era. To address this, methods, such as Mitsuda et al. (2024); Duan and Hsieh (2022), have been proposed to approximate the target quantum states and reduce the quantum resources needed for encoding.

Representation encoding The quantum states produced by these methods do not enable reconstruction of the original input data, but they are expected to retain essential features necessary for the learning task. To date, different approaches have been proposed. For instance, some studies rely on classical algorithms to preprocess the input and extract a reduced set of representative features, which are then encoded into quantum states for QML. Besides that, some studies, inspired by the data reuploading technique (Pérez-Salinas et al. 2020), reuse qubits by encoding multiple features sequentially into the same qubit, thereby reducing the overall quantum resource requirements. Furthermore, Hamiltonian embedding has also been proposed and studied, as seen in Schuld and Petruccione (2021); Wang et al. (2025).

3.1.3 Encoding techniques for representative data types

To date, there are various types of data, each with its own characteristics and requiring particular care when encoding it into the quantum domain. In the following, we summarize the proposed encoding techniques for several representative data types.

Encoding imagery data Imagery data is an important data modality that typically contains rich information and has been widely processed and analyzed in various applications. How to represent such data in the quantum domain accordingly has motivated extensive research. Notably, many studies employ patch-wise strategies, encoding image patches into quantum states to reduce quantum resource requirements. Since such techniques can often be extended to entire images, we also include them in this section.

Grayscale/multispectral image: To encode grayscale or multispectral images with retrievable encoding, a basic and intuitive approach is the Qubit Lattice method (Venegas-Andraca and Bose 2003), which assigns a single qubit to represent a pixel value using amplitude or angle encoding. While this approach requires only elementary gates, its high qubit demand limits its practicality for encoding entire images in the NISQ era. As a result, some studies, such as Liu et al. (2021); Jing et al. (2022); Henderson et al. (2020), have proposed patch-wise analysis based on this method within QML frameworks. To further reduce the required qubits, various methods exploit quantum entanglement. A representative example is Flexible Representation of Quantum Images (FRQI) Le et al. (2011), which uses superposition for spatial encoding while encoding grayscale pixel values through angle-modulated amplitudes. Building on this principle, new methods have been developed, such as Sun et al. (2013) for encoding multispectral images and Jiang and Wang (2015) for images of arbitrary size. Nonetheless, implementing such retrievable encoding methods for images remains challenging in practical applications. To mitigate resource limitations, studies based on these methods often employ input downsampling to fit available quantum resources, as seen in Fan et al. (2022, 2023, 2023, 2024), or adopt patch-wise analysis strategies, as in Chalumuri et al. (2021).

Instead of encoding exact input, there are studies exploring the validity of preparing a quantum state to approximate the retrievable encoding output with reduced quantum resources for further analysis. For instance, Wu et al. (2023) leveraged machine learning techniques and proposed a hybrid Autoencoder (AE), where the quantum decoder is designed to prepare quantum states for subsequent analysis. Similarly, Shen et al. (2024) introduced shallow PQCs for data encoding and optimized it to achieve high approximation fidelity while reducing quantum resource requirements. Zeng et al. (2022) conducted crop and average pooling to reduce encoded features, followed by angle encoding with a non-linear function for data encoding.

Furthermore, using classical algorithms to extract a small set of informative features from input images has attracted significant attention for representation encoding. To date, many classical algorithms have been considered. For example, Principal component analysis (PCA), a linear dimensionality reduction technique, was employed in Gawron and Lewiński (2020); Mishra and Tsai (2023) with angle encoding to map each principal component onto a separate qubit. Additionally, many machine learning algorithms have long been proposed for feature reduction prior to the advent of QML. Among these, Convolutional Neural Networks (CNNs) are particularly favored for image processing due to their strong performance and adaptability. Consequently, numerous studies, such as Zaidenberg et al. (2021); Senokosov et al. (2024); Sebastianelli et al. (2021, 2023); Kea et al. (2024); Ghosh et al. (2025), incorporate convolutional operations to extract a compact set of informative features, which are then encoded into quantum states. Instead of using vanilla CNNs, some works explore rotation-equivariant convolutional operations Sein et al. (2025) and dilated convolution layers Chen (2022) to further enhance feature extraction and improve the quality of quantum encoding. Other CNN-based deep learning methods have also been adopted for representation encoding, such as convolutional AE (Ji et al. 2024; Chang et al. 2022; Hur et al. 2022), VGG (Zollner 2022), VGG-autoencoder (Otgonbaatar and Datcu 2021), ResNet (Don et al. 2024; Geng et al. 2025), Inception-ResNets (Abdel-Khalek et al. 2023). Zollner et al. (2024) compared several dimensionality reduction techniques and concluded that AE models were best suited for generating compact representations of images, outperforming traditional methods such as PCA. Besides convolution operations, the attention mechanism has also gained popularity in image analysis, and its integration with QML has also been explored. For example, Papa et al. (2024) examined the validity of integrating QML into ViTs for image classification.

Moreover, rather than relying on classical algorithms for representation encoding, Easom-McCaldin et al. (2022) proposed a one-qubit encoding method that sequentially encodes multiple features into a single qubit for image representation, thereby reducing overall quantum resource requirements. Additionally, some studies have focused on training quantum kernels for embedding. For example, Rodriguez-Grasa et al. (2025) proposed training a PQC to construct quantum kernels, although they still employed PCA for image feature reduction in their experiments.

Hyperspectral image: For hyperspectral images, due to the richness of the spectral information and the current constraints of quantum resources, pixel-wise encoding is widely used. Most existing techniques leverage classical algorithms and conduct representation encoding to enable efficient quantum data processing. For instance, studies such as Priyanka and Venkatesan (2024); Shaik et al. (2022) employ PCA combined with amplitude encoding to map the obtained key features onto quantum states for further analysis. In addition, Lin and Chen (2023) used convolutional modules to extract representative features for encoding, while Mazur et al. (2025) encoded the binarized latent space representation from a Latent Bernoulli AE into a quantum system for subsequent analysis.

Radar (SAR) image: Radar systems often produce complex-valued data, and leveraging the inherently complex-valued nature of quantum computing to process such data has attracted growing attention. For instance, Chen and Li (2024) proposed a method to encode complex-valued data as a whole entity into a quantum state via amplitude encoding. Dutta et al. (2024) employed amplitude encoding to separately represent the real and imaginary components of SAR data for classification tasks.

Instead of directly utilizing complex-valued inputs, the use of intensity information with angle encoding for SAR data analysis has been explored. For instance, Naik et al. (2024) employed this method to classify X-band SAR images, Russo et al. (2025) applied it for segmentation tasks, and Painchart et al. (2024) used it for deforestation detection. Ghosh et al. (2024, 2025) proposed a UNET-inspired hybrid architecture for radar sound data, in which a PQC served as the bottleneck for segmentation and a Quantum Feature Maps (QFMs) regulated CNN Architecture where parameterized quantum circuits are used to generate high-dimensional feature representations in terms of quantum states for CNN-based semantic segmentation.

In addition, Otgonbaatar and Datcu (2021) focused on PolSAR images which carry signatures of polarized state and are the Doppelganger of a physical state. They leveraged this property to embed PolSAR signatures as a projection of the Poincaré sphere on the Bloch sphere. Bhattacharya et al. (2025) proposed to convert the standard Sinclair matrix into a spinor representation and encode PolSAR data for quantum algorithms to analyze and extract information from high complexity scattering signatures.

Encoding point cloud data Point cloud data represents objects as a collection of points in 3D space, where each point corresponds to a sampled location on the surface of an object. Although limited, several studies have explored the analysis of such data with quantum computing. For example, Baek et al. (2022) adopted the reuploading method to encode the geometric features obtained from the input point cloud data with a small number of qubits for classification. Rathi et al. (2023) proposed a quantum autoencoder for 3D point cloud data, in which they introduced an auxiliary value to transform each 3D vertex into a state vector and leveraged amplitude encoding to exploit the large Hilbert space.

Additionally, point cloud data exhibits unique properties such as permutation invariance, which can be leveraged in machine learning tasks to improve performance. Heredge et al. (2024) proposed a permutation-invariant encoding scheme that leverages quantum superposition to represent symmetric data structures by exponentially reducing the effective dimensionality of the quantum state. Li et al. (2024) proposed a quantum circuit design that enforces both rotational and permutation invariance. Specifically, this is achieved through the use of pairwise inner products during encoding and by applying identical parameters to each twirled operator in the subsequent PQC.

Encoding time-series data Time-series data consist of sequences of samples collected at successive time intervals, providing valuable information for a variety of tasks. For instance, long-term satellite missions enable repeated observations of the same regions, playing a crucial role in numerous applications, as reviewed in Miller et al. (2024). As a result, applying quantum computing to the analysis of time-series data has become an emerging area of interest. Wang et al. (2024) utilized 16 time-domain statistical features from radar return signals and employed angle encoding to embed these features into 16 qubits for target detection tasks. Malarvanan (2024) employed convolutional and fully connected layers to extract relevant features and reduce dimensionality for QML. The resulting features were then individually encoded into qubits using angle encoding for quantum feature extraction. Liu et al. (2025) combined a CNN with an LSTM to process radar inputs and mapped the extracted features into quantum states via angle encoding for further quantum processing. Schetakis et al. (2025) employed an encoder consisting of an LSTM and fully connected layers to process the input data, and applied the data reuploading technique with angle encoding for prediction tasks.

Encoding tabular data To represent tabular data in the quantum domain, Innan and Bennai (2024) employed amplitude encoding, and Bhardwaj et al. (2025) proposed a method based on computational basis encoding. Rath and Date (2024) investigated different fundamental encoding approaches for tabular data classification. In addition, Bhavsar et al. (2023) employed several classical machine learning algorithms to identify the most important features from the tabular data, which were subsequently encoded using a ZFeatureMap quantum circuit for classification. Rivas et al. (2021) also leveraged representation learning by applying a PQC to further process the output of the encoder in an AE architecture.

Encoding text data In quantum computing-based text analysis, such as for social media, how text data is represented plays a crucial role in extracting meaningful information. To construct quantum circuits for sentence encoding, the DisCoCat framework Coecke et al. (2010) has been widely employed. For instance, studies Meichanetzidis et al. (2020); Martinez and Leroy-Meline (2022); Meichanetzidis et al. (2023); Wazni et al. (2024) mapped the DisCoCat diagrams to the corresponding quantum circuits to represent the flow of information between words in a sentence, thereby constructing the meaning of the entire sentence. Additionally, Shi et al. (2024) leveraged quantum superposition states to model word ambiguity and proposed a method for word embedding, while Eisinger et al. (2025) suggested that amplitude encoding is particularly suitable for addressing linguistic ambiguity.

Furthermore, to accommodate the limited quantum resources available in the NISQ era, several studies have employed classical algorithms such as BERT to extract text embeddings for quantum processing (Zeguendry et al. 2024; Buonaiuto et al. 2025). To further reduce quantum resource requirements, Yu et al. (2024) proposed a multilayer variational encoding structure based on the data reuploading mechanism to encode vector representations of words using fewer quantum resources.

3.1.4 Comparative analysis of encoding strategies

Unlike classical machine learning, where data can be processed directly, the choice of data encoding is one of the most critical design decisions in QML. It not only determines how effectively critical information can be represented in quantum states for subsequent learning, but also directly affects the overall efficiency.

Different encoding methods exhibit different trade-offs from multiple perspectives. For instance, among the fundamental encoding approaches discussed above, amplitude encoding can represent high-dimensional data using fewer qubits but may require deep state-preparation circuits with high gate complexity. Building upon these fundamental principles, existing QML models typically construct more sophisticated encoding frameworks based on two design philosophies. One direction seeks to exploit the intrinsic structure or properties of the input data, such as complex-valued encoding (Chen and Li 2024), physical-model-based encoding for PolSAR (Otgonbaatar and Datcu 2021), and permutation-invariant encoding for point-cloud data (Heredge et al. 2024; Li et al. 2024). Such methods are modality-specific and allow QML models to participate more directly in feature representation learning from the original data. The other direction seeks to encode only compact representations rather than the complete input. In practice, this is typically achieved by combining classical algorithms, such as PCA, or deep learning models, such as CNNs and AEs, with subsequent quantum encoding. This strategy has been widely adopted for various data modalities, including images (Zollner et al. 2024), time-series data (Liu et al. 2025), and text (Buonaiuto et al. 2025), providing a practical compromise between representation capability and quantum resource requirements. The major characteristics and trade-offs of these encoding approaches are summarized qualitatively in Table2, and actual resource requirements depend on the specific implementation, input data, and hardware.

Beyond encoding design itself, additional strategies have been proposed to further reduce quantum resource requirements during data encoding. One approach reduces qubits by reusing them to sequentially encode multiple input features. Another approach reduces encoding cost through model architecture design. Rather than encoding the complete input with a single quantum circuit, multiple quantum circuits are employed, each processing only a subset of the input information. Such techniques require careful model design to preserve informative feature representations.

Taken together, there is no universally optimal encoding method. Instead, encoding selection should be guided by the characteristics of the input data, the downstream learning tasks, and the available quantum resources. Balancing these factors is essential for designing efficient and effective QML models, particularly in the NISQ era.

3.2 Quantum circuits for kernel-based learning

Kernel theory guarantees that training kernel-based models leads to optimal solutions due to the convexity of the training landscape. The exploration of quantum circuits for kernel-based learning has gained increasing attention, as they may offer computational advantages by leveraging the exponentially large Hilbert space of quantum states, as suggested by Havlíček et al. (2019). Within this framework, various quantum circuits have been designed, either parameterized or unparameterized, as Quantum Embedding Kernels (QEKs) to map classical data x into a high-dimensional Hilbert space $\psi(x)$, enabling similarity measurements to capture complex, nonlinear structures inherent in the data.

Rooted in this concept, Quantum Support Vector Machines (QSVMs) have been developed in which quantum computers are employed for similarity measurement. Specifically, each data point x is embedded into a quantum state $\psi(x) = U(x)|0\rangle$ via a quantum circuit. The Quantum Kernel Estimation (QKE) process then constructs the kernel matrix by evaluating the pairwise Hilbert-Schmidt inner products between quantum feature states $\psi(x_i)$ and $\psi(x_j)$, as defined in Eq. (13).

$$K(x_i, x_j) = |\langle 0| U^\dagger(x_j)U(x_i)|0\rangle|^2 \tag{13}$$

To estimate these inner products on a quantum computer, Fidelity Quantum Kernels (FQKs), as illustrated in Fig. 6, are widely adopted. These methods compute the kernel value based on the probability of measuring the all-zero state $|0\rangle$. An alternative approach for estimating the overlap between $\psi(x_i)$ and $\psi(x_j)$ is the SWAP test, which has been explored in studies such as Pillay et al. (2024). In comparison, the SWAP test requires an additional auxiliary qubit to control the SWAP operation, leading to an increased qubit count for estimation. Once the kernel matrix is obtained, a classical optimization algorithm is employed to determine an optimal separating hyperplane in the quantum feature space.

To date, various quantum circuits have been proposed for feature encoding, with representative examples including the ZZFeatureMap and the PauliFeatureMap. These circuits encode each classical feature as a rotation around a specific axis of a corresponding qubit and incorporate entangling operations between qubits to capture

Table 2 Qualitative comparison of representative encoding strategies in QML

Encoding strategy	Qubits	State Prep	Notes
Computational basis	High	Low	Simple implementation; large qubit requirement
Amplitude	Low	High	High qubit efficiency; expensive state preparation
Representation	Low	Moderate	Compact task-relevant features
Modality-specific	Variable	Variable	Intrinsic data properties; domain-specific design

 https://doi.org/10.1007/s10462-026-11686-4

Fig. 6 Quantum kernel estimation circuit

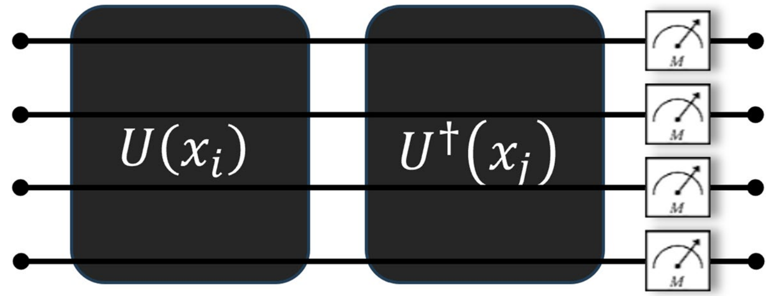


Fig. 7 Entanglement for PauliFeatureMap

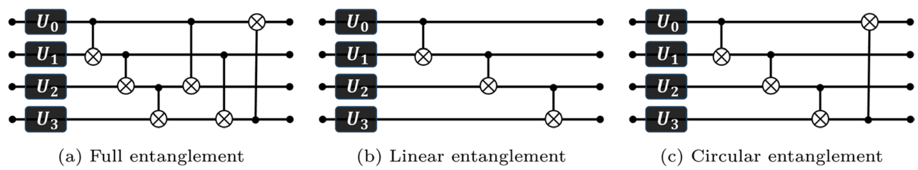
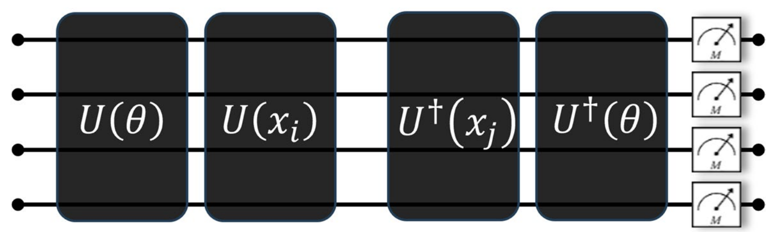


Fig. 8 Quantum kernel alignment circuit



correlations among features. Different entanglement configurations have been explored, such as full entanglement (Fig. 7a), linear entanglement (Fig. 7b), and circular entanglement (Fig. 7c), each offering distinct trade-offs between circuit complexity and representational capacity. Additionally, several successful classical computing approaches have been extended to the quantum domain. For example, quantum circuits have been developed to replicate classical kernel functions, such as the quantum Hartley kernel Wu et al. (2025).

The concept of kernel alignment has also been explored in quantum settings to improve task-specific performance. In this context, parameterized quantum kernels, as illustrated in Fig. 8, have been proposed in studies such as Hubregtsen et al. (2022); Zhou et al. (2024); Glick et al. (2024), aiming to tailor the quantum feature map to the learning task through trainable circuit components. Furthermore, studies such as Miroszewski et al. (2023) have explored combining different types of quantum circuits to construct valid quantum kernels. To enhance the expressivity of quantum kernels and capture complex data patterns, repeated circuit structures have been introduced as well, as demonstrated in Havlíček et al. (2019).

Note that, as indicated in studies Liu et al. (2021); Alvarez-Estevez (2025), a carefully designed QEK enables rigorous and robust quantum speed-up in supervised machine learning tasks, underscoring the importance of selecting an appropriate quantum feature map. To address this challenge, recent efforts Altares-López et al. (2021); Incudini et al. (2024) have focused on automatically constructing task-specific quantum kernels. For instance, Altares-López et al. (2024) applied such techniques to a segmentation task, demonstrating their practical effectiveness.

As illustrated in Fig. 6, the FQK relies on global observables for measurement to estimate kernel values. However, it could lead to exponential concentration, as demonstrated in Thanasilp et al. (2024); Slattery et al. (2023). To address this, Projected Quantum Kernels (PQKs) have been proposed, which avoid global measurements and instead rely solely on local observables, such as single-qubit or few-qubit measurements. Specifically, the quantum feature state $\psi(x)$ is projected back into the classical domain via local measurements, and the resulting

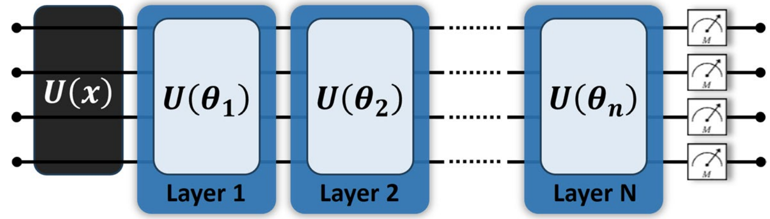


Fig. 9 Schematic of a general QDNN with n layers

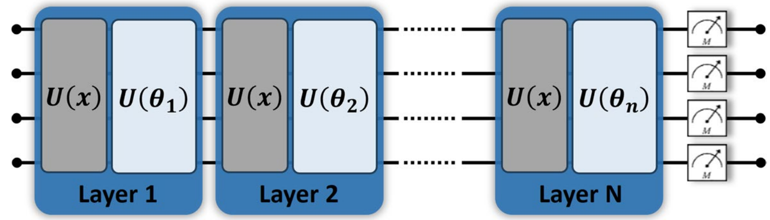


Fig. 10 Schematic of a general QDNN with data re-uploading, depicting repeated encoding of input x across layers

classical representations are used to compute the kernel matrix. This approach has been widely investigated in various studies such as Huang et al. (2021); Suzuki and Li (2024).

To deepen the understanding of FQKs and PQKs, Schnabel and Roth (2025) conducted a benchmarking study that systematically compared these approaches across a range of regression and classification tasks, offering robust and comprehensive insights into the behavior of quantum kernel methods. Gan et al. (2023) combined FQK and PQK into a common framework and introduced a systemic method to increase the complexity of quantum kernel models. Egginger et al. (2024) conducted a hyperparameter study for quantum kernels regarding performance and generalization. In parallel, Abdulsalam and Ahmad (2025) examined the performance of quantum kernels in comparison to classical kernels, highlighting the potential advantages of quantum algorithms for both classification and regression tasks.

3.3 Quantum circuits for neural network-based learning

Quantum Neural Networks (QNNs) have attracted significant attention due to their ability to automatically extract important features from data, leading to the development of various quantum circuit designs tailored to different tasks. Accordingly, diverse types of quantum neural networks have been proposed.

3.3.1 Quantum deep neural network (QDNN)

A general QDNN is composed of layers of quantum neurons and typically treats all inputs as independent features. As shown in Fig. 9, a typical QDNN consists of multiple layers of trainable quantum gates, and to date, various PQCs with different gate configurations, such as illustrated in Fig. 7, have been employed as layers in QDNNs. In addition, the data re-uploading technique (Pérez-Salinas et al. 2020) has been widely used to construct QDNNs, as in Wach et al. (2023); Rodriguez-Grasa et al. (2024); Sebastian et al. (2024). Figure 10 illustrates the basic framework of such QDNNs. Additionally, hybrid QDNNs have also been proposed, with representative examples including (Mukhanbet and Daribayev 2025; Schetakis et al. 2025).

3.3.2 Quantum convolution neural network (QCNN)

CNNs, which perform convolutions for feature extraction, are widely recognized for their strong performance and adaptability, particularly in image-related tasks. In this context, several QCNNs have been developed, each utilizing quantum computing in distinct ways.

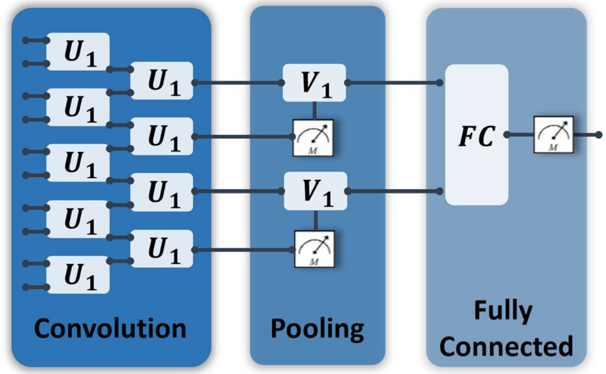


Fig. 11 QCNN architecture with quantum convolution, pooling, and fully connected layers, modified from Cong et al. (2019)

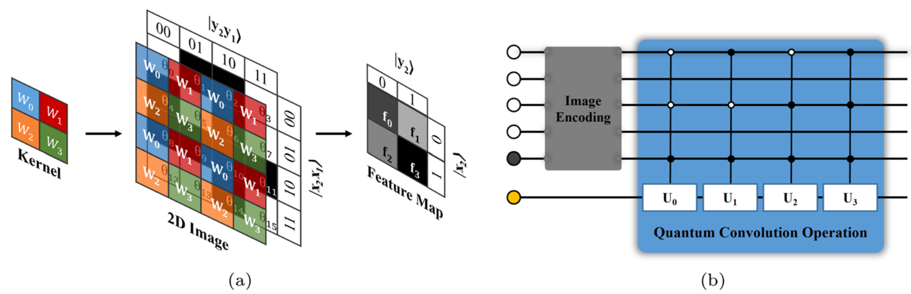


Fig. 12 Quantum convolution operation: **a** illustration of the quantum convolutional operation using a 2×2-sized kernel on a 4×4-sized image; **b** the circuit example of the corresponding quantum convolution layer. Figure adapted from Fan et al. (2023)

One type of QCNN was proposed by Cong et al. (2019), consisting of successive convolution and pooling layers. The model integrates the multi-scale entanglement renormalization approach with quantum error correction, as illustrated in Fig. 11. It has been evaluated across various tasks, including topological quantum phase recognition (Herrmann et al. 2022) and image classification (Chen et al. 2023). Notably, this model employs two-qubit gates on neighboring pairs of qubits to construct a PQC that functions as a quantum convolution layer. To implement pooling, a subset of qubits is measured, and the outcomes are used to control subsequent quantum operations, effectively reducing the feature dimension. Hur et al. (2022) further evaluated various quantum circuit designs suitable for constructing such PQC-based quantum convolution layers.

Note that the aforementioned QCNN requires vectorized inputs; therefore, when applied to image data, classical algorithms, such as convolutional AEs, as used in Hur et al. (2022), are needed to extract representative feature vectors for the adoption of such a model. In addition, as previously introduced, various other techniques have been proposed for encoding grid-based data. Accordingly, another type of QCNN that is compatible with such encoding strategies has been introduced. Representative examples include those proposed in Li et al. (2020); Fan et al. (2023) for gray-scale image classification, Fan et al. (2024) for multispectral image classification, and Fan et al. (2025) for processing extracted feature maps for classification tasks. In principle, these QCNNs employ two entangled quantum registers: one encodes the pixel locations, and the other encodes the corresponding values. Accordingly, a PQC is specifically designed to operate on this encoded quantum state to realize convolution operations, and Fig. 12 illustrates one representative example. As shown in Fig. 12a, a convolution operation with a 2×2 kernel is realized by ensuring that pixels with the same color are transformed using identical kernel weights. To achieve this, a PQC composed of controlled gates, illustrated in Fig. 12b, is applied. The parameters of these controlled gates correspond to the kernel weights and are optimized during the training process.

3.3.3 Quanvolutional neural network

Instead of encoding the entire input data for the quantum process, Henderson et al. (2020) proposed the quanvolutional operation. As illustrated in Fig. 13, this model utilizes PQCs as convolutional kernels to perform local feature transformations. Typically, each input patch is individually encoded and processed by a PQC, and the

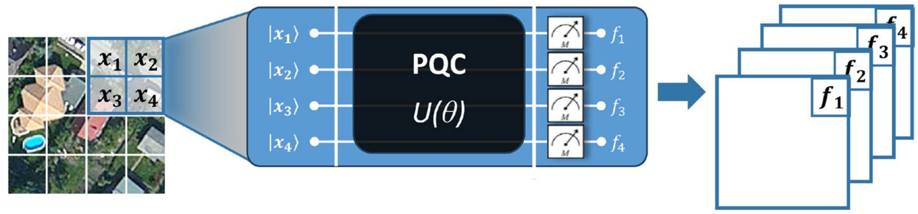


Fig. 13 Schematic of a quanvolutional operation, where a 2×2 classical patch is processed by a quantum circuit

measurement outcomes are used as feature representations for further analysis. Since this quantum operation is applied to small regions of the input, it enables the processing of large imagery with minimal quantum resources via a sliding window mechanism. Thus, this approach offers a promising pathway for image analysis using QML in the NISQ era, and numerous studies have been developed based on this principle. For example, Riaz et al. (2023) employed strongly entangled circuits with non-trainable parameters for quanvolution operations. In contrast, other works Matic et al. (2022); Chen et al. (2022); Wang et al. (2024) explored trainable PQCs, where measurement outcomes from the entire image were used as inputs to a classical dense layer for final classification.

3.3.4 Quantum vision transformer (QViT)

Transformers have achieved success across a wide range of tasks, largely due to the effectiveness of their attention mechanism in capturing intrinsic relationships between features. Recently, their integration with quantum computing has attracted considerable research interest, as reviewed in Zhao et al. (2025).

To leverage QML for implementing the attention mechanism, various quantum algorithms have been explored. For cases where the distribution of attention scores is discrete, Zhao et al. (2024) proposed the GQHAN to address the associated non-differentiability issue. For continuous distributions, Shi et al. (2024) proposed using quantum logic similarity to compute the self-attention score matrix. Zhao et al. (2024) designed a PQC based on FQKs for attention score computation, while Chen et al. (2025) employed the SWAP test for the same purpose. Additionally, Li et al. (2024) utilized PQCs to prepare the query, key, and value components, whose measurement outputs are then used to classically compute the self-attention matrix. Evans et al. (2024) proposed a quantum transformer that leverages kernel-based operator learning and employs multi-dimensional quantum Fourier transforms, whereas Kerenidis et al. (2024) leveraged quantum orthogonal layers based on PQCs to build a QViT. Furthermore, Chen et al. (2025) explicitly leveraged the complex nature of quantum states in the self-attention mechanism to achieve a more comprehensive representation and improved performance.

3.3.5 Quantum graph neural network (QGNN)

QGNNs aim to utilize quantum circuits to learn and make predictions about underlying graphs (Ceschini et al. 2024). To date, various types of QGNNs have been proposed. Verdon et al. (2019) employed Hamiltonian evolutions to simulate graph structures and proposed a general PQC framework, with convolutional and recurrent QGNNs variants. Zheng et al. (2024) designed a PQC to implement graph convolution operations, leading to a convolutional QGNN. Hu et al. (2022) leveraged multiple PQCs for node feature representation, graph structure embedding, and feature extraction, thereby integrating graph neural networks with QML.

Moreover, hybrid QGNNs have also been proposed Tüysüz et al. (2021); Vitz et al. (2024); Mauro et al. (2024). Specifically, Tüysüz et al. (2021) incorporated PQCs into the Multilayer Perceptron (MLP) layers of a classical GNN, while Vitz et al. (2024); Mauro et al. (2024) combined a classical GNN for input processing with a PQC for further analysis.

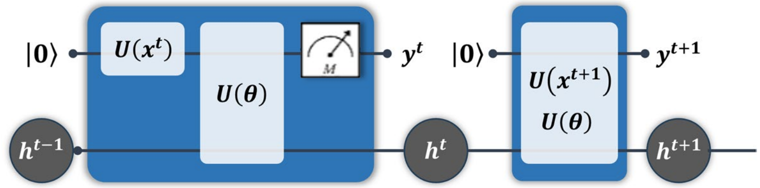


Fig. 14 Schematic of a general QRNN

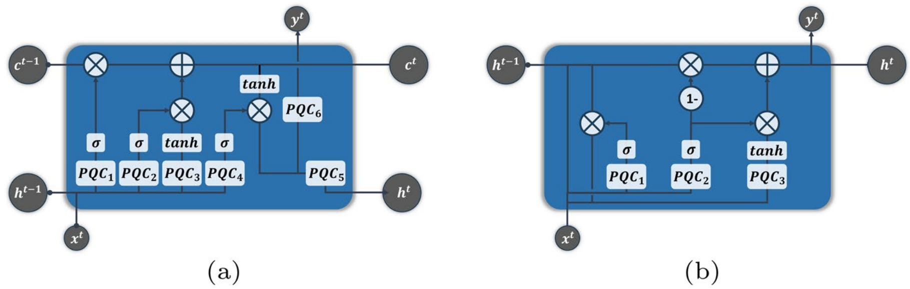


Fig. 15 **a** Hybrid LSTM cell; **b** hybrid GRU cell

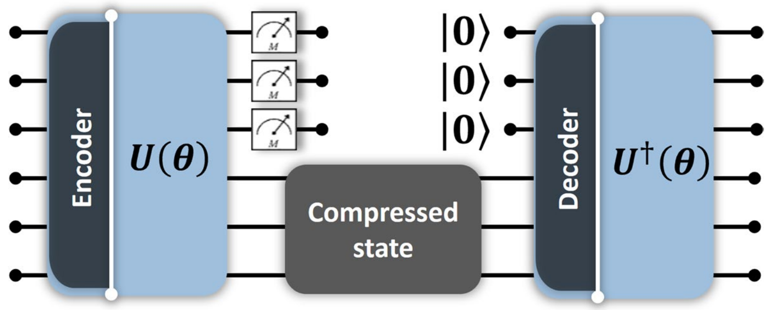


Fig. 16 Schematic of a general QAE

3.3.6 Quantum recurrent neural network (QRNN)

Recurrent neural networks are the foundation of many models analyzing sequential data. Figure 14 illustrates the structure of a typical fully quantum RNN model, where each QRNN cell is implemented using a PQC. Bausch (2020) proposed a highly structured PQC functioning as a quantum neuron, combined with amplitude amplification to realize nonlinear activation, forming the basis for a QRNN. Takaki et al. (2021) used a PQC with a recurrent structure and utilized the tensor product to achieve nonlinearity for temporal learning tasks. Li et al. (2023) introduced hardware-efficient quantum recurrent blocks and constructed two types of QRNNs by stacking these blocks according to different schemes, and later, Li et al. (2024) enhanced QRNN by integrating a gating mechanism to address the gradient vanishing and exploding issues. Siemaszko et al. (2023) proposed a QRNN implementation in the framework of continuous-variable quantum computing.

Besides, hybrid QRNNs have also been explored. For instance, studies Chen et al. (2022); Cao et al. (2023) integrated PQCs into LSTM cells (framework shown in Fig. 15a), while studies Jeong et al. (2024); De Falco et al. (2024); Moon et al. (2025) applied PQCs to GRU cells (framework shown in Fig. 15b), leading to different hybrid QRNN variants.

3.3.7 Quantum autoencoder (QAE)

Autoencoders learn latent-space representations of inputs by using an encoder-decoder structure, where the decoder reconstructs the input from the encoded representation. Inspired by this idea, Romero et al. (2017) introduced a PQC to form a QAE for quantum data compression. Figure 16 illustrates the general scheme of

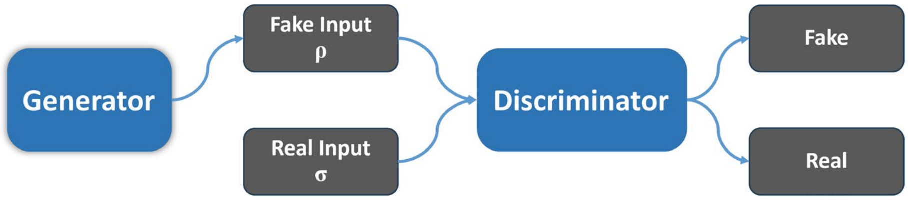


Fig. 17 Schematic of a general QGAN. Adapted from Lloyd and Weedbrook (2018)

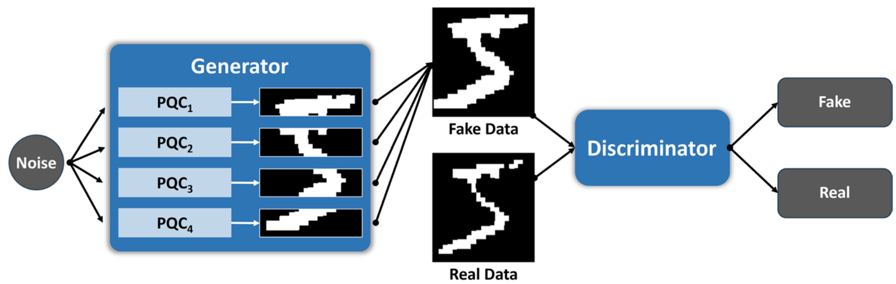


Fig. 18 General patch-based QGAN

a PQC-based QAE, where the parameters θ are optimized to maximize the fidelity between the original and reconstructed states. To date, several approaches have been developed to quantify fidelity, leading to different QAE variants. For instance, Romero et al. (2017); Ngairangbam et al. (2022) employed the SWAP test, whereas Mangini et al. (2022); Bravo-Prieto (2021) estimated fidelity by measuring the all-zero state $|0\rangle$ in the output qubits. Moreover, Asaoka and Kudo (2025) proposed reinitializing the decoder with the label state in a QAE model for image classification tasks.

Furthermore, hybrid QAEs have also been investigated. For example, Sakhnenko et al. (2022) integrated a PQC into the bottleneck of a classical AE, while Srikumar et al. (2021) employed PQCs to construct both the encoder and decoder, with a classical neural network processing the bottleneck. Khoshaman et al. (2018) focused on variational AEs and introduced a quantum generative process within a classical AE framework.

3.3.8 Quantum generative adversarial network (QGAN)

Generative Adversarial Networks (GANs) are based on game-theoretic principles and consist of a generator and a discriminator. The generator aims to produce data with statistical properties matching those of the real data, while the discriminator attempts to distinguish between real and generated samples. Lloyd and Weedbrook (2018) integrated quantum computing with GAN and proposed the concept of QGAN, as shown in Fig. 17.

To date, various types of QGANa have been proposed. We categorize them into fully quantum and hybrid QGANs, according to the role and placement of the quantum component within the overall architecture. More specifically, fully quantum GANs employ both a quantum generator and a quantum discriminator. Representative examples include (Dallaire-Demers and Killoran 2018; Stein et al. 2021; Romero and Aspuru-Guzik 2021; Assouel et al. 2022). Huggins et al. (2019) further explored the use of tensor network circuits for both generative and discriminative learning. As for hybrid GANs, a part of the GAN architecture has been replaced by a quantum algorithm. For instance, studies Zoufal et al. (2019); Situ et al. (2020) proposed a hybrid framework with a quantum generator for discrete distributions and a classical discriminator. Enabling more practical applications with an arbitrary number of different generated data, quantum generators for continuous distributions have then been proposed in Anand et al. (2021); Chang et al. (2024).

To reduce the quantum resources required for analysis, Huang et al. (2021) proposed a patch-based QGAN, as shown in Fig. 18, which employs multiple quantum generators, each implemented as a PQC dedicated to a specific portion of the high-dimensional feature vectors. The outputs from all PQCs are then aggregated and processed by a classical discriminator. This principle has been adopted in subsequent studies, including (Tsang et al. 2023; Yang et al. 2025; Pajuhanfard et al. 2025). Differently, Lin and Young (2025) proposed a QGAN with both a hybrid generator and discriminator, where classical algorithms were employed to facilitate the analysis of large inputs. In particular, the use of classically trained encoder-decoders allows for projecting large-scale data in a latent space where quantum processing becomes tractable, as demonstrated in Chang et al. (2024).

3.3.9 Quantum diffusion model (QDM)

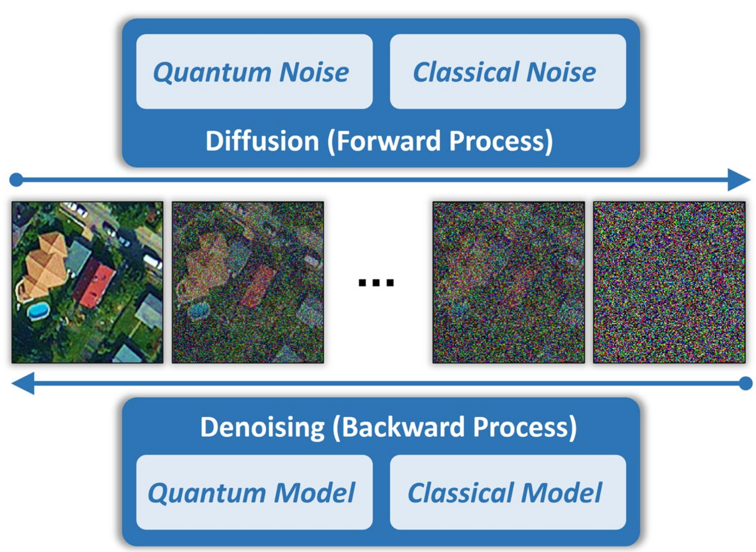
Diffusion models are generative models that progressively add noise to data until it becomes pure noise and then learn to reverse this process to generate high-quality samples. They have achieved state-of-the-art performance across a wide range of applications (Yang et al. 2023).

Regarding the integration of QML with diffusion models, recent studies (Parigi et al. 2024; De Falco et al. 2024; Han and Patel 2025) have proposed to exploit quantum noise as a beneficial ingredient rather than a problem to mitigate. In this context, Parigi et al. (2024) described a general QDM framework, illustrated in Fig. 19, and discussed its variants based on different quantum components. Following the early works on hybrid QDMs (De Falco et al. 2024) and fully-quantum QDMs (De Falco et al. 2024), several QDMs have been proposed, such as Cacioppo et al. (2023); Shah and Vatsa (2024), in which they implemented the forward Markov chain classically and employed different PQCs for the denoising procedure. In addition, Kölle et al. (2024) proposed quantum denoising diffusion models that improve the efficiency of the diffusion process by consolidating it into a single unitary matrix, thereby enabling one-step image generation, and Wang et al. (2025) introduced efficient QDMs by leveraging various quantum ordinary differential equation solvers during the diffusion process. Furthermore, Wang et al. (2024) extended quantum diffusion models to address the few-shot learning problem.

3.3.10 Quantum circuit born machine (QCBM)

A QCBM is a generative model that learns the probability distribution of classical data as quantum pure states. Samples from the learned distribution are obtained by measuring the quantum state in the computational basis. Benedetti et al. (2019) designed shallow quantum circuits tailored to NISQ devices to implement QCBMs. Liu and Wang (2018) proposed an efficient gradient-based algorithm for training QCBMs. Coyle et al. (2020) formulated QCBMs based on Ising Hamiltonians and introduced various enhancements to improve their performance.

Fig. 19 Schematic of a general QDM Adapted from Parigi et al. (2024)



3.3.11 Quantum Bayesian neural network (QBNN)

Bayesian neural networks learn a probability distribution over possible network parameters, enabling the integration of uncertainty estimation into their predictions (Arbel et al. 2023). The integration of Bayesian techniques with quantum computing has been explored in multiple ways. For instance, studies Nguyen and Chen (2022); Zhu et al. (2024); Mathur et al. (2025) proposed adapting Bayesian methods, which have been successfully applied in classical neural networks, to train PQC-based QML models. In contrast, studies Nikoloska and Simeone (2022); Sakhnenko et al. (2024) employed PQC to model the weight distributions of Bayesian neural networks. Furthermore, Berner et al. (2021) introduced quantum inner product estimation for efficient inference and prediction in Bayesian neural networks, while Zhao et al. (2019) developed a quantum algorithm for Gaussian processes that can be applied to arbitrary layers of deep neural networks.

3.3.12 Comparative analysis of QNN architectures

As can be observed, numerous QNN architectures have been proposed, most of which are inspired by classical deep learning models. They generally seek to preserve successful inductive biases of classical deep learning while replacing or enhancing selected learnable modules with quantum computing. For instance, QDNNs are conceptually analogous to dense neural networks, and they do not incorporate explicit architectural priors and are generally more suitable for vector-based data. QCNNs exploit locality and hierarchical features from the data, QRNNs utilize temporal dependencies from the data, QViTs capture long-range feature interactions through attention mechanisms, and QGNNs preserve graph topology and information-passing structures.

Within each architecture family, different variants have been proposed depending on the role of PQCs within the learning pipeline. Here, we use QCNN as one example to demonstrate this design flexibility. Some studies fully rely on quantum computing and build quantum convolution layers and pool layers Cong et al. (2019), some studies Fan et al. (2023) use PQC to conduct convolution operations and classical algorithms for final prediction, whereas others Sebastianelli et al. (2021) use classical convolution operations for feature extraction followed by quantum circuits for classification. Following the same principle of local feature extraction, quanvolution neural network has also been developed, which uses PQCs as kernels for feature map generation. To address the constraints of quantum resources in QNN models, additional strategies have been proposed. For instance, studies Malarvanan (2024) use multiple PQCs instead of one large circuit in their proposed models.

Similar to classical deep learning, there is no universally optimal QNN architecture as well. The design of QNN architectures involves two complementary decisions: selecting an appropriate architectural prior for the learning task and determining how quantum computation should be integrated within the network. These integration strategies are discussed in more detail in the next section.

4 Hybrid architecture design patterns

To date, hybrid QML models have attracted considerable attention for several reasons. Current NISQ devices are constrained by a limited number of qubits and gates and lack full fault tolerance, which restricts their standalone applicability, and the integration with classical algorithms might mitigate these limitations. Besides that, hybrid frameworks can leverage the complementary strengths of both quantum and classical computing for practical applications. To date, various strategies for integrating quantum and classical components have been explored. In this section, we review and discuss existing hybrid frameworks from multiple perspectives.

4.1 Position of quantum component in learning architectures

Among the proposed hybrid architectures, models can be categorized according to the position of the quantum component within the neural network. As illustrated in Fig. 20, two main categories emerge: early hybrid integration and late hybrid integration. The former primarily leverages quantum computing to process input data through iterative encoding and analysis using QML techniques, while the latter first employs classical machine learning to extract global feature representations, which are subsequently refined by QML components for final prediction.

4.1.1 Early hybrid integration

Leveraging quantum components in the early stages of neural networks to process input data poses challenges in terms of quantum resource requirements, especially when handling inputs with a large number of features. In principle, two strategies have been proposed. The first involves efficient encoding approaches, such as FRQI, which exploits superposition to achieve qubit-efficient encoding, or approximation-based methods that construct encoding states with reduced quantum resource requirements (Mitsuda et al. 2024; Duan and Hsieh 2022). The second strategy reduces quantum resource demands by partitioning the input and employing multiple PQCs to process the separated parts. For instance, the previously discussed element-based and patch-based methods fall into this category.

4.1.2 Late hybrid integration

These models employ classical machine learning approaches prior to the quantum component. The classical algorithms aim to extract global feature representations, and the quantum part further encodes the resulting features for further processing. As a result, the selection and design of classical feature reduction methods are critical to the overall performance of such hybrid architectures, particularly under the constraints of NISQ hardware. Since the classical algorithms in these models effectively serve as a preprocessing stage for the quantum component, various related approaches are discussed in Sect. 3.1. Regarding the quantum component, two main schemes have been adopted: (i) employing a single PQC to encode all features obtained from classical algorithms for further transformation, such as Zaidenberg et al. (2021), or (ii) subdividing the features into multiple groups, each processed by an individual PQC, such as Malarvanan (2024).

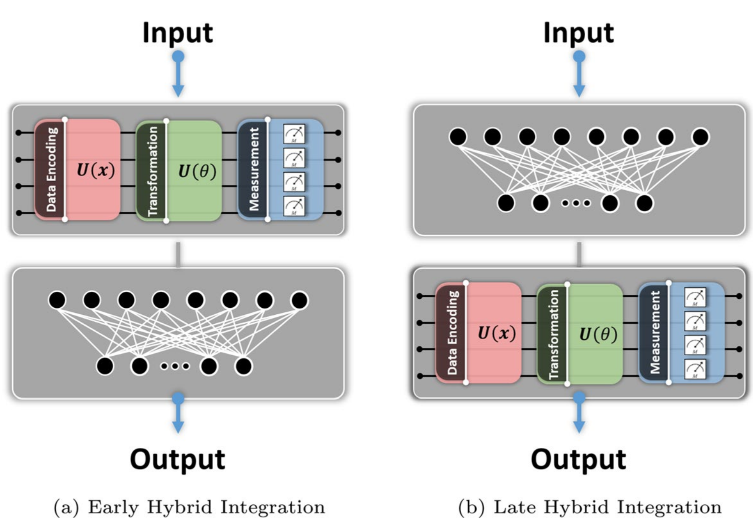


Fig. 20 **a** Quantum components applied near the input layers of the network; **b** quantum components applied at deeper layers or near the output stage

4.2 Level of quantum input granularity in machine learning

Based on the input for the quantum components within the hybrid QML models, we categorized them into three groups: *(a) Element-level*, *(b) Patch-level*, and *(c) Global-level*, as illustrated in Fig. 21.

4.2.1 Element-level quantum input

This type of hybrid QML model leverages a PQC to perform element-wise feature analysis. The features obtained from the PQCs are subsequently integrated and processed using classical algorithms. This framework has been widely applied to pixel-wise classification in image analysis, particularly for hyperspectral imagery.

4.2.2 Patch-level quantum input

For patch-level hybrid models, a group of elements, rather than individual elements, is encoded and analyzed within a PQC. A representative example is image analysis with QML, where multiple variants of this approach have been proposed. For example, as mentioned earlier, quanvolution neural networks divide the input into square patches, with each patch processed by a PQC. Additionally, dilated convolution-based hybrid models have been proposed, such as in Chen (2022); Khan et al. (2023); Tenali and Babu (2024). Chalumuri et al. (2021) treated a patch as a row of pixels in an image and applied a PQC to extract features for further analysis, while Malarvanan (2024) separated the feature vector obtained from a classical neural network and employed multiple PQCs to further extract features.

4.2.3 Global-level quantum input

Models leveraging a PQC to encode and analyze the entire input have also been investigated, particularly when the input has a small number of features. For larger and more complex inputs, classical algorithms for feature reduction are often employed to comply with quantum resource constraints in the NISQ era. As introduced earlier, some studies have also explored encoding entire images into a quantum state for classification with QML. Although the experimental images in these studies are relatively simple, they serve as proof of concept.

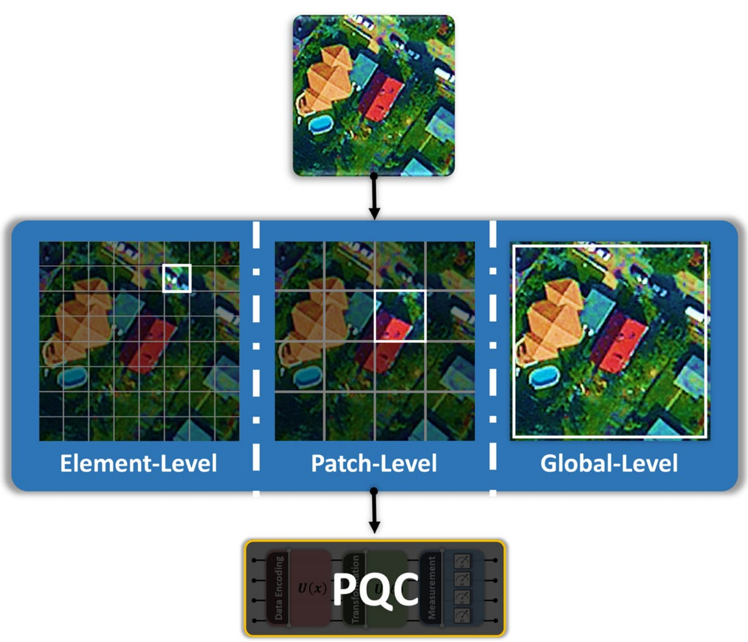


Fig. 21 Illustration of quantum input strategies in hybrid QML: element-level, patch-level, and global-level

In comparison, the amount of information encoded and analyzed by the PQC increases across these groups. Element-level frameworks require multiple PQCs to analyze a given input, with each circuit typically consuming fewer quantum resources but lacking the capacity to capture neighborhood relations. In contrast, global-level approaches encode the entire input into a single PQC, enabling the extraction of comprehensive features but generally at the cost of higher quantum resource demands. Patch-level frameworks could balance resource requirements with the amount of encoded information for feature extraction. Note that quantum resources can be further reduced by reusing quantum resources, for example, Easom-McCaldin et al. (2022) proposed to encode an entire input image into a single qubit for classification.

4.3 Degree of quantum contribution in machine learning

Hybrid QML models leverage quantum computing at varying levels of integration. We categorize existing approaches according to the degree of quantum contribution within neural networks into four groups: *(a) Quantum-Inspired Approaches*, *(b) Quantum Circuits for as Elementary Operations*, *(c) Quantum Circuits as Functional Modules*, and *(d) Quantum Circuits as End-to-End Networks*. It is worth noting that quantum-inspired and fully quantum models are not strictly hybrid; however, for completeness, we include them in this section to provide a broader perspective.

4.3.1 Quantum-inspired approaches

Some classical algorithms are inspired by quantum principles and are referred to as quantum-inspired neural networks. These models do not employ quantum circuits. Nevertheless, for completeness, we highlight a few representative studies. For instance, the tensor network, a key concept in many-body quantum systems, motivated Otgonbaatar and Kranzlmüller (2023) to apply it for reducing the number of parameters in a deep learning model and enhancing the spectral resolution of hyperspectral images. Similarly, Zhang et al. (2023), inspired by quantum theory, proposed a spectral-spatial network for hyperspectral image feature extraction, incorporating a phase-prediction module and a measurement-like fusion module for further analysis. Giuntini et al. (2023) described a quantum-inspired machine learning approach to multi-class classification, which does not make use of binary classifiers.

4.3.2 Quantum circuits as elementary operations

In many studies, PQCs are integrated only into specific operations within neural networks, rather than performing multiple operations within a single quantum circuit. For example, in some hybrid QRNNs, PQCs are applied to transform feature vectors within LSTM or GRU cells instead of replacing these classical cells with fully quantum counterparts. Likewise, in some hybrid QViTs, PQCs are employed to compute attention scores. Additionally, some hybrid QML models, such as quanvolutional neural networks and patch-based QGANs, as introduced earlier, use a PQC to process only a subset of the input, requiring multiple circuits to capture features across the entire input.

Beyond model architecture, quantum algorithms have also been proposed to accelerate specific training operations, such as inner product estimation in Bayesian neural networks and ordinary differential equation solvers for diffusion processes.

4.3.3 Quantum circuits as functional modules

The integration of PQCs as modules within neural networks has also been widely explored, leading to the development of various hybrid QML models. A common design pattern employs classical models to extract high-level global features, followed by a PQC layer that further transforms these representations for downstream tasks. This hybrid strategy has been evaluated with diverse classical backbones, including CNNs, AEs, Graph Neural Networks (GNNs), and Vision Transformers (ViTs), among others

Furthermore, unlike quanvolution-based approaches and the hybrid QRNNs mentioned earlier, quantum algorithms have also been proposed as modules that perform convolutional operations over the entire input with a single PQC, or realize an Recurrent Neural Network (RNN) cell within one PQC.

4.3.4 Quantum circuits as end-to-end networks

Note that exclusively using a single PQC as a neural network for data analysis is challenging in the NISQ era due to limited quantum resources. Nevertheless, notable contributions, such as Li et al. (2020); Wei et al. (2022), have proposed PQCs for image classification, primarily focusing on grayscale images, as proofs of concept.

5 Capabilities, limitations and practicality of quantum models

5.1 Learning capacity of QML

To understand the capacity of QML models, we summarize it from three complementary perspectives: *Expressivity*, which captures whether a model can represent the target functions in principle; *Learnability*, which reflects whether the model parameters can be efficiently optimized given the available training data; and *Generalizability*, which characterizes the ability of the trained model to perform well on unseen data.

5.1.1 Expressivity

The expressivity of a model refers to its ability to approximate target functions (Lu et al. 2017). To quantify the expressivity of a QNN, several methods have been proposed. A widely adopted approach considers the expressivity of a PQC as its ability to explore the Hilbert space. In this context, Sim et al. (2019) introduced a metric based on the deviation from the Haar distribution and the Kullback–Leibler divergence (Kullback and Leibler 1951). In addition to that, Du et al. (2020) exploited entanglement entropy to evaluate expressive power, Haug et al. (2021) used the effective dimension derived from the quantum Fisher information metric, and Wright and Mcmahon (2020) adopted memory capacity as a measure.

Regarding the factors contributing to the expressive power of QML models, Anschuetz et al. (2023) argued that quantum contextuality serves as the source of an unconditional memory separation underlying the expressivity advantage. Liu et al. (2025) associated the expressivity of QNNs with the types of quantum gates employed, while Wu et al. (2021) concluded that the target function can be accurately represented only when the input wave functions do not span the entire Hilbert space. Schuld et al. (2021) further examined the influence of data encoding strategies on expressive power. Moreover, Panadero et al. (2024) demonstrated that entanglement can enhance a QML model's expressive capacity, and Lin et al. (2025) proposed an adaptive non-local measurement framework to further improve expressivity. However, over-expressivity may lead to overfitting, and applying appropriate regularization techniques is a common strategy to address this issue.

5.1.2 Learnability

Learnability, also referred to as trainability, generally refers to a model's ability to be effectively optimized using available data. To optimize the trainable parameters in QML models, gradient-based approaches have been widely used. As noted in Gil-Fuster et al. (2024), such optimization typically begins with parameters randomly sampled from an initialization distribution, followed by iterative updates that explore the local region of the loss landscape around the current values at each step. There are several challenges to train QML models. One typical issue is the Barren Plateau (BP) problem McClean et al. (2018), where the loss landscape becomes exponentially flat with increasing problem size, thereby requiring exponential resources to navigate through the flat landscape.

To date, numerous factors have been identified as contributing to the BP phenomenon, including the adopted encoding method (Thanasilp et al. 2023; Leone et al. 2024), over-entanglement (Patti et al. 2021; Marrero et al. 2021; Sharma et al. 2022), excessive expressivity of the QML models (Holmes et al. 2022), the use of global observables for measurement (Cerezo et al. 2021), hardware noise (Wang et al. 2021), among others.

In response, various strategies have been developed to address this issue and improve the learnability of QNN models. For instance, Ceschini et al. (2025) investigated different optimizers for training QNN and highlighted the importance of optimizer selection. Du et al. (2021) showed that regularization operations can reshape the loss landscape and mitigate BP. Cerezo et al. (2021) established a connection between locality and learnability, suggesting the use of local operators for better trainability. Volkoff and Coles (2021) demonstrated that introducing correlations among parameters in QNN models can alleviate BP. In addition, studies such as Grant et al. (2019); Verdon et al. (2019); Kashif et al. (2024) investigated initialization strategies to mitigate this problem. Although hardware noise contributes to the BP problem, Wang et al. (2024) emphasized that careful error mitigation is essential, as it affects the learnability of quantum models as well. Besides that, Abbas et al. (2021) concluded that well-designed quantum neural networks can exhibit resilience to the BP phenomenon and train faster than classical models due to their favorable optimization landscapes. For instance, the QCNN model proposed by Cong et al. (2019) was reported by Pesah et al. (2021) to not exhibit BP. In addition, a layer-wise learning strategy (Skolik et al. 2021) has been proposed to mitigate the BP problem by incrementally increasing the depth of the PQC during optimization and updating only a subset of parameters at each step. Moreover, the alternating-layered ansatz technique (Cerezo et al. 2021; Suzuki and Li 2024) has also been introduced to address this issue.

5.1.3 Generalizability

Generalizability is a critical aspect of machine learning models, reflecting their ability to perform on unseen data. Numerous studies have examined the generalization bounds of QML models from different perspectives, as reviewed in Khanal et al. (2024).

Similar to classical machine learning, studies such as Caro et al. (2022); Du et al. (2023); Gibbs et al. (2024) suggest that the generalization capacity of QML models is strongly influenced by the number of available training samples. Additionally, several other factors that impact the generalization bounds of QML models have also been investigated. For example, Caro et al. (2021) quantified generalization using the Rademacher complexity and the metric entropy from statistical learning theory, highlighting the critical role of data-encoding strategies in shaping the generalizability of QML models. Similarly, Barthe and Pérez-Salinas (2024) concluded that quantum reuploading-based QDNNs are more generalizable and resistant to overfitting. In addition, Caro et al. (2023) linked generalizability to the number of trainable quantum gates in the circuit, Gili et al. (2023) investigated the effect of circuit depth on generalizability, and Qi et al. (2023) demonstrated a connection to the Hilbert space dimension. Furthermore, Gyurik et al. (2023) studied the impact of the chosen observables in QML on generalization performance, leveraging the Vapnik-Chervonenkis dimension as the evaluation framework. Regarding the impact of noise on generalizability, while adding certain noise can benefit the training of complex classical deep learning models (Neelakantan et al. 2015), excessive noise in quantum systems, particularly when the number of measurements is insufficient, can negatively affect the model's generalizability, as observed in Thanasilp et al. (2024); Wang et al. (2021).

However, Gil-Fuster et al. (2024) suggested that the ability of QNNs trained with few data to perform well on unseen data may stem from their memorization capacity. This implies that traditional approaches to understanding generalization might not be directly applicable to such quantum models, and further studies are required to understand the factors contributing to their successful generalization.

5.2 Observed benefits and quantum advantage in QML

Quantum advantage in machine learning can be interpreted from multiple perspectives. At the empirical level, it is typically reflected through enhanced performance, generalization capacity, or efficiency on benchmark tasks. At the theoretical level, it explores the properties and mechanisms that may enable such benefits.

5.2.1 Reported empirical quantum benefits

To date, numerous experiments have been conducted to evaluate QML models using simulators or real quantum devices on both real-world and synthetic datasets. Based on these studies, several empirical benefits have been reported. One frequently reported benefit is improved performance on benchmark tasks, as demonstrated by various empirical comparisons. For instance, studies Rainjonneau et al. (2023); Malarvanan (2024); Lin and Chen (2023); Hsu et al. (2024); De Falco et al. (2024); Bhavsar et al. (2023); Mauro et al. (2024); Sebastianelli et al. (2025); Chalumuri et al. (2021); Lin et al. (2024); Fan et al. (2023, 2024) directly compared their proposed hybrid QML models with classical baseline algorithms. Other studies Sebastianelli et al. (2021, 2023); Ghosh et al. (2024); Mauro et al. (2024); Chang et al. (2024) evaluated performance by replacing quantum components with classical counterparts within the same model architecture. Meanwhile, studies Priyanka and Venkatesan (2024); Zaidenberg et al. (2021) assessed the impact of quantum components by comparing model performance with and without them, thereby validating the potential of QML for data analysis.

Beyond that, generalizability represents another potential benefit that QML may offer to deep learning models. For instance, experiments in studies De Falco et al. (2024); Chang et al. (2024); Lin et al. (2024) have demonstrated that the proposed hybrid models can achieve strong performance on unseen data, even when trained with a reduced number of samples, compared to their classical counterparts. Xiao et al. (2024) observed that the learnable quantum latent space shows stronger generalization capability and increases diversity of the pretrained models in various computer vision problems. Building on this advantage, Shaik et al. (2022) incorporated quantum models into a pseudo-labeling framework to mitigate data scarcity.

Furthermore, efficiency is another key focus, as quantum computing is expected to accelerate computational tasks, and various related benefits have also been observed. For instance, studies Siemaszko et al. (2023); Zhu et al. (2024); Mauro et al. (2024); De Falco et al. (2024) reported that their proposed QML models converged faster during training than classical models, indicating potential efficiency gains. The number of trainable parameters is another commonly used indicator, as models with fewer parameters generally require less time for optimization. Notably, studies Huang et al. (2021); Nguyen and Chen (2022); Chang et al. (2024); Chalumuri et al. (2021); Moon et al. (2025); Fan et al. (2025); Farsian et al. (2025) demonstrated that hybrid models with relatively few trainable parameters can achieve comparable or even superior performance to classical models with substantially more parameters.

5.2.2 Theoretical perspectives on quantum advantage

To better understand the mechanisms underlying these reported empirical benefits, several studies have investigated theoretical properties of QML models. For instance, Schuld and Killoran (2019) interpreted quantum circuits as feature maps that embed classical data into high-dimensional Hilbert spaces, indicating that richer feature representations may provide a learning advantage. Huang et al. (2021) used the geometric difference between quantum and classical feature spaces as a theoretical indicator to identify tasks in which QML models may outperform classical approaches. Abbas et al. (2021) analyzed the effective dimension of QNNs from the perspective of information geometry and showed that QML can exhibit a larger dimension than comparable classical ones under certain settings, suggesting stronger learning capacity. Similarly, Xiao et al. (2023) quantified and compared this capacity using the local effective dimension and reported improved generalization behavior under the evaluated settings. Furthermore, Chen et al. (2021) suggested that quantum circuit learning may exhibit an inherent form of automatic regularization that helps prevent overfitting, providing a possible theoretical explanation for some of the reported empirical benefits of QML.

Taken together, these empirical observations and theoretical analyses provide supportive evidence regarding the potential of QML models, but note that they should not be interpreted as conclusive proof of a universal quantum advantage, because these evaluations and analyses are usually under specific experimental settings. It is still a relatively young research field compared with the extensive development of classical machine learning and deep learning.

5.3 Current maturity and limitations of QML

As an emerging field, besides the potential of QML, several fundamental challenges that may limit the practical deployment and scalability of QML systems have also been identified. Although future fault-tolerant quantum computers may alleviate some current constraints, certain issues are expected to remain important considerations.

To be more specific, some fundamental issues affecting the learning capacity of QML models have been identified in both quantum kernel methods and quantum neural networks. Barren Plateau, as introduced in the previous section, is one typical issue that could negatively impact the learnability of QNN algorithms, and this phenomenon was studied in McClean et al. (2018). They analytically and numerically concluded that as the circuit size increases, the gradient magnitude may vanish exponentially due to the concentration of measurement in quantum space, making optimization increasingly difficult. Similar concerns have been identified for quantum kernel methods. Kernel concentration may reduce the discriminative power of quantum feature spaces as the problem size increases, so simply scaling the dataset size may not be sufficient to improve performance unless measurement resources are increased accordingly. As a result, techniques to alleviate this issue are required, particularly for large-scale applications.

Another important limitation is quantum state preparation, particularly when dealing with content-rich data, such as images and videos. Preparing the corresponding quantum states may require complex quantum circuits, and the associated computational overhead may offset the potential advantages of subsequent quantum processing. In addition, it can also be observed that the evaluations of QML models follow different protocols for baseline selections and use different experiment settings. Furthermore, quantum resource requirements and training budgets are not always controlled or reported. As a result, the observed improvements should be interpreted with caution.

The gap between simulator-based studies and real quantum hardware deployments should not be overlooked. Many reported QML results are obtained using noiseless simulators, which can represent an upper bound on achievable performance. However, due to noise, performance gains observed in simulations may not directly translate to practical quantum hardware. Consequently, the scalability of QML remains an open challenge. Most studies are conducted on relatively small datasets using shallow circuits as proof-of-concept demonstrations. Whether such benefits can be retained in large-scale applications remains unclear.

5.4 Practical deployment considerations

5.4.1 Noise-resilient quantum machine learning

In the NISQ era, quantum noise remains one of the primary barriers to the practical realization of quantum computing, as it compromises computational reliability. To effectively harness QML in the near term, it is essential to understand the impact of quantum noise and develop strategies to alleviate its effect on model performance. Two different approaches have been explored: error mitigation and error correction. The former aims to suppress noise in noisy devices without requiring fault-tolerant hardware, and the latter is a hardware-oriented approach using many physical qubits to build logical qubits for fault-tolerant quantum computation. Since this study focuses on the development of circuit-based learning in the NISQ era, the following discussion emphasizes noise-resilient learning algorithms and error mitigation techniques.

To date, several types of quantum noise have been identified, including depolarization, bit-flip, and dephasing. Singh and Pokhrel (2025) systematically evaluated their effects on various QML models, whereas Wang et al. (2025) and Suzuki et al. (2024) examined noisy quantum kernels and found that the presence of noise had a minimal impact on performance as long as the noise level stays below a certain threshold.

To mitigate the negative effects of quantum noise in QML models, several strategies have been proposed. For instance, Miroszewski et al. (2024) analyzed how the number of quantum circuit runs affects successful computation on noisy quantum circuits. Anand et al. (2021) introduced a noise-resilient QGAN, demonstrating that its performance remains largely unaffected by the presence of noise. Similarly, Khanal and Rivas (2024) proposed a framework for learning observables that remain invariant under noisy quantum channels, thereby enhancing robustness to noise. Additionally, since deep quantum circuits can accumulate gate errors, the careful design of shallow PQCs for QML tasks can help extend the computational capabilities of NISQ devices. Following this principle, Alam and Ghosh (2022) and Incudini et al. (2023) proposed frameworks composed of multiple small PQCs, each executable on small-scale quantum processors, while Sahu and Gupta (2024) developed a framework that partitions large circuits into shallow subcircuits, assigns them to NISQ devices with minimal noise, and distributes QML tasks efficiently.

In an even more promising scenario, quantum noise could be exploited as a beneficial element in QML tasks, transforming what is typically a limitation into a potential advantage. For instance, studies Parigi et al. (2024); Han and Patel (2025) leverage quantum noise in their proposed diffusion models, whereas the study (Cao and Wang 2021) exploited quantum noise in their proposed QAE.

5.4.2 Hardware-efficient quantum machine learning

A quantum computing system consists not only of the software system, but also of the hardware system (Li et al. 2021). To effectively harness QML algorithms in practice, the capacity of quantum hardware plays a critical role in determining their feasibility and efficiency. However, current NISQ devices remain constrained by the limited number of qubits, shallow circuit depths, and inherent noise effects. As a result, the development of hardware-efficient QML models has attracted substantial attention, leading to numerous recent contributions.

Quantum circuit cutting, also known as partitioning, is a widely used technique that subdivides a quantum circuit into smaller subcircuits. This approach enables running large QML models on quantum hardware with limited capacity. In addition to mitigating the noise effects discussed earlier, it also enhances the practical feasibility of QML algorithms on current devices. To date, depending on the type of target being cut, this technique can be categorized into gate cuts (Ufrecht et al. 2023), qubit cuts (Tang et al. 2021; Brenner et al. 2025), or a combination of both (Brandhofer et al. 2023). Furthermore, hardware-specific information, such as device topology, qubit connectivity, and available gate types, is also taken into account during circuit cutting, as demonstrated in Sahu et al. (2025); Liu et al. (2025).

Besides cutting large PQCs, other techniques have been proposed to reduce quantum resource requirements and enhance hardware feasibility. For instance, studies such as Hasan and Mahdy (2023); Alam et al. (2023); Oh et al. (2025) leverage knowledge distillation to achieve this goal, while studies Wang (2025); Lei et al. (2024); Yu et al. (2024) focus on optimizing the PQC structure to minimize the required quantum resources.

6 Emerging paradigms in quantum circuit design

As QML continues to mature, recent advances highlight the demand for PQC that are not only effective but also transparent, adaptable, and scalable. In this context, several emerging paradigms are shaping the future of quantum circuit design. Interpretable circuit design aims to enhance the transparency and physical interpretability of

QML models; Quantum architecture search introduces automated strategies for circuit discovery and optimization; Distributed circuit designs support collaborative training under limited quantum resources and enable large-scale implementations.

6.1 Interpretable circuit design

Interpretability and explainability of machine learning models are of particular importance, as they are essential for developing trustworthy systems in practice. Since the PQC constitutes a core component of QML, research on interpretable circuit design has gained increasing attention, as reviewed in Wetzel et al. (2025).

To date, various conventional explanation techniques for classical deep learning models have been transferred and adopted in QML. For instance, Mercaldo et al. (2022) provided explainability behind the QML model predictions by adopting the Gradient-weighted Class Activation Mapping. Kadian et al. (2025) enhanced the interpretability of a QSVM by employing LIME (Ribeiro et al. 2016) and SHAP (Lundberg and Lee 2017). Pira and Ferrie (2024) proposed a LIME-based method tailored to PQCs for explaining QML models, while Steinmüller et al. (2022) introduced a SHAP-based approach designed for PQCs with the same objective.

Additionally, Heese et al. (2025) advanced explainability for PQCs by quantifying the contribution of individual gates to specific tasks using Shapley values (Shapley 1953). Tian and Yang (2024) introduced a model inversion technique to improve the interpretability of quantum generative models by tracing generated quantum states back to their latent variables, thereby revealing the relationship between inputs and generated outputs. Gil-Fuster et al. (2024) highlighted the challenges in explainability of QML and proposed two explanation methods tailored for the circuit-based machine learning models.

Moreover, Ruan et al. (2023) developed an interactive visualization system that facilitates the analysis of quantum state evolution throughout an entire circuit, thereby enhancing its interpretability.

6.2 Quantum neural architecture search

For quantum circuit-based machine learning models, the structure of the adopted PQC plays a critical role in determining its effectiveness for feature transformation and extraction. Moreover, since the architecture consists of a sequence of parameterized gates, it also dictates the required quantum resources and influences the overall efficiency. To optimize the design of PQCs in QML, the research field of Quantum Neural Architecture Search (QNAS) has emerged and gained significant attention. To date, various contributions have been made in this direction.

For instance, studies such as Altares-López et al. (2021); Lei et al. (2024); Incudini et al. (2024); Máté et al. (2022); Yu et al. (2024) propose automatically designing and optimizing the design of quantum circuits for quantum kernels and quantum neural networks. Anagolum et al. (2024) introduced a framework considering the quantum hardware and generating topology- and noise-aware circuits as candidates. Zhang et al. (2022) introduced a framework that enables automated quantum circuit design by relaxing discrete structural parameters into a continuous domain, thereby allowing end-to-end differentiable optimization where quantum architectures are sampled from a parameterized probabilistic model.

In addition to that, the power of reinforcement learning has also been adopted for optimizing PQC design. For example, studies Kuo et al. (2021); Ye and Chen (2021) used a classical learning agent to place possible quantum gates and evaluate the validity of the composed circuit. Suzuki et al. (2025) introduced a QML-oriented feature selection method and adopted it to compress QML models by evaluating the magnitudes of parameters to determine which part of quantum circuits are redundant.

6.3 Distributed quantum circuits

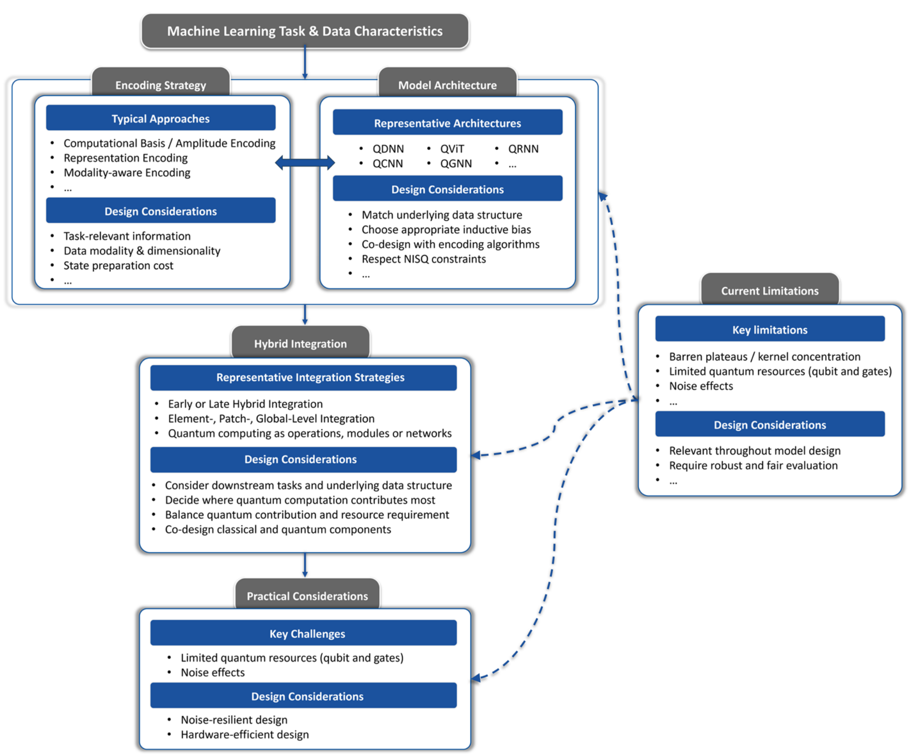
The principle of distributed quantum computing is to employ multiple quantum devices to process information and generate outputs, thereby enabling architectural scalability in the NISQ era. Pira and Ferrie (2023) reviewed the current progress in this area. To date, distributed quantum machine learning has been explored from two perspectives: (i) circuit partitioning for model parallelism and (ii) data partitioning for data parallelism. For model parallelism, cutting PQCs into sub-circuits has been widely studied, with horizontal splitting strategies receiving particular attention (Peng et al. 2020; Marshall et al. 2023; Lowe et al. 2023; Tomesh et al. 2023; Piveteau and Sutter 2023).

In the case of data partitioning, Quantum Federated Learning (QFL) represents a widely studied approach that integrates quantum computing with federated learning, thereby enhancing privacy and efficiency in training distributed quantum circuits. A comprehensive review of the field is provided by Nguyen et al. (2025). Both fully quantum and hybrid QFL frameworks have been investigated: the former relies entirely on quantum resources, while the latter combines classical and quantum techniques. A representative fully quantum QFL framework trains local PQCs on client data and employs a central quantum server to aggregate and redistribute local model weights, as demonstrated in Huang et al. (2022); Innan et al. (2024). In hybrid QFL, quantum components can be deployed at various stages of the framework. For example, Chen and Yoo (2021) implemented PQCs as local clients, while Song et al. (2024) utilized a quantum server with classical local clients. Hisamori et al. (2024) proposed hybrid local models in which PQCs are integrated with classical layers for local data training.

7 Design guidelines for circuit-based learning

Overall, the design of quantum circuit-based learning models should be viewed as a sequence of interrelated design decisions rather than the selection of a predefined quantum architecture. Figure 22 summarizes the major design considerations and provides an operational workflow for developing QML models. As illustrated in the

Fig. 22 Operational design workflow for quantum circuit-based learning



figure, it should start from the learning task and the characteristics of the available data, followed by the co-design of encoding strategies and quantum model architectures, the selection of hybrid integration strategies, and practical deployment consideration under NISQ constraints. Current limitations, such as limited quantum resources and training challenges, should be considered throughout the entire design process. Although these trade-offs are expected to evolve as quantum hardware advances toward fault-tolerant quantum computing, the overall design principles are likely to remain applicable.

8 Representative application domains of quantum machine learning

To date, researchers have been actively exploring the potential of quantum computing across a wide range of applications, despite current limitations in quantum hardware. In the following, we focus on three representative fields and discuss the adoption of QML within these application domains.

8.1 Earth observation and remote sensing

Earth Observation (EO) aims to monitor the condition of the Earth's surface and sub-surface using various Remote Sensing (RS) technologies, providing comprehensive information to support informed decision-making for sustainable development, environmental protection, and global security (Anderson et al. 2017). The exploration of the potentials of QML in various Earth Observation (EO) tasks has been conducted. Miroszewski et al. (2023) provide a broad overview of QML applications in RS, identifying both the potential and the limitations posed by current hardware.

8.1.1 Land cover classification

This task aims to extract essential information from RS imagery and provide valuable insights for diverse applications, including urban planning, resource management, and environmental monitoring. Both quantum kernel-based approaches and quantum neural networks have been applied to this task. For example, several studies Sarkar et al. (2024); Pai et al. (2024); Gupta et al. (2023) have employed QSVMs for land cover classification.

As for QNNs in EO data classification, most proposed models are hybrid. For instance, quanvolutional neural network-based models, one typical early hybrid model, have been proposed to process EO data. One representative example is introduced in Sebastianelli et al. (2025), as illustrated in Fig. 23, and studies Henderson et al. (2021); Miller et al. (2023); Ghosh et al. (2024) proposed different models based on this principle to classify various types of EO data. Besides that, late hybrid models have also been studied, which rely on classical deep learning algorithms to extract features from EO data first, then apply PQCs for further analysis. To date, various classical algorithms have been integrated with QML for classifying EO data, for instance PCA (Gawron and Lewiński 2020), CNN (Sebastianelli et al. 2021, 2023), convolutional AE (Otgonbaatar and Datcu 2021; Chang

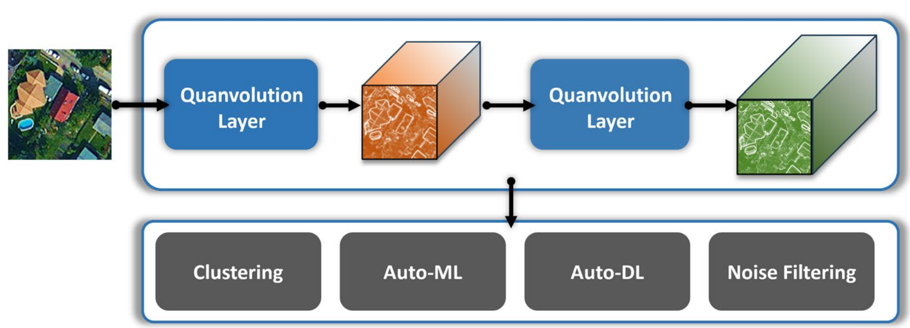


Fig. 23 QuanvNN for EO data classification. Figure adapted from Sebastianelli et al. (2025)

et al. 2022), and pretrained model (Otgonbaatar et al. 2023). Furthermore, a few proposed models encode the entire EO data and extract features with quantum computing, followed by a classical classifier for final classification, such as Xu et al. (2024); Fan et al. (2022, 2023, 2023, 2024). Regarding pure QNN for EO data analysis in the NISQ era, exclusively applying QML is challenging, as the limited quantum resources cannot yet accommodate the high dimensionality and complexity of EO data. Nevertheless, Yu et al. (2024) introduced an evolutionary algorithm-driven method for quantum circuit design, aiming to minimize quantum resource usage within a contrastive learning framework for effective representation learning of EO data for final classification.

8.1.2 Semantic segmentation

Semantic segmentation in EO aims to produce a dense semantic map that offers a fine-grained spatial understanding of the surface and sub-surface categories represented in EO imagery. To date, numerous classical deep learning architectures, such as U-Net and its variants, have been proposed and successfully applied to this task. To leverage quantum computing for this task, Ghosh et al. (2024, 2025) incorporated QML into a UNet-like architecture and proposed a QFMs regulated CNN architecture to develop hybrid models for semantic segmentation of sub-surface radar sounder data.

8.1.3 Change detection

This task involves identifying and quantifying changes on the Earth's surface by analyzing multi-temporal EO data, thereby enabling the monitoring of dynamic environmental and land surface processes. Exploring the potential of QML in change detection has also been conducted. For example, Lin et al. (2024) focused on hyperspectral image change detection by integrating pixel-level features derived from QML into a GNN architecture, whereas Painchart et al. (2024) introduced a pyramid-structured QNN to classify temporal sequence EO data with reduced quantum resource requirements.

8.1.4 Data reconstruction and restoration

This task addresses missing pixels or distorted information in EO imagery, thereby enabling more reliable analysis. To date, various hybrid QML models combining convolutional AEs with quantum latent space transformations have been proposed for hyperspectral image restoration tasks (Lin and Chen 2023; Hsu et al. 2024). Building upon the quantum generator introduced in Lin and Chen (2023), Lin et al. (2024) proposed a hybrid quantum discriminator, forming a quantum adversarial learning network for hyperspectral image restoration. In addition, Chang et al. (2024) addressed the image generation task by leveraging a pretrained AE to map high-dimensional data into a latent space. Within this space, they proposed a hybrid QGAN to generate synthetic latent features, which were subsequently decoded to reconstruct the original data. In a related study, De Falco et al. (2024) also exploited QML within the latent space and developed a quantum latent diffusion model integrated with a convolutional AE for EO imagery generation.

8.1.5 Multi-modality data fusion

In EO, a variety of sensors are used to capture information, resulting in diverse data modalities, including RGB imagery, multispectral imagery, hyperspectral imagery, and SAR, each offering complementary insights. The potential of QML for fusing multiple EO modalities has been investigated. For example, Majji et al. (2022) and Miller et al. (2024) applied different PQCs to integrate SAR and optical imagery, with the fused features subsequently processed by classical deep learning models for classification.

8.1.6 Weather and climate

Climate and weather sciences have also emerged as promising application areas for quantum computing, as reviewed in Rahman et al. (2024); Schwabe et al. (2025). Tennie and Palmer (2023) provided a nontechnical analysis regarding the opportunities and challenges of applying quantum computing in weather prediction and climate simulation, while Otgonbaatar et al. (2023) assessed the feasibility of quantum computing for climate-related problems, including climate change detection, climate modeling, and climate digital twins.

To be more specific, Suhas and Divya (2023) proposed a hybrid framework that leverages quantum algorithms to process complex meteorological data for weather forecasting. Jaderberg et al. (2024) adopted QML to accurately reproduce real-world global stream function dynamics, demonstrating its potential for modeling complex dynamical systems governed by partial differential equations. Pastori et al. (2025) introduced a QML model for cloud-cover parameterizations in climate models, and experimental results indicated that the proposed QML model maintained stable performance under noisy conditions.

8.1.7 Others

QML has also been explored in other EO applications, such as satellite mission planning (Rainjonneau et al. 2023), satellite-ground communication (Park et al. 2024), ocean Niño index prediction (Mauro et al. 2024), InSAR phase unwrapping (Glatting et al. 2024), and air pollution prediction (Farooq et al. 2024).

8.2 Healthcare

In the healthcare industry, discovering associations and extracting patterns from large volumes of data can provide valuable insights to support informed decision-making (Raghupathi and Raghupathi 2014). The potential of QML for analyzing complex healthcare data and improving predictive performance has also been explored in recent studies, as reviewed in Ullah and Garcia-Zapirain (2024); Gupta et al. (2025). In the following, we focus primarily on several representative tasks.

8.2.1 Medical image analysis

To address the challenges when applying machine learning to analyze medical images, numerous studies that combined quantum computing with machine learning have been conducted to explore more advanced algorithms (Wei et al. 2023), and Fig. 24 illustrates a typical pipeline. To be more specific, for medical image classification tasks, in which models aim to categorize images according to disease type or distinguish between normal and abnormal cases, various QML models have been proposed to deal with different types of medical images, such as X-ray (Houssein et al. 2022), MRI (Amin et al. 2022a), CT (Amin et al. 2022b). Besides, segmentation is another crucial task that contributes to the process and interpretation of medical images, and many QML models

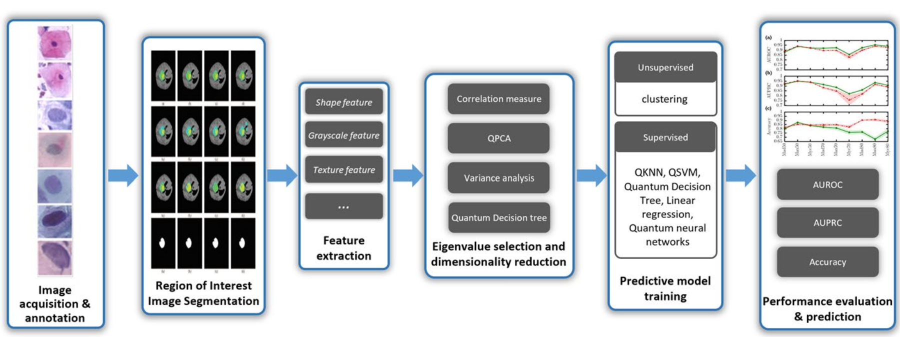


Fig. 24 Typical process of applying QML for medical image analysis. Figure adapted from Wei et al. (2023)

have been proposed to tackle it, such as Jamal et al. (2023); Domingo and Chehimi (2024); Wang et al. (2025). Furthermore, quantum computing has also been adopted for medical image preprocessing, such as image denoising (Qasim et al. 2022), image quality improvement (Pashaei and Pashaei 2023), and image reconstruction (Li et al. 2020).

8.2.2 Diagnosis assistance

To date, researchers have explored the adoption of QML to detect various diseases through the analysis of medical data. For instance, QSVM, a famous kernel-based QML model, has been adopted to detect COVID-19 (Ullah et al. 2022), cardiovascular disease (Maheshwari et al. 2023), and breast cancer (Jose et al. 2024; Rv 2024). In addition, Abdulsalam et al. (2023) integrated QSVM with other models and developed an ensemble learning model for heart disease detection, Belay et al. (2024) exploited classical deep learning algorithms to get features for a QSVM model to detect Alzheimer's disease, and Khushal and Fatima (2025) integrated fuzzy logic with QML and proposed multiple quantum models accordingly, including fuzzy QSVM, for medical diagnosis. Regarding QNN models, several algorithms have been proposed to address this task as well. Xiang et al. (2024) proposed a hybrid QCNN to accelerate breast cancer diagnosis. Similarly, Ajay et al. (2025) designed a dual-track framework in which two classical deep learning algorithms extract features independently, while a proposed QNN performs colorectal cancer detection based on the extracted features. Furthermore, Tudisco et al. (2025) proposed a QNN consisting of multiple PQCs, which are optimized iteratively for disease detection. Matic et al. (2022) tested different hybrid quantum-classical QCNN with varying quantum circuit designs and encoding techniques on radiological image classification.

8.2.3 Drug discovery

To date, machine learning approaches have already been widely explored to facilitate drug discovery by automatically analyzing a large amount of available data. Since quantum computing is expected to speed up certain computational tasks, its potential in drug discovery has also been extensively studied, and numerous models have been proposed inspired by the success of classical deep learning algorithms, such as QSVM (Mensa et al. 2023), QCNN (Domingo et al. 2023; Smaldone and Batista 2024), QGAN (Kao et al. 2023; Anoshin et al. 2024). Several studies provide comprehensive overviews on this topic, such as Smaldone et al. (2025); Haque et al. (2025), to which interested readers may refer for further information.

8.3 Finance

QML has also been widely explored in finance and is expected to enhance efficiency and accuracy in financial modeling for various tasks. Numerous contributions have been made in *Portfolio Optimization*, *Risk Analysis*, *Market Trend Prediction*, and *Fraud Detection*. For readers seeking a more comprehensive introduction, several overview papers are available, such as Herman et al. (2023); Bunescu and Vârtei (2024); Zhou (2025).

8.3.1 Portfolio optimization

This task aims to select the best combination of assets based on a predefined objective, typically maximizing expected return while minimizing risk. To tackle this task with quantum computing, many studies explored the possibility of using quantum annealing, such as Palmer et al. (2022); Mugel et al. (2021). The leverage of quantum circuit models has also attracted significant attention, and many contributions have been made. For instance, Mugel et al. (2022) leveraged VQE for this optimization task, whereas Lim and Rebentrost (2024) proposed a quantum version of a classical online portfolio optimization proposed in Helmbold et al. (1998), which provides a quadratic speedup in the time complexity.

8.3.2 Risk analysis

In the financial domain, this task focuses on analyzing adverse events associated with potential financial losses, which is crucial for financial institutions Wilkens and Moorhouse (2023). To quantify such risks, Monte Carlo simulations are widely used on classical machines. Accordingly, the exploration of quantum algorithms for Monte Carlo has been investigated in Rebentrost et al. (2018); Woerner and Egger (2019) which shows the proposed quantum algorithm could achieve a quadratic quantum speedup. In addition, Thakkar et al. (2024) designed and proposed quantum neural network architectures for credit risk assessment, which match classical performance with significantly fewer parameters.

8.3.3 Market trend prediction

The accurate prediction of the financial market trend has long been a focal point in the financial domain, and investigations into the use of QML for this task have also been conducted. Besides the studies leveraging quantum annealing for this task, such as Srivastava et al. (2023), quantum circuit-based learning models have also been proposed. For instance, Paquet and Soleymani (2022) presented a hybrid quantum model for financial prediction, where a quantum algorithm is employed to predict the density matrix, while classical algorithms are used for input transformation and final prediction. Orlandi et al. (2024) proposed a QGAN to generate synthetic financial data aimed at improving model performance in the presence of extreme events. Mourya et al. (2025) proposed a quantum architecture, as shown in Fig. 25, tailored for stock price prediction across multiple assets and developed the quantum batch gradient update method for efficient training.

8.3.4 Fraud detection

This task aims to identify and prevent deceptive activities that are intended to obtain financial gains. The adoption of QML to address the current challenges in this task has attracted great attention in these years, and numerous contributions have been made. For example, Kyriienko and Magnusson (2022) proposed a QSVM with data reuploading for fraud detection in an unsupervised manner, highlighting the high expressivity of quantum kernel-based methods, while Grossi et al. (2022) exploited quantum computing to select the most important features for accurate detection and also defined a mixed quantum-classical ensemble method to further improve the performance. Tscharke et al. (2025) addressed the anomaly detection problem by applying Quantum Support Vector Regression. Additionally, Innan et al. (2024) developed a QGNN model to detect financial frauds and found their QML model more effective and efficient than its classical counterpart in this task.

8.4 Transport and logistics

The potential of QML for addressing challenges in transportation systems has also been studied. Existing studies have investigated tasks, such as routing optimization, vehicle dynamics modeling and prediction, and traffic state forecasting, exploring the potential and challenges of QML across transportation planning, control, and monitoring tasks. A comprehensive overview of recent developments in this area can be found in Guerrero-Domínguez et al. (2026).

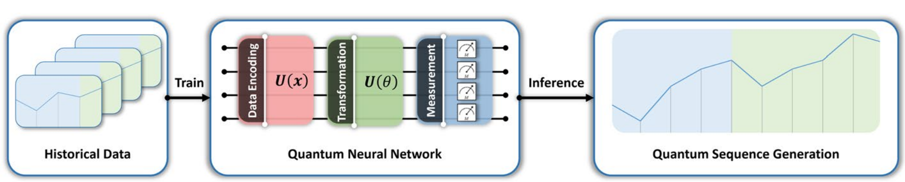


Fig. 25 Representative QML model for stock price prediction. Figure adapted from Mourya et al. (2025)

8.4.1 Routing optimization

This task aims to find the best routes through a network while satisfying various constraints, often requiring substantial computational resources (Osaba et al. 2022). To address this challenge, both quantum annealing approaches (Warren 2013; Irie et al. 2019) and gate-based quantum computing methods (Papalitsas et al. 2019; Azad et al. 2022) have been explored. A comprehensive review of existing quantum approaches for this task was recently provided by Liu et al. (2025).

8.4.2 Traffic forecasting

The goal of this task is to predict vehicle dynamics and future conditions. Various QML approaches have been explored in this context. For example, Emu et al. (2024) and Saini and Sharma (2024) proposed to employ QRNN models for this task, and their experiments demonstrated the validity of the introduced methods. Qu et al. (2022) introduced a quantum graph convolutional neural network to capture spatiotemporal information in transportation systems. In addition, Schetakis et al. (2025) investigated the use of the data re-uploading technique within a QML framework (shown in Fig. 26) for transport forecasting and analyzed its effectiveness in modeling transportation data.

8.5 Energy system

As global energy demand continues to increase, QML has also garnered significant attention for addressing challenges in energy production, storage, and distribution. Strata et al. (2025) recently reviewed representative quantum approaches for energy-related applications, providing a comprehensive overview of current developments in the field.

8.5.1 Energy demand forecasting

It is one of the fundamental challenges in energy systems. Depending on the application, the model may focus on spatial demand across locations or on temporal demand change over time. To address this challenge, different QML models have been explored. For example, Nutakki et al. (2024) proposed a QSVM to predict periodic power consumption, while Safari and Badamchizadeh (2024) introduced a QNN framework for it. In addition, Ajagekar and You (2024) studied how to combine the strengths of quantum and classical computing and proposed a hybrid approach whose experimental results demonstrated promising efficiency and scalability.

8.5.2 Energy generation forecasting

This task aims to predict the output of the energy generation process to ensure grid stability, particularly for wind and solar energy, which are often volatile and intermittent. For instance, many studies have focused on solar irradiance prediction, and accordingly, many QNN models have been proposed, such as Sushmit and Mahbubul (2023); Santos et al. (2024). Besides that, Yu et al. (2023) introduced a QRNN model with hybrid LSTM cells for

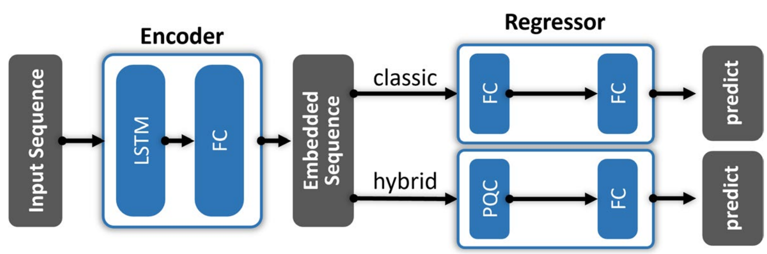


Fig. 26 Representative QML model for traffic forecasting. Figure adapted from Schetakis et al. (2025)

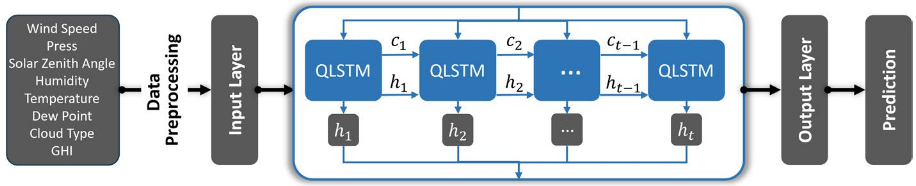


Fig. 27 Representative QML model for energy generation prediction. Figure adapted from Yu et al. (2023)

this task, and Fig. 27 illustrates the structure of the proposed hybrid model, which combines PQC and LSTM for rich time-dependent information.

8.6 Astrophysics and astronomy

The usage of QML in the fields of astronomy and astrophysics shares many common traits with that in other disciplines, seen above in this Section: in particular, it has been explored in use cases where the training datasets are relatively small and/or the expressivity of the QML approach can be favorable, with respect to classical methods.

8.6.1 Astronomical object classification

To date, several studies have investigated the application of QML to astronomical object classification using different types of observational data. For instance, Kordzanganeh et al. (2021) presented a single-qubit QNN with a quantum asymptotically universal multi-feature encoding for pulsar classification using radio astronomy data. Hassanshahi et al. (2023) employed a QSVM for galaxy classification based on optical data from the Galaxy Zoo 1 data set (Lintott et al. 2008, 2010).

8.6.2 Transient event detection

As for transient event detection, specifically the detection of Gamma-Ray Bursts, Rizzo et al. (2024) tested different QCNN architectures and compared them against their classical counterpart. Those results, referred to the AGILE space mission, have been extended to simulated data from the Cherenkov Telescope Array Observatory by Farsian et al. (2025). This last study, as well as Ziiatdinov et al. (2025), addressed the critical role of data encoding in model performance.

Although QML has been explored across a wide range of application domains, with many studies reporting performance comparable to or better than their evaluated classical baselines, this field is still at the proof-of-concept stage, and practical deployment on NISQ devices remains constrained by limited qubit resources, imperfect qubit fidelity, and circuit-depth restrictions.

9 Outlook and discussion

Despite the valuable efforts and contributions made toward integrating quantum computing with machine learning tasks, numerous open questions and challenges remain in this emerging field that require further investigation. Building on the knowledge and insights gained so far, we believe the following research directions deserve significant attention, as they could deepen our understanding of quantum circuit-based learning models, provide feasible solutions across a wide range of applications in the NISQ era, and pave the way for broader adoption once large-scale, fault-tolerant quantum devices become available.

9.1 Data properties favoring QML

Machine learning techniques aim to learn meaningful representations from input data to solve various tasks. However, many researchers have observed that the performance of QML models varied significantly across different datasets in experiments. In addition, Gupta et al. (2022) argued that there exist datasets that are easy for QML models but hard for classical models, regardless of the model architecture or training algorithm, based on their empirical studies. Similarly, Huang et al. (2021) demonstrated a strong and robust prediction advantage over classical machine learning models on engineered datasets.

These observations suggest that certain data properties may be inherently more suitable for QML than for classical approaches. One important research direction is to establish a comprehensive framework that can identify the properties under which QML might deliver meaningful advantages in practice.

9.2 Advantageous properties of QML

To date, various hybrid QML models have been proposed and empirically shown to offer certain advantages over classical algorithms, and there have been studies exploring the reasons for these superior performances of QML models from different perspectives, such as expressivity, learnability, and generalizability as introduced before. Note that most of these investigations have examined these properties using concepts adapted from classical machine learning. However, a recent study by Gil-Fuster et al. (2024) conducted systematic experiments and the empirical results indicate QML models have a strong ability to memorize data. Thus, traditional approaches to evaluating the generalizability of QML models may not be suitable, highlighting the need to reconsider the methods for studying the properties of QML models.

In addition, as previously introduced, hybrid QML models have received significant attention in recent years, with many demonstrating superior performance in various tasks. However, comprehensive studies that systematically examine the contributions of the quantum components in the hybrid models to these gains are still lacking.

Further work should establish evaluation frameworks tailored to QML for systematically characterizing its properties, e.g., expressivity and generalizability, while also quantifying the contribution of the quantum component in hybrid models. Such studies could provide guidance for the design and evaluation of QML models as well as the interpretation of reported quantum advantages.

9.3 Efficient and valid data encoding

Compared with classical machine learning algorithms, the importance of the encoding process in QML has been well recognized. This step directly affects the required quantum resources for encoding, thereby affecting the overall efficiency of QML algorithms. As argued in Aaronson (2015), how to load a large amount of classical data into quantum devices in an efficient way so as to preserve the quantum speed-up is one challenge for quantum computing.

Regarding QML, this step not only impacts the overall efficiency but also the validity of the following feature extraction, as poorly encoded quantum states can significantly hinder the effectiveness of feature extraction. Developing modality-specific encoding guidelines that consider appropriate encoding strategies based on the data modalities, downstream learning tasks, and required quantum resources is one promising research direction.

9.4 Extending QML for data fusion

At present, the benefits of integrating multiple data resources for machine learning tasks have been recognized, and many classical frameworks have been proposed accordingly, as reviewed in Lahat et al. (2015). Leveraging the large Hilbert space of quantum states for data fusion holds certain potential.

To fully explore this potential, suitable encoding techniques for different data modalities are preliminary. However, as discussed in Sect. 3.1, current research efforts are heavily made toward only a few modalities. To achieve data fusion in the quantum domain, it is necessary to further investigate the valid encoding approaches for a broader range of data types. Besides that, effective strategies for fusing data with quantum computing also require investigation. To date, only a few studies have explored this direction (Majji et al. 2022; Miller et al. 2024), and further investigations are essential to fully understand the potential of QML across diverse tasks.

9.5 Systematic quantum circuit design

Since quantum gates perform distinct transformations on quantum states, the design of PQCs plays a critical role in QML, affecting not only its efficiency but also its capabilities, such as expressivity, learnability, and adaptability in practical applications. Currently, most quantum circuits are designed and selected primarily based on empirical knowledge and experimental results, and some are optimized using the techniques for quantum neural architecture search. A systematic understanding of how different quantum gates and circuit configurations affect learning capacity is still lacking.

Therefore, further work should systematically study the effects of various quantum gates and operations and develop quantum circuit design frameworks which could help more principled and efficient circuit design in QML applications.

9.6 Effectively integration in hybrid QML

As can be observed, most proposed QML models adopt a hybrid framework due to the fact that current classical deep learning models are already powerful, and NISQ devices remain constrained by limited quantum resources and noise.

The design of hybrid QML models offers a feasible solution in the NISQ era, but the current integrations are relatively simple, typically employing quantum algorithms for either local low-level feature transformation or latent feature processing. One significant research direction is to establish hybrid model design protocols that can strategically integrate quantum and classical components to fully leverage the unique strengths of each, thereby maximizing performance across diverse learning tasks.

Note that the integration is not limited to the structural design of the models. Quantum algorithms can also be leveraged to enhance the training process of classical machine learning models. A representative study in this direction is presented by Liu et al. (2024), in which they argue that fault-tolerant quantum computing could possibly provide provably efficient resolutions for solving the gradient descent dynamics for large-scale classical machine learning models.

9.7 Towards natural quantum information processing

Since quantum computing exploits quantum properties to perform computation tasks, incorporating physical models of the input data into quantum information processing could enhance the performance of QML models for data analysis. A particular area is EO, in which the data records are based on physical principles, such as PolSAR and InSAR. To date, few studies Otgonbaatar and Datcu (2021, 2021); Bhattacharya et al. (2025) have been conducted to explore this direction. Further investigations are meaningful, as leveraging physical models can provide theoretically consistent ways to represent and transform the data, potentially improving both the effectiveness and interpretability of QML approaches.

9.8 Quantum foundation models

Foundation models have attracted significant attention in recent years due to their adaptability to process diverse data types and to support a broad range of tasks. Inspired by their success, the exploration of quantum foundation models has also been conducted. As discussed in Du et al. (2025), many existing studies have focused on quantum system characterization using foundational models, such as Wang et al. (2022); Tang et al. (2024); Rende et al. (2025), but quantum foundation models for classical data analysis remain largely unexplored. As outlined in previous sections, QML models demonstrate potential benefits in terms of generalizability and efficiency, highlighting the promise of integrating quantum computing into foundation models to address challenges in training foundation models, such as computational and resource constraints. Therefore, further investigation that contributes to scalable quantum foundation model architectures and pretraining protocols tailored to quantum computing is significant.

9.9 Developing robust evaluation benchmarks

Another important research direction is the development of robust evaluation benchmarks. Currently, many QML models are evaluated using different protocols, which makes it challenging for fair comparisons between different quantum models, as well as between quantum and classical models.

To be more specific, different types of baselines have been selected to evaluate QML models, such as studies Malarvanan (2024); Hsu et al. (2024) directly comparing hybrid models with classical baselines, studies Ghosh et al. (2024); Mauro et al. (2024) replacing quantum components with classical ones in the same architecture, and studies Priyanka and Venkatesan (2024); Zaidenberg et al. (2021) comparing performance of the models with and without quantum parts. Besides the inconsistent baselines, different metrics have also been adopted in evaluation to investigate potential benefits, for example, training epochs (Mauro et al. 2024), quantum gates (Li et al. 2020), inference time (Lin and Chen 2023), and trainable parameters (Chang et al. 2024). Furthermore, as highlighted in Khanal et al. (2024), the datasets used for evaluation also vary widely, ranging from synthetic cases to real-world datasets.

To facilitate systematic progress and fair comparison, robust and standardized benchmarks should be developed, containing several key aspects. First, they should include representative datasets spanning diverse data modalities. Second, evaluations should incorporate strong classical baselines with clearly defined selection criteria to ensure meaningful and fair comparisons. Third, beyond conventional machine learning metrics, quantum-specific factors should also be reported, such as quantum resources and hardware configuration. Such considerations could not only enhance reproducibility and transparency but also provide a foundation to evaluate and identify the advantages and limitations of QML.

9.10 Scalability deyond the NISQ era

As quantum computing has only recently entered the NISQ era, most existing studies investigate the potential of QML under current hardware constraints and primarily serve as proof-of-concept demonstrations. As discussed earlier, distributed quantum architectures may provide a practical pathway toward scaling QML models. By splitting quantum computation across multiple quantum processors, more complex QML models that would otherwise exceed the capabilities of a single quantum processor may be constructed and deployed for larger-scale learning tasks.

However, as quantum hardware evolves, we may enter the future fault-tolerant era, in which quantum devices can support complex computation with quantum error correction. Between today's small-scale and noisy quantum computers and future large-scale and fault-tolerant devices, a transition period known as the early-fault-tolerant quantum computing (EFTQC) era is expected to emerge (Katabarwa et al. 2024). In this regime, quantum error correction is available but remains resource-intensive due to limited hardware scalability. As a result, balancing model expressivity, circuit depth, and error-correction overhead may become a central challenge for scalable QML systems during this transition period.

In addition, although large-scale fault-tolerant quantum computing may alleviate many of the depth and noise constraints that currently limit QML models, several scalability challenges are expected to persist. Larger numbers of logical qubits may enable deeper PQCs, larger quantum neural network architectures, and more sophisticated hybrid learning frameworks that are currently infeasible on NISQ devices. However, increasing model size may also lead to severe trainability issues such as barren plateaus. Furthermore, the cost of quantum state preparation, measurement overhead, and the resources required for quantum error correction might continue to constrain practical scalability. Therefore, future QML architectures should be designed not only for current NISQ devices but also with scalability toward fault-tolerant quantum platforms in mind.

9.11 Beyond computational efficiency

The primary expectation of quantum computing is to accelerate computation, which is particularly important in the machine learning community in the big data era. However, beyond efficiency, other significant challenges, such as data scarcity, domain shifts, and data heterogeneity, also exist. Therefore, exploring potential benefits of quantum computing beyond efficiency, such as generalizability as discussed before, should not be overlooked, as they may offer solutions to address such challenges.

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Declarations

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