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Review article

Quantum machine learning: Classifications, challenges, and solutions

Wei Lu [a], Yang Lu [b], Jin Li [b,c,*], Alexander Sigov [d], Leonid Ratkin [e], Leonid A. Ivanov [f]

[a] School of Economics and Management, Communication University of China, Beijing, China
[b] Beijing Technology and Business University, Beijing, China
[c] School of Computer and Artificial Intelligence, Beijing Technology and Business University, Beijing, China
[d] Russian Technological University, Moscow, Russia
[e] Russian Academy of Sciences, Moscow, Russia
[f] Russian Academy of Engineering, Moscow, Russia

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ABSTRACT

Recently, research at the intersection of quantum mechanics and machine learning has gained attention. This interdisciplinary field aims to tackle the computational efficiency of machine learning by leveraging quantum computing and to derive novel machine learning algorithms inspired by quantum principles. Despite substantial progress in quantum science research, several challenges persist, including the preservation of quantum coherence, mitigation of environmental constraints, advancing quantum computer development, and formulating comprehensive quantum machine learning algorithms. To date, a comprehensive theoretical framework for quantum machine learning is lacking, with much of the research still in the exploratory and experimental stages. This study conducts a thorough survey on quantum machine learning, with the aim of classifying quantum machine learning algorithms while addressing the existing challenges and potential solutions in this emerging field.

1. Introduction

In recent decades, machine learning has developed rapidly, emerging as an essential technology in this era of big data. Machine learning explores learning strategies and discovers latent structures based on existing data. It makes predictions and analyses associated with relevant mechanisms. With origins in artificial intelligence and statistics, machine learning provides solutions for a diverse array of applications. From data mining to social media, from natural language processing to biometric recognition, from traffic alerts to self-driving, from product recommendations to dynamic pricing, many facets of society are affected by machine learning [1,2].

With the continuous development of information technology, informatization has closely linked various industries, and the amount of relevant data has shown explosive growth. This growth is not just an increase in the volume of the relevant data but also its variety, velocity, veracity, and value. Related to data services and machine learning capabilities, many IT companies have established a strong presence in the data mining and digital transformation market. These companies have generated valuable data and use machine learning to reap potential benefits. The growth of data brings both undeniable profits and technical challenges. Traditional machine learning algorithms have difficulty in coping with the processing and analysis of all issues of data analytics. Hence, we need to find new ways to structure and process the data [2,3].

As early as 1982, Feynman pointed out that computers based on quantum mechanics could solve specific problems that are beyond the reach of classical computers. In 1994, Dr. Peter Shor proposed a quantum factorial algorithm called Shor's algorithm. The traditional optimal algorithm for factorizing large numbers increases exponentially with the problem's complexity, while Shor's algorithm can be completed in polynomial time. In 1997, Grover proposed a quantum search algorithm, which has a quadratic improvement in efficiency compared with the traditional unordered database search algorithm. Many of the existing quantum algorithms exhibit significant improvement in speed compared to their classical counterparts. Since quantum computing has the potential to accelerate the solution of specific problems, rendering it a candidate for addressing the current computational inefficiencies in data analytics within the field of machine learning [3,4].

Research in the field of quantum machine learning began as early as the 1990s, originally on quantum neural networks and quantum neural computing. Models are based on a combination of quantum mechanics

* Corresponding author.
E-mail addresses: luwei@cuc.edu.cn (W. Lu), jinli@btbu.edu.cn (J. Li), sigov@mirea.ru (A. Sigov), rathkeen@bk.ru (L. Ratkin), l.a.ivanov@mail.ru (L.A. Ivanov).

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and data infrastructures. One of the challenges is how to integrate the nonlinear mapping structure of the neural network with the linear transformation of quantum computing – that is, how to realize the quantum evolution of the neural network [4,5].

The research of quantum computing and machine learning has further promoted the development of quantum machine learning. Quantum random access memory (QRAM) facilitates the generation of other quantum machine learning algorithms. Numerous classical machine learning algorithms boil down to solving optimization problems, which involve the solution of systems of linear equations. QRAM can facilitate the optimization in classical machine learning, such as combining quantum support vector machines and the quantum linear equation. Many algorithms are based on the physical implementation of QRAM to realize the potential quantum state and perform subsequent quantum computing [5,6].

In this study, we aim to highlight on two key aspects: (1) the classification of quantum machine learning algorithms, and (2) the thorough examination of challenges encountered in quantum machine learning along with solutions. The structure of the paper is as follows: Section II provides an overview of the foundational principles of quantum machine learning. In Section III, we expand on prior reviews of the field. Section IV presents a systematic analysis of studies on quantum machine learning. In Section V, we categorize different quantum machine learning algorithms. Section VI explores the challenges in the field and offers potential solutions. Section VII highlights future trends, while Section VIII concludes the paper.

2. The foundations of quantum machine learning

Quantum machine learning is a discipline that merges the advantages of quantum computing and machine learning to potentially enhance the efficiency of addressing computationally intensive problems. The underpinnings of quantum machine learning consist of quantum algorithms, quantum information theory, and classical machine learning techniques.

2.1. Quantum computing basics

In contrast to classical bits, which can only represent either a 0 or a 1, qubits (quantum bits) have the remarkable property of existing in a superposition of both states simultaneously [1,2]. Much like classical logic gates, quantum gates exert control over the state of qubits to execute operations. Quantum circuits are constructed as a series of quantum gates applied to qubits, facilitating complex computations. Quantum entanglement, a phenomenon, occurs when two or more qubits become correlated in such a manner that their states are intricately interconnected [6–8].

2.2. Quantum algorithms

Quantum algorithms represent a discipline within computer science that facilitates the functions of quantum mechanics to address computational challenges with superior efficiency compared to classical algorithms. These quantum algorithms have the transformative potential to reshape a multitude of domains, such as cryptography, optimization, and machine learning, to open up a frontier in the field of computing [8,9].

2.3. Quantum information theory

Quantum mechanics furnishes a mathematical framework for expressing the behavior of quantum systems. These quantum systems are characterized by wavefunctions that evolve over time in accordance with the Schrödinger's equation. Consequently, measurements conducted on quantum states yield outcomes with inherent probabilistic attributes. The development and deployment of quantum information systems remain in their nascent phases, primarily due to persisting technical challenges, related to decoherence and error correction [4,10,11].

2.4. Hybrid quantum-classical machine learning

Quantum algorithms can be strategically employed in conjunction with classical machine learning techniques to enhance learning performance. As an illustrative example, the variational quantum eigensolver (VQE) represents a hybrid methodology that melds classical optimizers with quantum computing and generates energies for molecules. Additionally, the quantum neural network (QNN) serves as a quantum analog of classical neural networks, qubits and quantum gates for advanced information processing tasks [8,12].

2.5. Quantum data

Quantum data pertains to information representation, processing, and storage grounded in the status of qubits. Unlike classical data, which relies on binary bits (0s and 1 s) within computer systems, quantum data is encoded in qubits. These qubits can concurrently exist in multiple states due to the phenomenon of quantum superposition. This unique property bestows exponentially heightened computational capabilities upon quantum computers, enabling the solution of complex problems that currently defy classical systems. However, quantum data is exceptionally susceptible to environmental interactions and necessitates meticulous handling to preserve its coherence [5,13].

2.6. Quantum simulations

Quantum simulation stands as a computational technique employing quantum systems to emulate and analyze problems that pose significant challenges or even impossibility for classical computers to solve. Quantum simulators excel in representing and manipulating vast volumes of data concurrently. This capacity empowers researchers to explore and comprehend physical phenomena, such as the behavior of molecules or the properties of materials, with a high level of accuracy and speed. Ultimately, quantum simulation holds the transformative potential to reshape a wide spectrum of fields, e.g., chemistry, physics, and other relevant domains [3,14].

The convergence of quantum algorithms, quantum information theory, and classical machine learning techniques lays the foundation for pioneering applications spanning diverse domains, potentially ushering in an era marked by quantum-driven computational advancements.

2.6.1. The extant reviews of quantum machine learning

This section considers the top ten highly influential and cited papers of quantum machine learning, ordered by the number of their citations

Table 1
Top 10 reviews of quantum machine learning.

Article	Google citation	1	2	3	4	5	6	7	8
[15]	3789	✓	✓	✓	✓	✓	✓		
[16]	1230	✓	✓		✓	✓			
[17]	940	✓	✓		✓	✓			
[18]	868	✓	✓		✓	✓			
[19]	462	✓	✓		✓	✓	✓	✓	
[20]	416	✓	✓		✓	✓		✓	
[21]	296	✓	✓		✓	✓			
[22]	294	✓	✓		✓	✓			
[23]	238	✓	✓	✓	✓	✓			✓
[24]	125	✓	✓		✓	✓			
This Paper	—	✓	✓	✓	✓	✓	✓	✓	✓

Notes: 1. quantum machine learning, 2. quantum computing, 3. quantum communication, 4. superposition, 5. entanglement, 6. artificial intelligence, 7. big data, 8. 6G.

in Google Scholar as of July 22, 2024. Among the ten papers (Table 1), the total number of citations reached 8658; this reflects that quantum machine learning, and the relevant topics are attracting a lot of attention in the real world. It also means that quantum machine learning is accelerating the development of the entire society.

The ten papers have attracted much attention, covering eight topics: quantum machine learning, quantum computing, quantum communication, superposition, entanglement, artificial intelligence, big data, and 6G

This study sketches a relatively comprehensive content of quantum machine learning: those associated with top papers analysis, descriptive and prescriptive analytics, categories of quantum machine learning algorithms, future directions, and relevant prospects.

2.6.2. Bibliographic analytics of quantum machine learning

Quantum machine learning related topics are an attractive field. We mainly place our focus on articles collected by the WoS (Web of Science). Google Scholar was used to check the citations. The keywords used to search papers are: "quantum machine learning", "quantum deep learning", and "quantum mathematical algorithm." The time scope is between 2002 and 2024. In the database, we narrow down the searching disciplines to quantum technology, computing and information systems, economics, management, operational management, etc. The collected articles consist of peer-reviewed papers and conference proceedings. After excluding duplicate papers or papers published outside the specified year range (2002–2024), the quantity of eligible papers related to quantum machine learning is 723 (Table 2).

2.6.2.1. Descriptive analysis

2.6.2.1.1. Basic information of selected articles (2002 - 2024). The featured articles are from 278 different leading journals. The average total number of citations per article is 28.36 (Table 3). It can be seen that quantum machine learning is an interdisciplinary subject; the amount of collaboration is the indicator.

2.6.2.1.3. Publication trend of selected articles (2002 - 2022). From 2002 to 2024, research in quantum machine learning has grown dramatically. From 2002 to 2012, the number of publications was extremely low, with only a single publication in 2002, 2006, and 2010, and two publications in 2004 and 2012. This indicates a slow start in the research activity during this period. Starting from 2013, there is a gradual increase in the number of publications. In 2013, there were 4 publications, which increased to 11 by 2016. This period marks the beginning of more consistent research output. There is a significant jump in the number of publications starting from 2017 with 23 publications, increasing to 38 in 2018. This upward trend continues in 2019 with 64 publications and reaches 100 in 2020. This period indicates a rapid growth in research interest and output. The number of publications continues to grow, with 109 publications in 2021 and 132 in 2022. The peak is reached in 2023 with 167 publications. Overall, the trend indicates a significant increase in the number of publications over the years, particularly from 2017 onwards, reflecting growing research activity and interest in the field. The dotted trendline suggests a positive overall trend despite the fluctuations in individual years (Fig. 1).

Table 2
Paper selection procedure.

Mainstream	Quantum machine learning
Time Range	2002 - 2024
Database	WoS (Web of Science) Google Scholar
Selection Subject	Title, Keyword, Abstract
Selection Discipline	Quantum Technology, Computing and Information System, Economics, Management, Operational Management
Selection Keyword	"quantum machine learning", "quantum deep learning", "quantum mathematical algorithm"
Quantity of Articles	All Articles Searched (956) Identical Papers (57), Out-of-Time-Range Articles (176) Qualified Articles (723)

Table 3
Main information of featured articles.

Description	Result
Timespan	2002:2024
Source	278
Documents	723
Average citations per documents	28.36
References	21,826
Keywords	546
Authors	1256
Collaboration Index	3.64

2.6.2.4. Prescriptive and predictable analysis

2.6.2.4.1. The major research areas. Keyword analysis was conducted by Biblioshiny of R Project. A total of 723 articles containing 546 keywords were screened. The most frequently occurring keywords were identified, as shown in the following diagrams (Fig. 2). The minimum frequency of keywords is 20, and there are five groups of keywords which represent the direction of quantum machine learning research from different perspectives.

For the selected 723 articles, a keyword word cloud was constructed (Fig. 3). The word cloud consists of the 10 most common words used across all of the keywords of the selected articles.

The ten most frequently used keywords are machine learning (95), quantum machine learning (49), quantum computing (37), quantum chemistry (16), artificial intelligence (9), neural networks (8), quantum algorithms (7), quantum information (7), deep learning (6), and qsar (6).

2.6.2.4.2. Research topic analysis. For the selected 723 articles, links between specific topics were constructed (Fig. 4). The topics related to quantum machine learning research are broad. In general, it can be considered that the beginning of quantum machine learning research is the exploration of fundamental theory. After the basic theory forms a certain foundation, quantum machine learning is gradually applied in practice. With the emergence of various problems in the actual process, corrections and verifications are made at the theoretical level.

According to the co-citation network (Fig. 5), influential scholars can easily be divided into three categories. Furthermore, as expected, there is a high degree of cross-reference among scholars from the three clusters. Obviously, quantum machine learning is not a single discipline, but rather, it is the interweaving of multiple areas, which requires researchers to be familiar with relevant knowledge in different fields, and to further seek deeper research in a collaborative manner, so as to contribute to the overall development of quantum machine learning.

2.6.2.4.3. The collaborative network among countries. The figure below (Fig. 6) depicts a study conducted in collaboration with researchers from countries around the world. The US and China are by far the most engaged countries in quantum machine learning. Other major countries include the United Kingdom, Canada, Japan, Switzerland, and other European countries.

3. Classifications of quantum machine learning algorithms

Quantum machine learning algorithms synergize the principles and capabilities of quantum computing and machine learning, offering approaches to data analysis and processing. These algorithms are crafted to harness the power and advantages of quantum computers to solve complex computational problems in machine learning more efficiently and accurately. In this section, our objective is to categorize these algorithms into six distinct classes (Table 4): quantum-enhanced classical machine learning algorithms, quantum feature selection algorithms, quantum data classification algorithms, quantum optimization models,

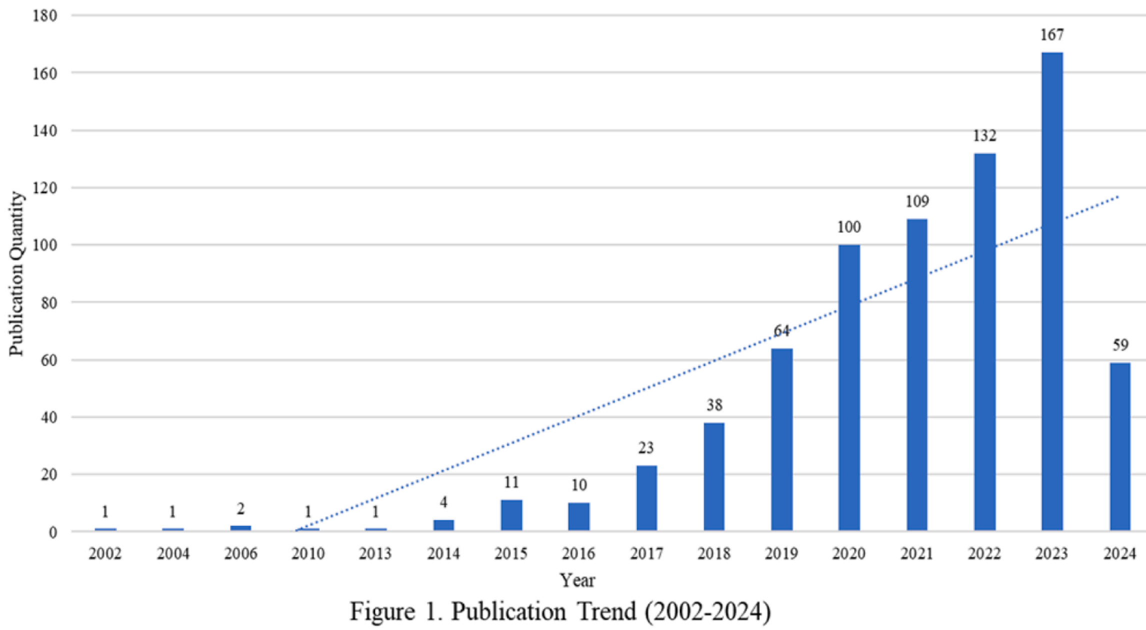

Fig. 1. Publication trend (2002–2024).

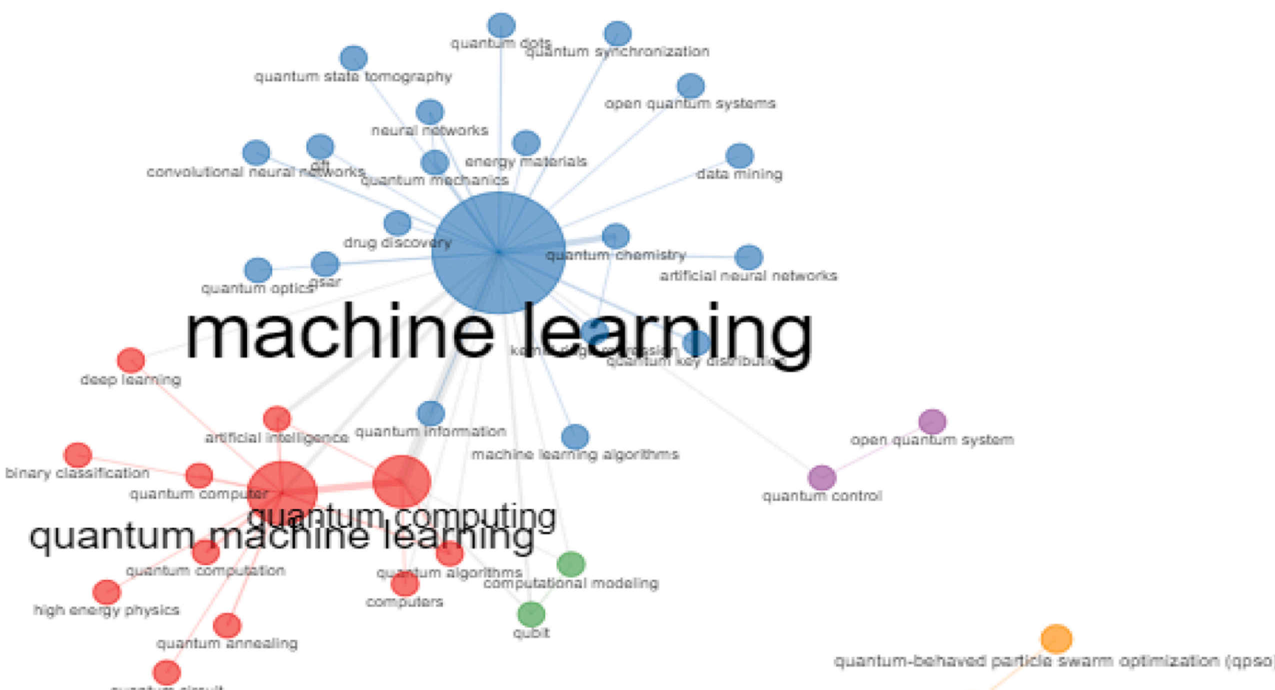

Fig. 2. The network of main research areas.

quantum generative models, and quantum dimensionality reduction algorithms.

3.1. Quantum-Enhanced classical machine learning algorithms

Quantum-enhanced classical machine learning algorithms encompass methods that implement quantum computing techniques to enhance the efficacy of conventional classical machine learning approaches. Here are several examples:

3.1.1. Quantum neural networks (QNNs)

Quantum neural networks are engineered to leverage quantum properties such as superposition and entanglement, with the primary objective of enhancing the performance of machine learning tasks, including but not limited to pattern recognition and classification [9, 10].

3.1.2. Quantum monte carlo methods

Quantum Monte Carlo methods adopt quantum computing to simulate quantum systems more accurately, potentially leading to better

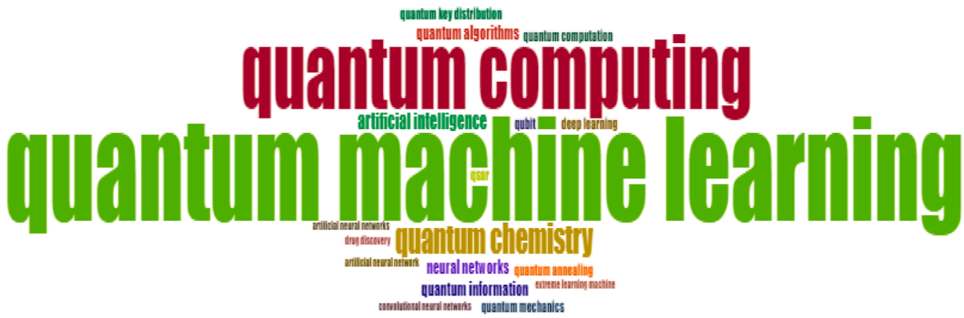

Fig. 3. The world cloud.

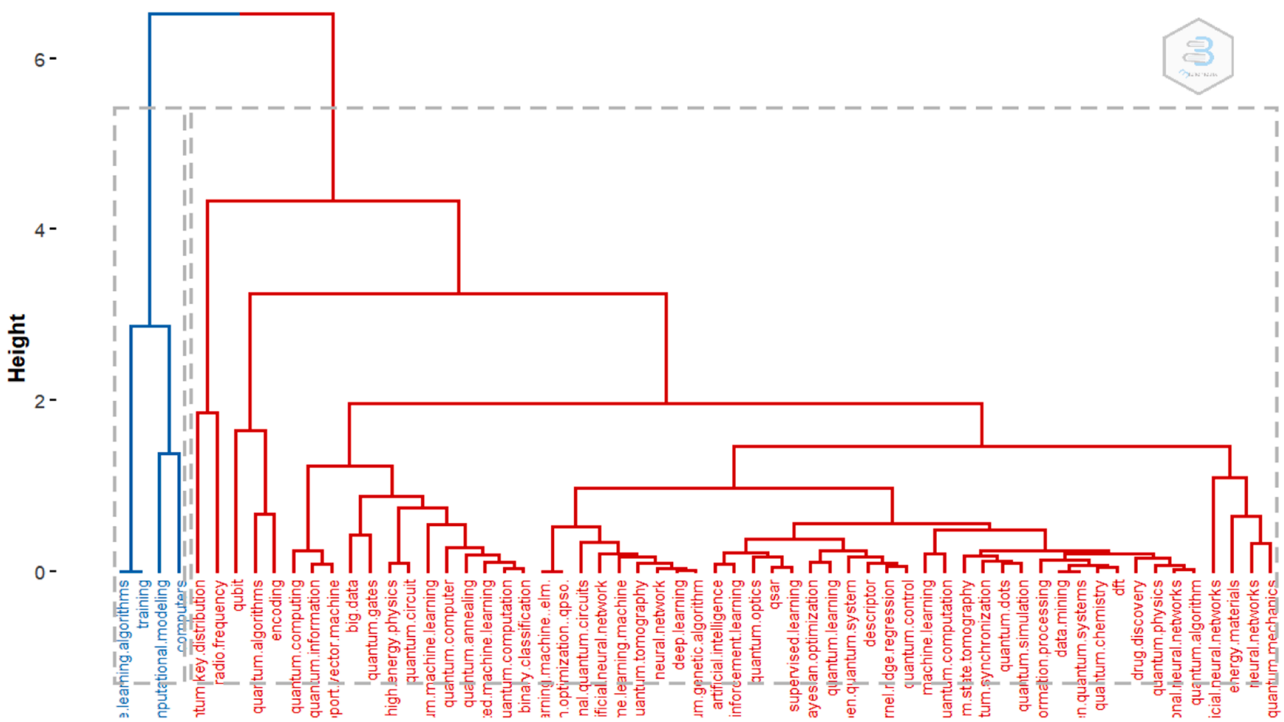

Fig. 4. The topic dendrogram.

solutions for various scientific and financial simulations [11].

3.1.3. Quantum optimization for hyperparameter tuning

Quantum optimization algorithms can be used to explore hyperparameter search spaces more efficiently, leading to better-tuned models [12].

3.1.4. Quantum kernels for support vector machines

Quantum kernels aim to enhance the performance of SVMs by using quantum algorithms to compute kernel functions more efficiently [13].

3.2. Quantum feature selection algorithms

Quantum feature selection algorithms hold the capabilities of quantum computing to effectively pinpoint the most pertinent features within a dataset. Here are a few examples:

3.2.1. Quantum-Inspired feature selection (QIFS)

QIFS is a hybrid approach that combines classical machine learning techniques with quantum-inspired optimization. It uses a quantum-inspired algorithm to search for the optimal feature subset. QIFS aims to improve feature selection efficiency by exploring feature subsets more effectively than classical methods. It can be applied to various classification and regression tasks [14,25].

3.2.2. Quantum annealing (QA)

This approach combines quantum annealing hardware, such as. D-Wave systems, with classical feature selection techniques. Quantum annealing is used to find optimal feature subsets. Quantum annealers can explore large solution spaces efficiently, potentially leading to improved feature selection results for complex datasets [26].

3.2.3. Quantum-Inspired genetic algorithms (QIGA)

This approach combines classical genetic algorithms with quantum-inspired operators, which are used to generate and evolve feature subsets within a genetic algorithm framework. Quantum-inspired genetic algorithms aim to enhance the search capability of genetic algorithms for feature selection, potentially leading to better feature subsets [6].

3.2.4. Variational quantum circuits (VQC)

Variational quantum circuits are used to encode and select relevant features. The optimization of the circuit's parameters helps identify the most important features. This approach explores the potential of quantum circuits for feature selection, potentially improving the efficiency of

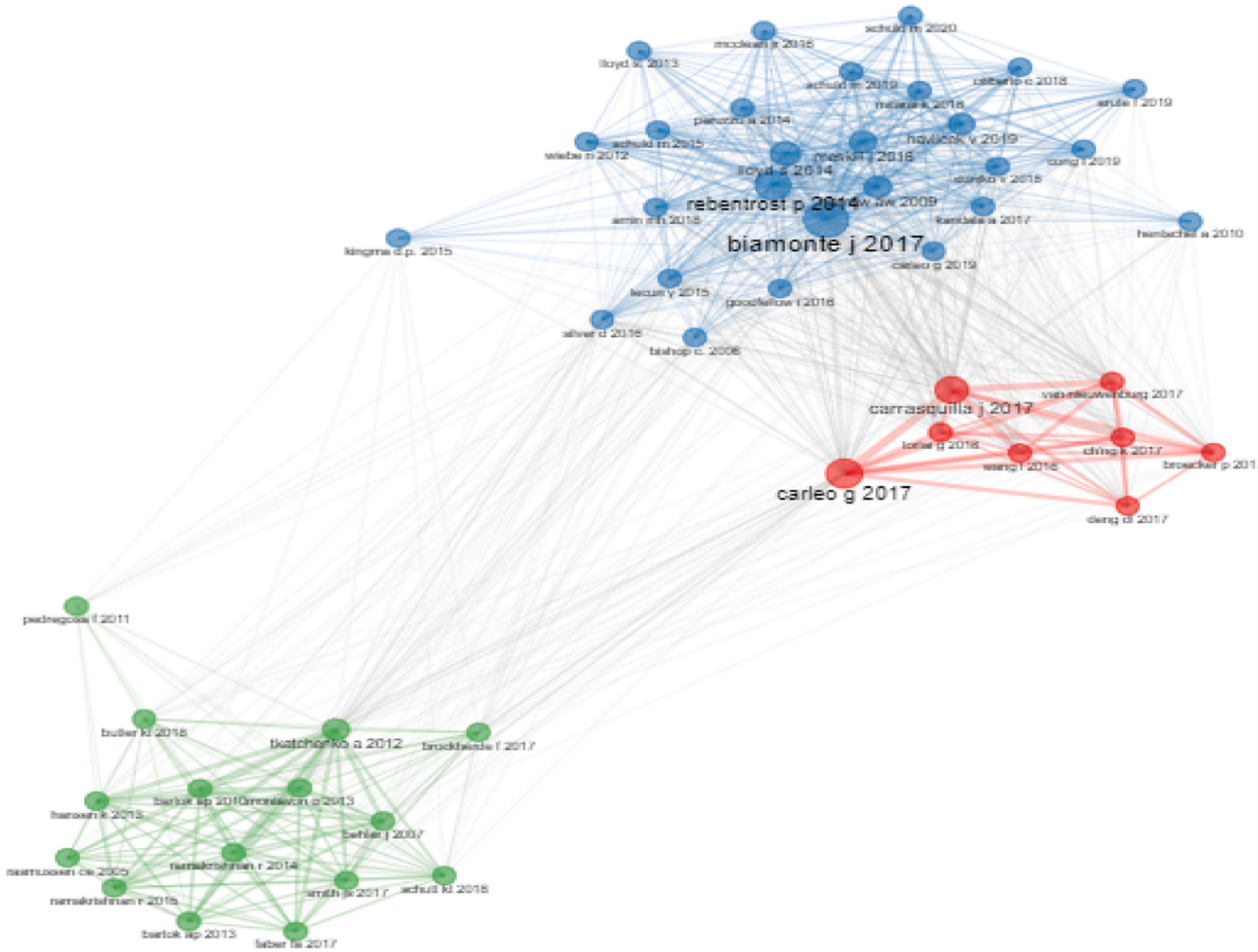

Fig. 5. The network of co-citation.

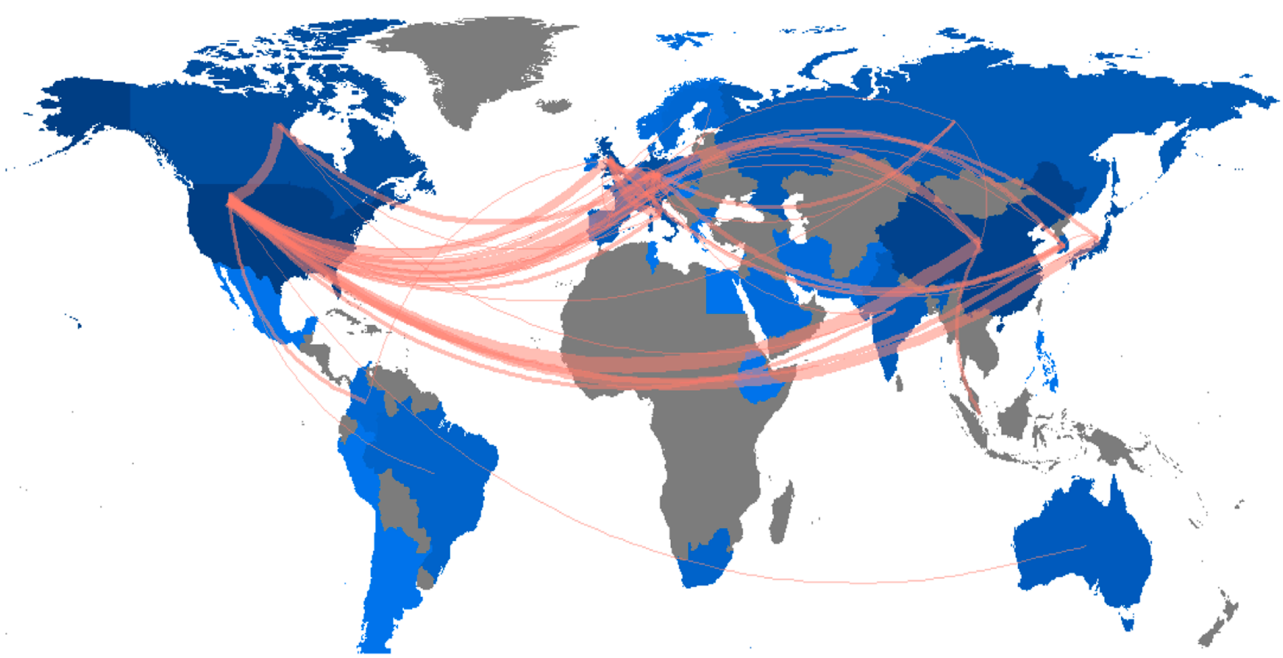

Fig. 6. The collaboration and network among countries.

Table 4
Categorization of quantum machine learning.

Categorization	Functions	Algorithms	Problems solving
A. Quantum-Enhanced Classical Machine Learning	Combining classical machine learning techniques with quantum algorithms to improve computation speed and accuracy in solving complex problems.	1) Quantum Neural Networks (QNNs) 2) Quantum Monte Carlo Methods 3) Quantum Kernels for Support Vector Machines 4) Quantum Optimization for Hyperparameter Tuning	Requiring the exploration of vast solution spaces and make non-trivial decisions based on large amounts of data.
B. Quantum Feature Selection Algorithms	Identifying the most relevant features from a dataset while leveraging quantum principles to enhance efficiency and accuracy in various machine learning tasks.	1) Quantum-Inspired Feature Selection (QIFS) 2) Quantum Annealing (QA) 3) Quantum-Inspired Genetic Algorithms (QIGA) 4) Variational Quantum Circuits (VQC) 5) Quantum-Inspired Particle Swarm Optimization (QPSO) 6) Quantum Feature Selection for Support Vector Machines (QFS-SVM)	Related to feature selection in large and complex datasets, leading to improved accuracy and efficiency.
C. Quantum Data Classification Algorithms	Utilizing quantum computing to categorize data points into distinct classes or groups, often with the aim of achieving improved performance in machine learning and data analysis tasks.	1) Quantum Support Vector Machines (QSVM) 2) Quantum k-Nearest Neighbors (Qk-NN) 3) Quantum Neural Networks (QNNs) 4) Quantum Ensemble Learning 5) Quantum-Inspired Decision Trees 6) Quantum Clustering Algorithms 7) Quantum-Inspired Random Forests	Extracting patterns, correlations, and insights from large datasets.
D. Quantum Optimization Models	Leveraging quantum computing capabilities to find optimal solutions for complex optimization problems, offering potential efficiency advantages over classical optimization techniques.	1) Quantum Variational Optimization (QVO) 2) Quantum Gradient Descent (QGD) 3) Quantum Annealing for Hyperparameter Tuning 4) Quantum Genetic Algorithms 5) Quantum Simulated Annealing 6) Quantum-Inspired Bayesian Optimization	With a large number of variables and constraints, finding optimal solutions for tasks like portfolio optimization or supply chain management.
E. Quantum Generative Models	Employing quantum computing to generate synthetic data that closely resembles real-world data distributions, facilitating tasks like data augmentation and simulations.	1) Quantum Variational Autoencoders (QVAE) 2) Quantum Boltzmann Machines (QBM) 3) Quantum Restricted Boltzmann Machines (QRBM) 4) Quantum Generative Adversarial Networks (QGAN) 5) Quantum Variational Gibbs Sampling (QVGS) 6) Quantum Recurrent Neural Networks (QRNN) 7) Quantum Circuit Born Machine (QCBM)	Complex optimization problems, simulate quantum systems, and generate novel molecules with desired properties.
F. Quantum Dimensionality Reduction Algorithms	Reducing the number of features or dimensions in a dataset while preserving important information, thereby enhancing the efficiency of data analysis and machine learning tasks on high-dimensional data.	1) Quantum Principal Component Analysis (PCA) 2) Quantum Singular Value Decomposition (SVD) 3) Quantum Autoencoders 4) Quantum t-SNE (t-Distributed Stochastic Neighbor Embedding) 5) Quantum Feature Mapping	Reducing the number of features in high-dimensional datasets, leading to improved computational efficiency and better analysis of complex data patterns.

feature selection tasks [27].

3.2.5. Quantum-Inspired particle swarm optimization (QPSO)

QPSO is a quantum-inspired variant of classical Particle Swarm Optimization (PSO). It incorporates quantum concepts into the PSO algorithm to optimize feature subsets. QPSO aims to apply quantum-inspired principles to enhance the feature selection process, making it more efficient and effective [28].

3.2.6. Quantum feature selection for support vector machines (QFS-SVM)

QFS-SVM combines quantum feature selection with Support Vector Machines. It uses quantum algorithms to find feature subsets that can improve SVM classification performance. QFS-SVM aims to enhance the efficiency and effectiveness of feature selection specifically for SVMs, potentially leading to better classification results [29].

3.2.7. Quantum data classification algorithms

Quantum data classification algorithms employ quantum computing techniques to improve the accuracy of data classification. Several quantum-inspired algorithms have emerged to tackle data classification tasks [30].

3.2.8. Quantum support vector machines (QSVM)

QSVM is a quantum-inspired algorithm that enhances the efficiency of training Support Vector Machines (SVMs) for classification tasks. QSVM aims to accelerate SVM training by encoding classical data into quantum states and exploiting quantum algorithms for efficient classification. It has the potential to improve the speed of SVM-based classification [21,32].

3.2.9. Quantum k-Nearest neighbors (Qk-NN)

Qk-NN is a quantum-inspired variant of the classical k-Nearest Neighbors algorithm. It uses quantum principles to efficiently search for nearest neighbors in a dataset. Qk-NN aims to improve the speed of the k-NN algorithm by applying quantum algorithms, making it suitable for large-scale classification tasks [33].

3.2.10. Quantum neural networks (QNNs)

QNNs are quantum-inspired neural networks which are designed for various machine learning tasks, including classification. QNNs have the potential to enhance the performance of classical neural networks for classification tasks by exploiting quantum principles during training and inference [34,35,67].

3.2.11. Quantum ensemble learning

Quantum-inspired ensemble learning algorithms combine multiple quantum models or classical models with quantum enhancements to improve classification accuracy. Quantum ensemble methods aim to enhance classification performance to boost model diversity and accuracy [36,65,68].

3.2.12. Quantum-Inspired decision trees

Quantum-inspired decision tree algorithms are designed to efficiently construct decision trees for classification tasks using quantum computing. These algorithms aim to speed up the decision tree construction process by exploiting quantum algorithms, making them suitable for large datasets [37,71].

3.2.13. Quantum clustering algorithms

Quantum-inspired clustering algorithms, such as quantum k-Means, can be adapted for classification tasks by assigning labels to clusters. Quantum clustering algorithms aim to enhance classification accuracy by efficiently identifying data clusters and assigning labels based on quantum principles [38].

3.2.14. Quantum-Inspired random forests

Quantum-inspired variants of random forests combine classical random forest techniques with quantum enhancements to improve classification accuracy. Quantum-inspired random forests aim to boost classification performance for feature selection and ensemble learning [39,74].

3.2.15. Quantum optimization models

Quantum algorithms can optimize classical machine learning models by utilizing quantum computing to improve the efficiency of optimization processes. Here are examples:

3.2.16. Quantum variational optimization (QVO)

Quantum Variational Optimization is a quantum-inspired algorithm that combines classical machine learning models with quantum computing. It leverages quantum circuits to optimize the parameters of classical models. QVO aims to accelerate the optimization process for classical machine learning models, potentially leading to faster convergence and improved model performance [7,77,80].

3.2.17. Quantum gradient descent (QGD)

Quantum Gradient Descent is a quantum-inspired variant of the classical gradient descent algorithm. It uses quantum principles to compute gradients more efficiently, which can be beneficial for optimizing the parameters of machine learning models. QGD aims to speed up the optimization process by quantum computing, potentially reducing training time for classical models [40].

3.2.18. Quantum annealing for hyperparameter tuning

Quantum annealing hardware, such as. D-Wave systems, can be used to optimize hyperparameters of classical machine learning models. Quantum annealing efficiently navigates the hyperparameter space to discover optimal configurations. Quantum annealing can accelerate hyperparameter tuning, leading to better-performing classical models [41].

3.2.19. Quantum genetic algorithms

Quantum-inspired genetic algorithms can be applied to optimize the selection of machine learning models, including choosing the best model architecture and hyperparameters. Quantum genetic algorithms aim to improve the efficiency of model selection, helping to identify the most suitable models for specific tasks [42,69].

3.2.20. Quantum simulated annealing

Quantum-inspired simulated annealing algorithms are used to optimize classical machine learning models. They explore model configurations more efficiently. Quantum simulated annealing can speed up the optimization process, making it easier to find optimal model parameters [43,72].

3.2.21. Quantum-Inspired bayesian optimization

Quantum-inspired Bayesian optimization algorithms use quantum-inspired techniques to optimize the acquisition function in Bayesian optimization, which is commonly used for hyperparameter tuning to yield better-performing classical models [44,70].

3.2.22. Quantum generative models

Quantum generative models utilize quantum computing to generate data samples conforming to predefined probability distributions, offering potential applications across diverse fields such as quantum chemistry, materials science, and others. Here are several examples:

3.2.23. Quantum variational autoencoders (QVAE)

QVAEs are quantum-inspired generative models that combine the principles of variational autoencoders (VAEs) with quantum circuits. They encode input data into quantum states and use quantum circuits to generate samples from the latent space. QVAEs can be used for generative tasks, such as generating molecular structures in quantum chemistry or optimizing quantum algorithms [45].

3.2.24. Quantum boltzmann machines (QBM) and quantum restricted boltzmann machines (QRBM)

Quantum Boltzmann Machines are generative models inspired by classical Boltzmann Machines but enhanced with quantum principles. They can capture complex probability distributions of quantum systems. QBMs are designed for quantum applications, such as modeling quantum states and quantum annealing problems [46,62].

QRBM is a quantum variant of Restricted Boltzmann Machines (RBMs). It is used for modeling joint probability distributions of binary data and can be applied to quantum data as well. QRBM can be used for quantum data compression and feature extraction tasks [47].

3.2.25. Quantum generative adversarial networks (QGAN)

QGANs are quantum-inspired versions of Generative Adversarial Networks (GANs). It employs quantum circuits to generate data samples that mimic the distribution of a given dataset. QGANs have potential applications in generating quantum datasets for training quantum machine learning models [48].

3.2.26. Quantum variational gibbs sampling (QVGS)

QVGS is a quantum-inspired algorithm for generating samples from complex probability distributions, particularly in the context of quantum systems. QVGS can be used to simulate the behavior of quantum systems and generate quantum data samples [8,63].

3.2.27. Quantum recurrent neural networks (QRNN)

QRNNs are quantum-inspired recurrent neural networks that incorporate quantum gates and principles to capture temporal dependencies in data. They can be used for generative tasks in time-series data. QRNNs aim to improve the modeling of quantum dynamics and other sequential data with quantum-inspired techniques [49].

3.2.28. Quantum circuit born machine (QCBM)

QCBM is a generative model that uses quantum circuits to parameterize a quantum state that can generate data samples according to a desired probability distribution. QCBMs are designed for generative tasks and can be applied to quantum data generation and quantum state modeling [50].

3.2.29. Quantum dimensionality reduction algorithms

Quantum algorithms for dimensionality reduction endeavor to reduce the number of features or dimensions in a dataset while retaining pertinent information. Here are examples:

3.2.30. Quantum principal component analysis (PCA)

Quantum PCA is a quantum-inspired algorithm that is a classical technique for dimensionality reduction. It aims to find the principal components of a dataset, which are linear combinations of the original features that capture the most variance. Quantum PCA may offer speedup compared to classical PCA for large datasets [51].

3.2.31. Quantum singular value decomposition (SVD)

Quantum SVD is a quantum-inspired technique that factors a matrix into three other matrices, which can be used for dimensionality reduction. It is often used in conjunction with quantum PCA. Quantum SVD can potentially provide faster matrix factorization, which is useful for dimensionality reduction tasks [52].

3.2.32. Quantum autoencoders

Quantum autoencoders have a specific neural network architecture. They can be used for both feature extraction and dimensionality reduction by encoding high-dimensional data into a lower-dimensional representation. Quantum autoencoders may offer advantages in terms of data compression and feature representation [53].

3.2.33. Quantum t-SNE (t-Distributed stochastic neighbor embedding)

Quantum t-SNE is a quantum-inspired variant of the classical t-SNE algorithm, which is used for dimensionality reduction and data visualization. Quantum t-SNE aims to find a lower-dimensional representation of data that preserves pairwise similarities. Quantum t-SNE may provide computational advantages in certain scenarios, especially when dealing with large datasets [54].

3.2.34. Quantum feature mapping

Quantum feature mapping techniques leverage quantum circuits to map high-dimensional classical data into a higher-dimensional quantum space. This can be used as a preprocessing step for dimensionality reduction. Quantum feature mapping can introduce additional dimensions that may reveal hidden patterns in the data [55].

3.2.35. Challenges and potential solutions

Quantum machine learning has the potentials to solve complex problems with unprecedented efficiency, it also brings forth a unique set of challenges. In this section, we pay attention to the challenges encountered in quantum machine learning, spanning issues related to algorithmic complexity, quantum error and noise, quantum scalability, quantum data encoding, quantum interoperability, limited quantum availability, quantum hardware constraints, and algorithm design. Meanwhile, potential solutions are also discussed, providing insights into the practicability of quantum machine learning in various disciplines.

3.3. Complexity

Quantum machine learning algorithms frequently entail the solution of optimization problems, which can be computationally demanding and time-consuming. Expanding the accessibility and capabilities of quantum computers plays a role in alleviating this complexity issue by facilitating swifter and more efficient calculations. Quantum algorithm design should prioritize the minimization of quantum gates or qubits needed for specific computations, to diminish overall complexity. In parallel, the deployment of robust error correction techniques serves to mitigate the influence of noise and errors on quantum machine learning calculations, to reduce the complexity of error correction processes [2,51,56].

3.4. Error and noise

Quantum computers are inherently susceptible to errors and noise due to technological limitations. It forms the accuracy and dependability of results obtained through quantum machine learning algorithms. To address these challenges, quantum error-correcting codes can detect and rectify errors that occur during quantum computations. Additionally, a spectrum of remedial strategies, including error mitigation, error averaging, and error extrapolation, can be deployed to mitigate the impact of noise on quantum machine learning algorithms. Developing algorithms that inherently withstand noise emerges to explore. Techniques like dynamical decoupling and quantum error avoidance can be effectively implemented to suppress or minimize the disruptive effects of noise on quantum machine learning algorithms [3,10,57].

3.5. Scalability

Quantum computers are currently limited in terms of the number of qubits they can handle. As a result, quantum machine learning algorithms may face challenges when it comes to scaling up to handle larger and more complex datasets. The key to addressing this challenge lies in the development of tailored, efficient quantum algorithms explicitly designed for machine learning tasks. Equally vital is the creation of efficient encoding schemes capable of representing classical data in a quantum-compatible format, associated with larger datasets on quantum systems. The utilization of more efficient simulators for quantum system emulation empowers researchers and developers to rigorously test and optimize quantum machine learning models before deploying them on physical quantum hardware. Ongoing advancements in quantum hardware technology, including the expansion of qubit numbers and improvements in qubit coherence times, directly contribute to enhancing the scalability of quantum machine learning [1,30,78].

3.6. Quantum data encoding

Quantum machine learning algorithms necessitate the transformation of classical data into quantum states, a task laden with challenges. The method chosen for encoding exerts a critical influence on the accuracy and efficiency of the algorithm. Quantum embeddings offer an elegant solution to facilitate the streamlined representation of classical data in a quantum format and enable quantum algorithms to seamlessly interface with classical datasets. An alternative strategy for overcoming data encoding challenges has the potential to adopt hybrid classical-quantum approaches and capitalize on the strengths of both classical and quantum components. Furthermore, data compression techniques tailored to the unique requirements of quantum machine learning can help address the challenges of encoding data for quantum computers

[44,53,60].

3.7. Interpretability

Quantum machine learning algorithms involve complex mathematical operations that can be difficult to interpret and understand. This lack of interpretability can impede the extraction of insights from the outcomes produced by these algorithms. One approach of mitigating this challenge is to design quantum circuits characterized by transparent and comprehensible structures and facilitate the interpretation of quantum machine learning models. Additionally, the development of techniques for identifying the most influential quantum features can augment interpretability. The creation of visualization tools capable of representing the quantum states and operations employed in the learning process can further enhance interpretability. Moreover, applying post-hoc explanation techniques, such as adversarial examples or LIME (Local Interpretable Model-Agnostic Explanations), to quantum models can furnish valuable supplementary avenues for achieving interpretability [4,14,75].

3.8. Limited availability

The limited availability of quantum computers poses constraints on the accessibility and feasibility of deploying quantum machine learning algorithms in practical real-world applications. However, there are strategies to tackle this challenge. For instance, expanding quantum computing infrastructure, embracing cloud-based quantum computing solutions, adopting hybrid quantum-classical approaches, harnessing quantum machine learning simulations, and exploring algorithmic optimizations, etc. [6,13,58].

3.9. Quantum demanding requirement

Quantum computing has demanding cooling requirements, especially for certain quantum computing platforms like superconducting qubits and trapped ions. These systems need to operate at very low temperatures, typically close to absolute zero (−273.15 °Celsius), in order to preserve superposition and entanglement. The cooling systems required for quantum computers are not challenging and expensive to achieve, but make the system very large and bulky. As such, it is difficult to scale up quantum computers and to deploy them in real-world settings outside of sophisticated lab environments [8,31,64].

Despite these challenges, quantum machine learning is capable of revolutionizing various fields. Research efforts are underway to develop and refine quantum machine learning algorithms that can benefit the unique capabilities of quantum computers and overcome the limitations of classical machine learning techniques.

4. Discussions and future trends

The development of quantum machine learning algorithms requires expertise in both quantum computing and machine learning. The convergence of these two domains necessitates researchers and practitioners to possess a comprehension of both quantum physics and advanced machine learning techniques.

4.1. Compensation of classic computing

A qubit is usually in a superposition state. Due to the probabilistic nature of quantum mechanics, a single measurement (readout) will not provide complete information about the state. As such, multiple measurements (can be a few hundreds) are typically performed in order to obtain reliable statistics about the state of the qubit. This makes quantum computing very inefficient compared to the classic computing which only requires a single measurement/readout. Due to this circumstance, we are better off with classic computing on most occasions, and quantum computing is superior only for certain type of applications such as the Shor's and Grover's algorithms [1,29,73].

4.2. Quantum data analysis

Quantum algorithms offer the potential for expedited data analysis and pattern recognition in comparison to classical techniques. A primary advantage of quantum machine learning algorithms lies in their capacity to effectively manage exponentially large datasets. Quantum computers leverage superposition to process and store extensive data volumes concurrently, enabling parallel processing across multiple instances. Consequently, quantum machine learning can be applied in the scenarios of big data analytics, for swift access to insights and informed decision-making [11,33,66].

4.3. Quantum hardware development

The swift expansion of quantum computing hardware is set to intensify efforts in crafting quantum algorithms expressly tailored for machine learning purposes. This trajectory is expected to yield more efficient and precise algorithms for both training and inference, marking an advancement in the field of quantum machine learning [3,45,61].

4.4. Quantum machine learning as a service

As quantum computing becomes increasingly accessible, companies may offer quantum machine learning as a service, providing businesses with the opportunity to tap into quantum computing resources and algorithms without the need for substantial investments in hardware and specialized expertise [2,4,79].

4.5. Quantum security

Quantum machine learning also holds the potential to bolster security measures, e.g., the development of more robust encryption algorithms. By employing quantum machine learning techniques, security protocols can be optimized, and vulnerabilities can be identified more efficiently, contributing to enhanced cybersecurity practices [46,59,76].

5. Conclusion

The synergistic combination of machine learning and quantum mechanics give rise to the field of quantum machine learning. Quantum computing has opened broad prospects for the exploration of machine learning. Quantum machine learning has potential to breaking through algorithms' limitations, ensuring accuracy, increasing computing speed, and improving the overall performance. Based on state-of-the-art quantum machine learning, this paper explored the in-depth categories of quantum machine learning algorithms, and explained the challenges and potential solutions. This study represents a commendable effort to categorize and explore the field of quantum machine learning.

CRediT authorship contribution statement

Wei Lu: Writing – original draft. **Yang Lu:** Writing – review & editing. **Jin Li:** Methodology, Resources, Visualization. **Alexander Sigov:** Conceptualization. **Leonid Ratkin:** Data curation. **Leonid A. Ivanov:** Methodology.

Declaration of competing interest

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

Data availability

No data was used for the research described in the article.

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