

REVIEW PAPER

A Comprehensive Review: Exploring QML: Foundations, Applications and Future Prospects

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ABSTRACT

The paradigm of QML is a transformative and cutting-edge research domain that fuses the methodologies from Machine Learning (ML), Quantum Computing (QC) together forming a novel framework for enhancing system throughput and problem solution finding potential intelligently. Belonging to the broader realm of Artificial Intelligence (AI) technologies, machine learning (ML) leverages advanced computing capabilities and diverse algorithm approaches to address the challenges for application spanning areas like chemistry, agriculture, hospitals, drug manufacturing, NLP, etc. Notwithstanding heritage in the processing of classical data, quantum machine learning processes the classical data by using the machine learning algorithm to explore the quantum phenomenon in the learning system. Quantum machine learning is a ground breaking change to computer science that may exponentially speed up the processing, as well as work with large, and complex datasets. This study emphasizes the contrasting aspects of classical and quantum machine learning and concludes with a discussion on the potential pathways and existing challenges in achieving quantum advantage through the framework of QML.

Keywords: Quantum computing, Machine learning, Quantum (QML), Data Encoding, Artificial Intelligence (AI)

Quantum computing is a revolutionary discipline that integrates the principles of quantum mechanics, mathematics, and computer science. Based on qubits, it differs fundamentally from traditional or classical systems, which depend on binary digits (0s and 1s) and transistors. A classical bit can exist only in one of two discrete states either 0 or 1 where as a qubit can exist in a superposition of both $|0\rangle$ and $|1\rangle$ simultaneously. The core principles of quantum physics—superposition, entanglement, and interference—are central to quantum computing and are realized through the behavior of qubits^[1]. Quantum computing handles the information in a manner beyond the potential of conventional computer. In contrast to classical

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bits, which can only take the value of 0 or 1 qubits can exist in a superposition of states, enabling parallel operations and superior computational performance^[23].

Among all AI (Artificial Intelligence) discipline, it is regarded as most advanced and impactful branch that has benefited from an extraordinary potential impact in many domains like healthcare, transportation, agriculture, education, robotics, social media, data security, finance, etc. AI is able to provide an intelligent solution and makes modern life favorable^[4]. Quantum models offer a promising alternative to classical ML techniques, exploiting their ability to express complex and intricate patterns by operating in a higher-dimensional computational space obtained through the principles of superposition and entanglement^[22]. These quantum unique properties allow for enhanced feature representation and the ability to explore complex data, potentially making quantum models more effective in addressing challenges such as imbalanced dataset^[22].

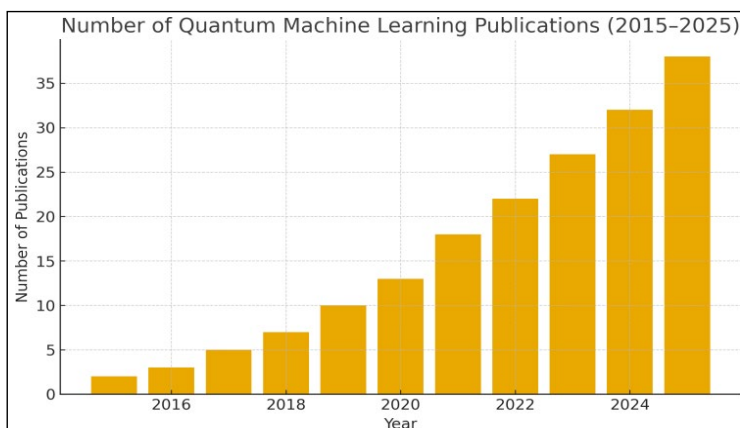


Fig. 1: Number of Quantum Machine Learning Publications (2015–2025)

LITERATURE REVIEW

Quantum Machine Learning (QML) has emerged as a rapidly developing interdisciplinary field that combines the computational power of quantum mechanics with classical machine learning techniques. Early foundational studies demonstrated quantum-enhanced feature spaces capable of improving classification performance in high-dimensional datasets^[1]. Variational Quantum Neural Networks implemented on near-term processors further established the feasibility of hybrid classical–quantum training frameworks under NISQ constraints^[2].

Supervised quantum models such as Quantum Support Vector Machines (QSVM) and Quantum Neural Networks (QNN) have been widely investigated for healthcare and biomedical analytics^{[3],[4]}. Comparative evaluations indicate that QML models can enhance nonlinear feature representation in structured medical datasets. Additionally, systematic reviews integrating QML with classical optimization techniques emphasize improvements in diagnostic sensitivity and classification robustness^[5].

Recent research has also explored Quantum Federated Learning architectures, enabling distributed training of quantum models while preserving data privacy^{[6],[7]}. Applications extend to molecular recognition, drug discovery, and computational chemistry, highlighting the interdisciplinary potential of QML^[8].

Experimental validation of Quantum Generative Adversarial Networks (QGANs) and variational circuits confirms the transition from theoretical modeling to practical implementation^[9].

Despite significant advancements, major challenges remain, including hardware noise, limited qubit scalability, reliance on simulation-based validation, and lack of standardized benchmarking. Therefore, further research is required to develop scalable, hardware-efficient, and statistically validated QML frameworks suitable for real-world healthcare deployment.

BACKGROUND

Quantum is the tiniest unit of a physical entity, like energy and mass. Before 1900, It was considered that energy was measured as a continuous flow of particles. But in 1900, According to Max Planck, energy exists in discrete quantities that can be measured in terms of discrete packets^[13] quantum, discontinuous flow of energy. In the quantum theory, it is characterized by wave-particle duality as well probability. With in quantum mechanics, it utilizes mathematical framework of quantum mechanics uses vectors to describe states and matrices to represent operators, i.e., $a|$ and $|a$. In this notation, for convenience, the inner product is expressed as $b|a$ are bracket vectors. Similarly, let H be a Hermitian matrix; its eigen vector equation is given by $H|a = \lambda_a|a$, where $a|$ is the eigen vector and λ_a is the corresponding eigen value.

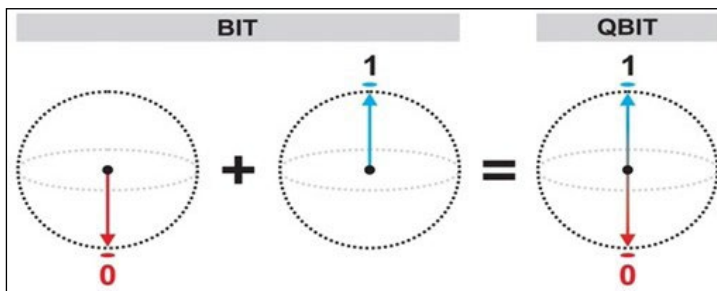


Fig. 2: Quantum super position

(A) Super position

Qubits can exist in multiple states simultaneously, which allows the quantum system to explore multiple solutions in parallel. This feature is beneficial for solving complex problems like heart disease detection^[5].

(B) Entanglement

Quantum entanglement allows qubits to be linked together, enabling the model to capture intricate relationships and correlations between medical features that are difficult to detect using classical methods^[5].

(C) Qubit

In classical framework, the fundamental unit of information is represented using bits, with each bit represents either 0 or 1. Similarly quantum computer uses a qubit or a quantum bit represents both 0 and 1 concurrently in a single quantum state, or it can be viewed as zeros and ones in a fuzzy combination. In quantum computation a qubit serves as the fundamental unit of information in quantum computing and

can be represented by: An electron or bits a nucleus: where $|0\rangle$ and $|1\rangle$ are the ground state and excited state, respectively and A photon: where $|0\rangle$ and $|1\rangle$ are its polarization states^[13]. Qubit can run in two directions, and due to this nature, it is favorable in a multitasking environment. Moreover, mathematically, a qubit is represented by a two-dimensional vector. However, the key difference between a bit and a qubit is that besides states $|0\rangle$ and $|1\rangle$, a qubit may take the super position states, $|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$, where α and β are complex numbers and called amplitudes satisfying $|\alpha|^2 + |\beta|^2 = 1$. That is, the states of a qubit are unit vectors in a two-dimensional complex vector space, and states $|0\rangle$ and $|1\rangle$ consist of an orthonormal basis for the space and are often referred to as computational basis states^[14].

(D) Quantum gates

Quantum gates holds a vital function in the functioning of Quantum computers, similar to how classic logic gates are essential in conventional computers. However, unlike classical gates, which manipulate binary bits, a quantum gate executes a quantum operation on a set of qubits, changing their state according to the rules of quantum mechanics^[17]. These operations are reversible and can be represented mathematically by unitary matrices.

(E) Basic difference between classical computing and quantum computing

Table 1: Detailed Comparison between Classical and Quantum Computing

Aspect	Classical Computing	Quantum Computing
Basic Unit	It depends on one of two bits, i.e., either 0 or 1.	Due to the principle of superposition, qubits maintain the ability to represent numerous states at the same time.
Data Processing	Deterministic and sequential processing.	Parallel processing due to superposition and entanglement.
Operation	Logical operations based on Boolean algebra.	Operations use quantum gates that can create complex correlations.
Problem Solving	Effective for an extensive variety of tasks but limited by linear or exponential scaling with data size.	Can tackle certain computational tasks with exponential efficiency.
Limitation	Scalability issues with large-scale data or complex computations.	Practical challenges include error rates, qubit coherence, and current hardware limitations.
Parallelism	Limited parallelism, achieved through multi-threading.	Intrinsic quantum parallelism through super position.
Algorithm Used	Sorting algorithms (Quick Sort, MergeSort), Binary Search, and algorithms in cryptography.	Shor's algorithm (integer factorization), Grover's algorithm (database searching).

(F) Quantum circuit

Quantum circuits serve as the basic framework for performing quantum computations^[15]. Each circuit is composed of quantum gates which manipulate the state of one or more qubits in a controlled and reversible manner, ensuring that the system's overall probability distribution is preserved^[16]. The qubit stays in its original state if no quantum gates are applied to it. The total number of qubits existing

under those conditions is represented by a slash followed by a marked on that particular circuitwire. A quantum circuit represents a computational framework by combining classical real-time operation with quantum gate acting on quantum data, maintaining essential quantum properties like entanglement and superposition throughout the process.

In machine learning, algorithms are categorized into four different distinct types -supervised, unsupervised, semi-supervised, and reinforcement^[5].

Supervised machine learning: Supervised learning is deployed when specific objectives are predetermined in advancement of achieve goal sandrealized on labeled datasets^[6]. Examples include classification of distinguishing data, regression for data fitting, text- categorization. This method is often referred as goal-driven technique^[7].

Unsupervised machine learning: A unsupervised learning algorithm is one that analyzes data without predefined labels^[6]. An unsupervised learning algorithm is also recognized as a data-driven approach to uncover hidden patterns through clustering similar points, feature generation and exploratory analysis. The major tasks included in unsupervised algorithms are clustering, density estimation, feature learning, dimensionality reduction, finding association rules, anomaly detection, etc.^[7].

Semi-supervised machine learning: Semi-supervised learning algorithm is a distinct type of algorithm that hybridizes characteristics of supervised and unsupervised machine learning algorithms to make a function or classifier^[6]. This approach is helpful in real-life problems where there is limited labeled data and a lot more unlabelled data. The data is employed for generate accurate prognosis allowing the model to recognize trends, correlations, and dependencies present in the input features. Semi-supervised learning is widely applied in various domains like machine translation, identifying fraudulent activities, labeling data, and Text classification, etc.^[7].

Reinforcement machine learning: Reinforcement learning is a machine learning technique in which a policy is developed through interaction with the environment^[6]. Each action within this environment produces feedback that influences the algorithm's learning process forming an environment-driven approach^[7] operates on the concept of rewards and penalties. It has proven as an effective strategy for training AI models to enhance the functional efficiency of complex systems such as robotics, autonomous vehicles, industrial automation, and logistics. However, it is less appropriate for solving simple or straightforward problems. Although, the tremendous achievements of classical machine learning in multiple domains, it suffers from limitation in efficiency and scalability as data volumes and complexity continue to increase exponentially^[15]. With larger datasets, the need for computational power intensifies, prolonging training durations and processing times. Moreover, classical models struggle to meet the demands of dynamic and real-time applications that depend on instantaneous response and rapid decision-making.

(G) Review of existing QML approaches

This review is chiefly emphasized on structured and methodological process to identify, gather, evaluate, and analyze the prior research in Quantum Machine Learning (QML). This approach ensures an extensive overview of major developments within supervised, unsupervised, and reinforcement learning paradigm grantees a broad coverage of major development across supervised, unsupervised and reinforcement learning paradigms. Here, all the publication papers are systematically assessed based on some parameters like datasets, algorithm, comparative tables, quantum framework, model architecture that measure

quantum performance, accuracy level and computational cost. Here, trends are identified through cross-analysis of methods and their outcomes. This survey is constrained with many limitations because, most of the QML approach is still in simulation stage due to lack of quantum hardware. There are only few standard datasets that makes complicated to examine differences and similarities from diverse research publication. The systematic approach of this survey makes a clear understanding of state-of-art in QML approach. The comparison and classification of this survey highlights the key trends, existing challenges, and future opportunities in Quantum Machine Learning (QML).

Quantum machine learning models: QML models are divided into three basic categories: supervised model, unsupervised and semi-supervised.

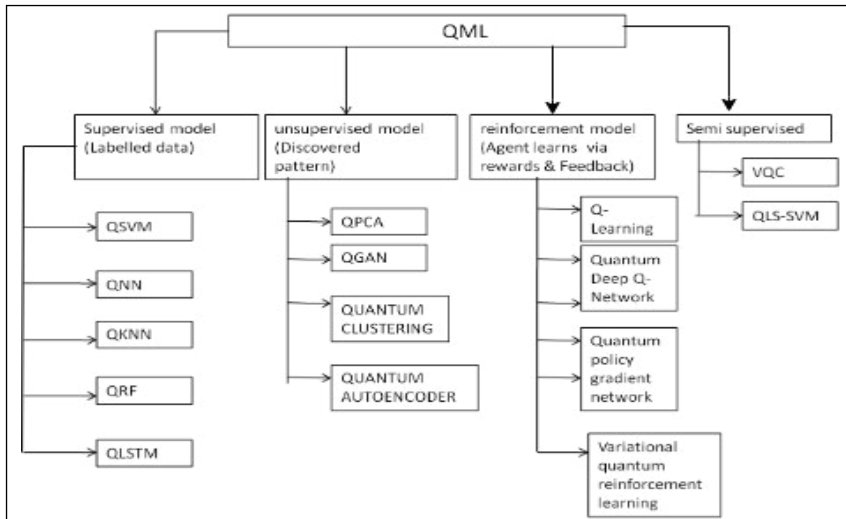


Fig. 3: Categories of QML algorithm

In this paper, we are mainly focus on supervised model. The following section provides a concise summary of supervised learning models that incorporate quantum computing concepts.

Quantum Neural Network (QNN)

This is a neural network algorithm based on quantum mechanics. Unlike the classical model, it works on superposition states. This update ability of quantum computers with the power to carry out quantum nature. In QNN, the basic building blocks are addition of quantum layers^[17], which is similar of artificial neuron in classical neural network. The quantum neuron processes and transmits information using quantum operations that based on a qubit. The state of a quantum neuron is represented by a qubit, and its state is modified through the application of quantum gates. In this model, the conventional activation function found in classical neural networks is substituted with a quantum gate that modifies the qubit's state in response to input signals. Quantum gates such as Hadarmard, Controlled-phase, or other similar operators can be applied on the qubits. These gates bring about distinct quantum effects like superposition and entanglement, enhancing the computation with quantum characteristics. The most distinguished advantages of quantum neural networks are to process and manipulate and examine large-scale information resources simultaneously because of superposition states. This might represent

especially useful for activities including pattern recognition, optimization, and machine learning, where large-scale parallelism can provide computational advantages.

Quantum Support Vector Machine (QSVM)

QSVM is a hybrid approach that integrates the methodologies of classical machine learning with quantum computing. It is primarily designed for classifying quantum data. The traditional SVM, supervised learning algorithm is applied to labeled dataset for both regression and classification tasks, identifying an optimal hyperplane in a multi-dimensional feature space. Hyperplane serves to effectively distinguish data points into distinct group^[17]. From another perspective, in QSVM, leverage the quantum phenomenon like superposition and entanglement and perform classification. Here, the input data is mapped into quantum feature space using quantum kernel feature. Quantum kernel computes the similarities and distance between the data points. The classical data is fed into quantum states using various algorithms. Then the quantum data is fed into quantum circuit that applies the quantum kernel function

Quantum K-Nearest Neighbor (QKNN)

QKNN functions as an additional supervised learning model that uses quantum properties to process classical KNN classification algorithm. It leverages the quantum mechanics principles that exploit the quantum representation of data to perform distance calculations more easily^[17]. Instead of using n bit in classical computers, it uses n qubits to process data faster and more efficient. During QKNN execution, the Hadarmard gate function is employed to produce a state of superposition by harnessing the power of quantum parallelism. It enables to determine the distance between training and test data points simultaneously. Finally, after the quantum measurement, the algorithm predicts the class label for the new data point by choosing the label that appears most often among the K nearest neighbors.

Quantum Random Forest (QRF)

As a category of supervised algorithm, QRF leverage quantum mechanical phenomenon such as superposition, entanglement with the standard RF model^[17]. It represents a refined Version of traditional RF algorithm, capable of managing both classification and regression analysis. RF works by creating large number of decision trees. Each decision tree is trained with random sample of dataset. Each tree is given own prediction. Final result is decided by combining the outputs of all trees through majority voting. Conversely, QRF replaces the classical decision tree with quantum decision tree which are modeled using quantum circuit based on qubits and quantum gates. To build a QRF, several quantum decision trees are created using a process known as quantum bagging. Each quantum tree is trained separately and their results are combined through majority voting to produce the final prediction. This parallel quantum processing contributes faster computation and potentially higher accuracy than typical Random Forest (RF) model.

Quantum Long Short-Term Memory (QLSTM)

QLSTM represents another variant under supervised model that reflect the replacement with Variational Quantum Circuit (VQC) with classical part of LSTM. LSTM is a special type of recurrent neural network (RNN) designed to learn and remember information from long sequence of data. This algorithm is specially used for speech recognition, language translation, time-series prediction etc. It is composed of cells. Each cell is equipped with three main components-input gate, output gate and forget gate. These three gates

regulate the flow of information into, out of, and within the cell. In contrast, QLSTM consists of three layers - the data encoding layer, the variation allayer, and the quantum measurement. The input classical vector is converted in to a quantum state by the data encoder layer and the variational layer is the learn able component, where circuit parameters are fine-tuned with optimization approach^[17].

METHODOLOGY

This study adopts a hybrid classical–quantum framework designed to enhance predictive modeling performance in healthcare analytics. The methodology integrates systematic preprocessing, quantum feature encoding, variational circuit design, hybrid optimization, and statistical evaluation.

Data Preprocessing

Healthcare datasets are preprocessed using statistical imputation for missing values, normalization through Min–Max scaling or Z-score standardization, and feature selection techniques such as correlation analysis or principal component analysis (PCA). Dimensionality reduction ensures efficient qubit utilization and reduced circuit complexity. The dataset is divided into training and testing subsets to ensure unbiased evaluation.

Quantum Feature Encoding

Classical features are encoded into quantum states using angle encoding, where normalized feature values are mapped to rotation angles of single-qubit gates. This encoding strategy minimizes qubit requirements and ensures compatibility with NISQ-era devices while enabling nonlinear feature transformation.

Variational Quantum Circuit Design

A parameterized quantum circuit (PQC) composed of rotation gates and entanglement layers is constructed. Circuit depth is optimized to balance model expressiveness and noise resilience. Measurement operations generate expectation values used for classification.

Hybrid Optimization Strategy

A classical optimizer such as Adam or COBYLA iteratively updates circuit parameters based on measurement-derived loss values. Gradients are estimated using the parameter-shift rule, enabling efficient hybrid quantum–classical training.

Evaluation Metrics

Model performance is evaluated using Accuracy, Precision, Recall, F1-score, and ROC-AUC. Comparative benchmarking against classical machine learning models ensures statistical validation and performance reliability.

CHALLENGES AND LIMITATION

In the domain of QML, extensive innovative research efforts have been conducted; nevertheless, several complex and unresolved challenges persist that demand further exploration in case of practical implementation. The current challenges in Mainly involve noise interference, hardware limitation, data-encoding techniques, input- output bottleneck, catastrophic forgetting.

Noise Interference

To genuinely implement QML algorithm, real quantum computing devices based on preparation of qubits. In the existing scenario, several categories of physical qubits including semiconductor quantum dot qubits, spin qubits, super-conducting qubits, trapped-ion qubits, photonic qubitsetc. For quantum computation, we are now in NISQ (noisy intermediate-flip noise), and others^[9]. In this era, quantum devices are naturally affected by noises, hence affected by negative impacts to QML model.

Hardware limitation

In the current NISQ era, the quantum devices are employed with small number of qubits to represent data. Consequently, it remains a challenging task to encode large-scale data into quantum state data and execute QML algorithms. Therefore, it is necessary to implement feature extraction or other kinds of reduction operations to implement high-dimensional data set^[9].

Data-encoding technique

The data-encoding technique in QML plays a critical role. However, in the recent research in QML, it is seen the development of hybrid classical-quantum models present some exciting opportunities for enhancing encoding strategies^[19].

Hybrid methodologies utilize the advancement of classical system along with quantum benefits in some particular computation functions including state preparation and data classification.

Input-output bottleneck

It is common problem in QML^[9]. QML algorithm, the classical data need to encode into quantum states in advance. For output, it is not possible to give result directly since most algorithm can only offer the quantum states corresponding to the classical solution. As an example, Situ *et al.* proposed a QGAN model. This is a special quantum classical hybrid architecture, able to directly receive input and output classical solutions^[19].

Catastrophic Forgetting

This can be viewed as a common problem in Quantum Machine Learning, during the optimization process of neural network, many models quickly forget the already-learned knowledge in the process of updating neural network^[19]. In neural network incremental or continual learning is mandatory to accumulate long term knowledge. Therefore, this problem negative impacts to these models. Based on this problem Situ *et al.* designed a quantum continual learning scheme based on gradient episodic memory strategy that is able to overcome catastrophic forgetting and realize knowledge backward transfer for quantum state classification tasks^[20].

FUTURE DIRECTION

Day by day, the area of QML has rapidly progressed with continued research and innovative ideas across various domain. Prospective research primary focus on the quantum hardware capabilities, expanding hybrid computational model combining quantum and classical computing and innovating more effective data-encoding strategies^[21].

Hardware improvement

A prominent barrier of QML is hardware constraints. Future quantum system aims to achieve higher qubit, super-conducting circuit and quantum dots count with longer coherence time and better gate fidelity. Companies like IBM, Microsoft, and Atom Computing are working toward fault-tolerant, scalable quantum processors, which will enable the execution of more complex QML models with reduced errors^[21].

Integration with Classical ML

Hybrid quantum–classical systems are expected to govern future applications. These systems divide tasks—quantum processors handle complex optimization, while classical systems manage pre-processing and visualization. As are search example Microsoft Azure Quantum^[21], already combine both domains by optimizing efficiency in applications.

Quantum Simulation Applications

Quantum simulations are likely to transform fields like drug discovery, materials science, and climate modeling. By using QML-based simulations^[21], with complex molecular and physical models will unlock new possibilities in research and development.

Ethical and Responsible QML

As QML becomes crucial to sensitive fields such as healthcare and surveillance, ethical concerns regarding privacy, fairness, and transparency must be maintained^[21]. The formulation of a standardized ethical framework is crucial for promoting responsibility, accountability and equity in the equitable deployment of QML based system.

Inter-disciplinary collaboration

Collaborative efforts between quantum scientists and professionals in domains such as healthcare, climate science, and finance act as a key component in advancing QML adoption^[21]. It will foster the rapid advancement and adoption of QML. Quantum computing already shows promise in areas such as drug discovery, disease prediction, and climate modeling, proving its ability to solve real-world problems.

Error Mitigation Techniques

Reducing noise and errors in quantum systems is vital for practical QML. Advanced methods such as adaptive error correction, tensor-network-based mitigation, and noise-resilient algorithms^[21] are improving the reliability of quantum circuits on Noisy Intermediate-Scale Quantum (NISQ) devices.

Table 2: Summary and Comparison of Selected Quantum Machine Learning (QML) Studies

Sl. No.	Author and Year	Model	Dataset	Findings
1	Havlicek, V. et al. (2019). <i>Supervised Learning with Quantum-Enhanced Feature Spaces</i> . <i>Nature</i> .	QSVM	MNIST, UCI	Demonstrates the superior performance of quantum kernel methods over classical Support Vector Machines (SVMs).

2	Farhi, E. & Neven, H. (2018). <i>Classification with Quantum Neural Networks on Near-Term Processors. arXiv.</i>	QNN	MNIST	Demonstrates variational quantum circuits for ML.
3	Li, W. et al. (2022). <i>Quantum Federated Learning: A Survey. IEEE Trans. On Neural Networks.</i>	Hybrid Learning	Federated systems	Reviews quantum-enhanced distributed ML approaches and their challenges.
4	Tacchino, F. et al. (2020). <i>Quantum Machine Learning: A Classical Perspective. Quantum Sci. & Technol.</i>	Hybrid quantum-classical ML	IBMQ datasets	Analyses practical implementations and limitations of near-term quantum models.
5	Jerbi, S. et al. (2023). <i>Quantum Machine Learning for Natural Language Processing. PRX Quantum.</i>	NLP Applications	Text datasets	Applies QML techniques to real-world text processing tasks.
6	Xia, Q. & Li, Q. (2021). <i>Quantum Federated Learning (Quantum Fed).</i>	Quantum Fed	Simulated federated Quantum nodes	Proposes a framework enabling collaborative training across quantum nodes.
7	Innan, N. et al. (2024). <i>Quantum Federated Neural Network (FedQNN).</i>	FedQNN	Genomics & health care datasets	Uses quantum neural networks for distributed model training across federated systems.
8	Tianzhu Yin (2024). <i>Quantum Support Vector Machine (QSVM) Theory.</i>	QSVM	Large-scale classification	Studies QSVM scalability on computationally challenging datasets.
9	QDNN: “Deep Neural Networks with Quantum Layers” (2021).	QDNN	General classification tasks	Shows quantum layers can increase expressive power versus classical networks.
10	“Coherent Feed-forward Quantum Neural Network” (2024).	Feed-forward QNN	NISQ tasks	Introduces a hardware-efficient QNN architecture that reduces quantum resource needs.
11	Amandeep S. Bhatia et al. (2025). <i>Quantum Inspired Tensor Networks for Federated Learning.</i>	QITN-FL	MNIST & FMNIST (federated)	Proposes a hybrid tensor-network + federated approach for scalable learning.
12	“QSVM & QSV Rona Trapped-Ion Quantum Computer” (2024).	QSVM&QSVR	Fraud detection, MNIST, finance	Demonstrates feasibility of QSVM/QSVR on ion-trap hardware.
13	“Enhancing QSVM through Variational Kernel Training” (2023).	QVK-SVM	Iris	Proposes a hybrid kernel-variational optimization to boost QSVM accuracy.
14	“QML for QKD: A Research Review” (2025).	QML for QKD	Cryptography	Explores QML applications to quantum key distribution and secure comms.

CONCLUSION

This study investigates and highlights the systematic review to identify, evaluate, and analyze the different aspects in quantum machine learning. During the literature review, we find the different QML designs and implementations. However, the primary trend of the QML algorithm was QNN, which were VQC, QDNN, RQNN, and QHM, along with different standardization of data encoding techniques for the classification of images and UCI well-known datasets such as Cancer, diabetes, liver, heart, and lungs. The limits of noisy intermediate-scale quantum devices, the restricted number of quantum bits, and the limited size of sample data were all noted by the majority of writers in their research papers. Future approaches to QML algorithms open up endless possibilities for researchers. A large number of quantum bits and a vast amount of data will contribute to enhancing and developing quantum technology. Later on, the data encoding methods for QML are explored and show high potential of improving the efficiency and effectiveness of machine learning systems by using fundamentals of quantum computing. The development of creating encoding-based quantum algorithm, as well as leveraging entanglement for feature encoding. It can lead to the advancement of QML field.

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