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Review

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Review

An Overview of Quantum Machine Learning Research in China

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Abstract: Quantum machine learning (QML) is an emerging discipline that combines quantum computing and machine learning and is able to exhibit exponential superiority over classical machine learning regarding computing speed on specific problems. This article provides a comprehensive review of the QML research in China. The QML development in China is presented in terms of research ideas and tasks, and the algorithms and application fields are sorted out. We have also highlighted some typical creative studies and illuminated their innovation points. Furthermore, the current challenges and future prospects are discussed. This review may provide inspiration for both China's and global QML-domain progress.

Keywords: quantum computing; quantum machine learning; quantum deep learning; quantum neural network

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1. Introduction

As a major area in artificial intelligence, machine learning has become a hotspot technique in both academic and industrial fields, extensively applied in quite a few areas including image recognition, data mining, medical care, natural language processing, and so forth [1]. In machine learning algorithms, data are often stored in matrices [2]. However, with the exponential growth of the amount of data and the increase in algorithm model volume (e.g., in the popular GPT-4 model, there are 1.76 trillion parameters to be trained [3,4]), the processing efficiency of classical machine learning rapidly declines since conventional computers require a great amount of time and computing resources to perform matrix operations [1,2]. In the future era of data explosion, classical machine learning algorithms will face more severe challenges in processing massive data, and the utilization of quantum computing is a highly anticipated solution.

Quantum computing is a methodology of computation that makes use of quantum phenomena in physics [5]. The initial idea originated in 1982 when physicist Feynman pointed out that quantum computers might have advantages that classical computers could not parallel in solving specific problems [6]. These advantages are achieved based on quantum properties, such as quantum superposition and quantum entanglement [5]. They make quantum computers superior to classical computers in terms of computation cost, and theoretically quantum computing can solve extremely complex problems that classical computing is impossibly able to deal with [7]. In the 1990s, Shor (from Bell Laboratory) proposed an integer factorization algorithm based on quantum computing, which has an exponential advantage compared to classical factorization algorithms [8]; Grover (also from Bell Laboratory) proposed a quantum search algorithm that can realize square-level acceleration compared with classical search algorithm [9]. In 2008, Harrow et al. proposed the well-known HHL algorithm for solving linear systems of equations, which achieved exponential acceleration against classical solutions [10]. These early achievements have laid the foundation for the development of quantum computing.

Quantum machine learning (QML) is a technique that combines the advantages of quantum computing and machine learning, aiming to solve specific difficult problems in classical machine learning based on quantum computing methods [11–14]. The fundamental idea of QML is to utilize quantum advantages, i.e., the superposition and/or entanglement of quantum bits (qubits), to accelerate the training process of machine learning [5]. A classical bit can only be in one of two binary states (0 or 1), while a qubit can stand in a superposition state of $|0\rangle$ and $|1\rangle$. Therefore, the quantum superposition property can provide QML algorithms with extraordinary parallel processing capabilities and, hence, realize exponential acceleration compared to classical algorithms [15]. As to the quantum entanglement property, it can help us generate qubits in entangled states, such as Bell states. Bell states are a set of maximally entangled states in quantum mechanics that describe two-qubit systems. The maximum entanglement orthogonal basis of a two-qubit system is composed of four Bell states, with their mathematical expressions being $|\Phi^{\pm}\rangle = (|00\rangle \pm |11\rangle)/\sqrt{2}$ and $|\Psi^{\pm}\rangle = (|01\rangle \pm |10\rangle)/\sqrt{2}$. For two qubits in Bell states, measuring the state of one qubit can instantly determine the state of the other, hence realizing the non-local correlation. This property can be beneficial to simplifying the construction two-qubit operation gate, such as controlled NOT (CNOT) gate [16]. Therefore, the quantum entanglement property can realize more complicated computational operations for various QML applications, such as constructing loss functions through entanglement effects [17], establishing quantum teleportation protocols for secure QML [18], and implementing quantum competition based on entanglement measures [19,20]. The basic principles of computational acceleration brought by quantum superposition and quantum entanglement are illustrated in Figure 1.

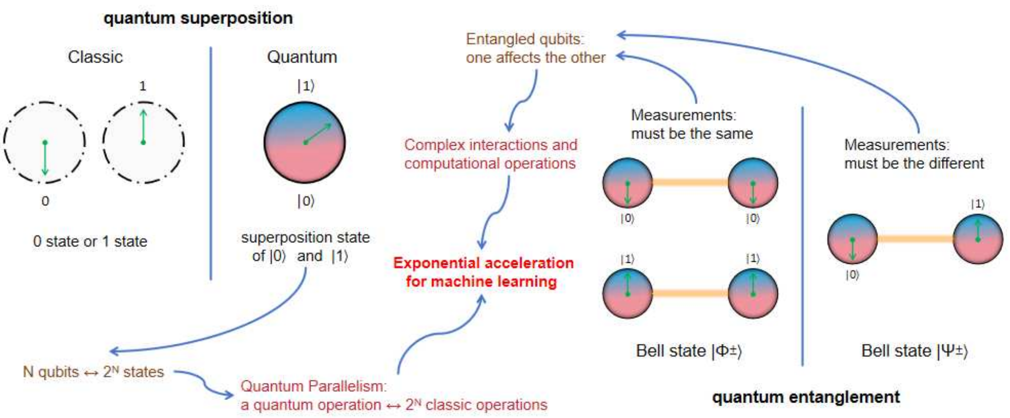

Figure 1. Schematic diagram of the principle of computational acceleration based on quantum superposition and quantum entanglement. Quantum superposition enables N qubits to represent 2^N superposition states, hence allowing quantum computing parallelism (i.e., one quantum operation is equivalent to 2^N classical operations). Quantum entanglement enables the change in one of two entangled qubits (such as qubits in Bell states) to synchronously affect the other qubit, hence allowing for more complicated interactions and operations.

Quantum computing may help classical machine learning at various stages, such as data collection/preprocessing, feature engineering, model training, and model validation/optimization. For data collection/preprocessing, assuming each sample is an N-dimensional data, in the classical framework, one cannot directly alter the data dimensionality. In quantum computing, however, one may employ quantum state encoding techniques like amplitude encoding to map such data, requiring only $\log_2 N$ qubits to represent the N-dimensional data. This exponential data compression can drastically reduce computational cost.

As to feature engineering, classical approaches like principal component analysis (PCA) rely on covariance matrix calculation and eigenvalue decomposition, with the time complexity scaling as $O\left(N^3\right)$, meaning that the computational time increases drastically with data dimensionality. In contrast, quantum PCA (QPCA) can theoretically leverage quantum state preparation and quantum phase estimation to achieve a time complexity of $O(\text{poly}(\log N))$ [21], significantly accelerating the feature dimensionality reduction.

Regarding model training, taking neural network methodology as an example, classical training methods such as stochastic gradient descent compute gradients for each weight parameter sequentially. For deep learning networks with billions of weight parameters, the training can be dramatically time-consuming. Quantum computing can address this issue by carrying out parallel computing to compute gradients for all parameters simultaneously (e.g., parameterized quantum circuits [22]) or by improving parameter updating strategy to compute the best updating directions in the geometric structure of quantum state space (e.g., quantum natural gradient [23]).

For model validation, classical approaches need to validate multiple dataset partition schemes one by one, whereas quantum methods can leverage quantum superposition to validate multiple schemes in parallel. With regard to model optimization, classical methods need to attempt a great many hyperparameter combinations to search the optimal combination set. By employing quantum searching algorithms, such as quantum annealing [24] and Grover's algorithm [9], the required number of searching iterations can be considerably reduced, and the computation time can be significantly saved.

In recent years, the quantum science and technology in China has flourished, with a constant stream of high-level scientific and technological achievements. For example, Pan's team has made important progress in quantum computing fields such as quantum computational chemistry [25] and quantum walk [26], as well as in ultra-distant satellite communication based on quantum key distribution by collaborating with Wang's team [27,28]. These achievements have made significant contributions not only to the quantum field in China but also the whole quantum realm throughout the world. As one of the leading countries in the quantum field, China has provided fertile soil for the growth of quantum technology in recent years. Therefore, although QML research did not start very early in China, Chinese researchers have made quite a lot achievements in QML domain in the past a few years, and QML is still in a phase of vigorous development in China at present.

In this article, we have reviewed the development of QML research in China. The scope is limited to the achievements of Chinese institutions, while those studies conducted by Chinese academicians in foreign institutions are not included. To the best of our knowledge, this is the first article that provides a comprehensive overview of China's QML research.

The structure of the following parts is arranged as below. Section 2 presents the development history and current research status of QML research in China. Section 3 displays the QML algorithms and their application areas. Section 4 highlights some typical creative studies and analyzes their innovation aspects from different perspectives. Section 5 discusses both the current challenges and the future prospects. Finally, Section 6 provides a conclusion of this article.

2. QML Development History and Current Status in China

In this section, we discuss the historical development of QML in China, with a strong focus on the current research landscape.

2.1. Development History

Due to the lack of a clear division of China's QML development period, in this article, we have proposed a rough partition scheme that divides China's QML research into three stages, namely, the preliminary stage, transition stage, and explosion stage. The partition scheme is formulated based on the number of QML-related paper publications.

We have conducted the searching and selection of paper publications based on the following methodology, referring to that adopted in [7]. Firstly, we choose two academic searching platforms, i.e., Web of Science (WOS) and China National Knowledge Infrastructure (CNKI), as our basic literature source. Secondly, we set the searching keywords as "quantum machine learning" OR "quantum deep learning" OR "quantum neural network". Thirdly, we filter the publication results according to these criteria: (1) the contributing institutions of the publication must include at least one Chinese institution; (2) the publication must be a research paper (excluding review papers, comment papers, dissertations, patents, etc.); (3) the publication must be written in English. After the above filtering, we finally obtain 359 appropriate paper publications, with the specific number achieved via manual counting.

Although the publication data source platforms in this work are WOS and CNKI, note that there are also some other good literature data platforms, such as Dimension.ai and PubMed. Meanwhile, it is worth emphasizing that there may exist discrepancies in the publication numbers between different platforms. For example, when we use the keyword "quantum machine learning" for literature searching, different platforms can yield quite different numbers of results: Dimension.ai yields about 498,000 results, WOS about 14,000, PubMed about 25,000, and CNKI about 1300, respectively. In fact, since these platforms may employ a fuzzy search mechanism, many results are actually not highly relevant contents. Therefore, careful manual examination and filtering are necessary for accurate counting of publication quantity.

As shown in Figure 2a, the time before 2018 is regarded as the preliminary stage; at that time, the cumulative number of papers is less than 30. The period from 2018 to 2021 is defined as the transition stage; just the sum of paper numbers for 2018 and 2019 surpasses the total number throughout the preliminary stage, with the cumulative number of papers in the transition stage falling within the 90 to 100 range. The period starting from 2022 is considered as the explosion stage; within just three years since 2022, the number of papers has exceeded 240, and it still keeps increasing steadily year by year. In addition to the rough stage division, we have also counted the publication numbers in each year (from 2005 to 2024). In Figure 2b, we illustrate the growth trend of QML-related publication quantity over time. It can be found that the growth trend can be well fitted by an exponential curve (red dashed line), indicating that there is an exponential growth in China's QML-related publications.

In the preliminary stage, researchers usually employ classical machine learning algorithms as a foundation and use quantum computing in specific modules that too complicated for classical computing. By such a mode of algorithm replacement, a quantum version of a classical machine learning algorithm can be created (denoted as "quantum replacement mode" hereinafter). Most studies in the preliminary stage were based on the quantum replacement mode and mainly focused on unsupervised machine learning tasks. For example, in 2017, Sheng et al. proposed a protocol for distributed secure QML, which can be applied in the field of cybersecurity [29]; He et al. constructed two kinds of quantum feature selection (dimension reduction) algorithms in 2018, and square level acceleration can be achieved compared to the corresponding classical feature selection algorithms [30].

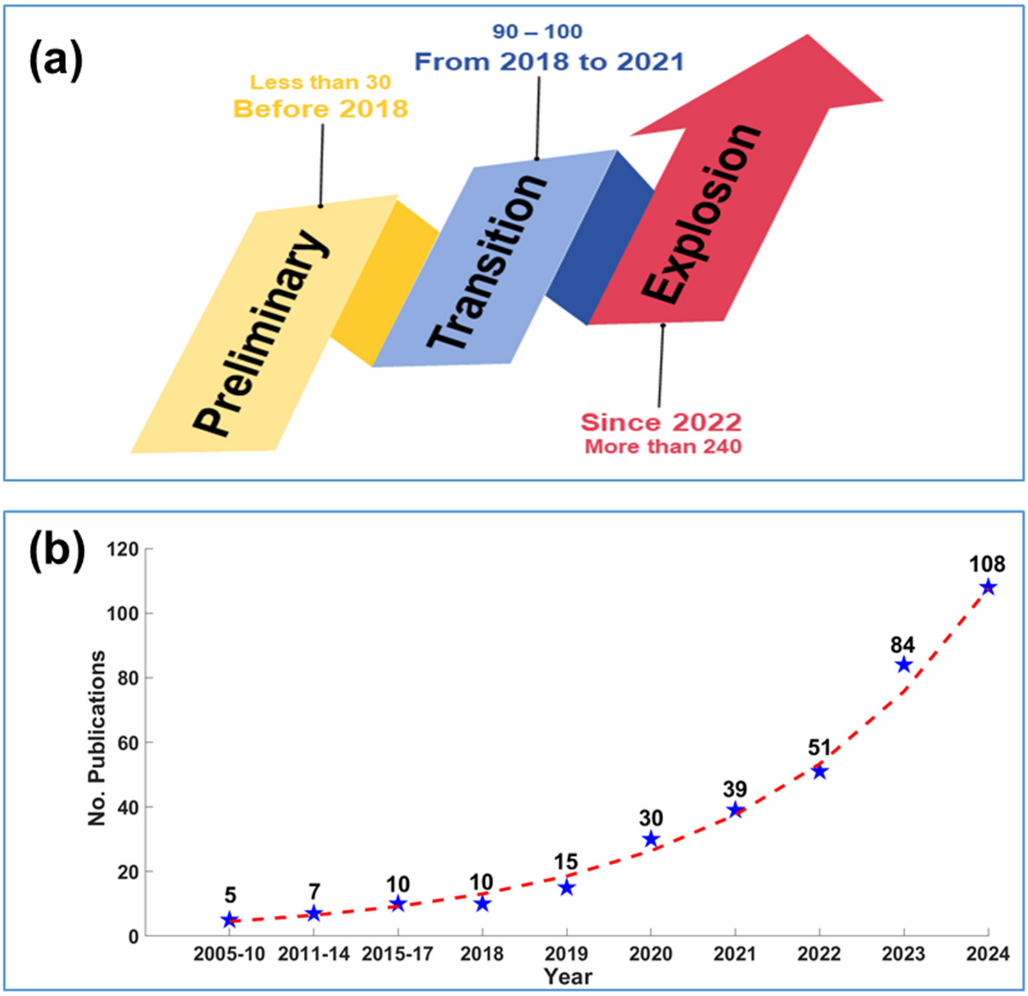

Figure 2. Information of China's QML development and research papers. (**a**) A proposed three-stage division of China's QML development period based on the number of research paper publications. (**b**) The growth trend of China's QML publication quantity over time, indicating an approximate exponential growth.

During the transition stage, researchers began to make more efforts to improve the performance of the QML algorithms already proposed. By such a mode of algorithm improvement, an upgraded version of a QML algorithm can be established (denoted as "quantum improvement mode" hereinafter). Despite the fact that the quantum replacement mode was still the mainstream (e.g., a quantum data compression algorithm based on PCA was proposed [31]), the number of studies based on the quantum improvement mode was gradually increasing. Meanwhile, there were more and more studies focusing on supervised machine learning tasks. In 2020, He et al. reported two quantum locally linear embedding (QLLE) algorithms for nonlinear dimensionality reduction on the basis of a linear algebra procedure and variational hybrid quantum–classical procedure, respectively [32]. The linear algebra implementation can be considered as an example of the quantum replacement mode (replacing the classical LLE), while the variation implementation can be regarded as an example of the quantum improvement mode (improving the linear algebra implementation in terms of global manifold structure maintenance). Another representative instance of the quantum improvement mode is what Wang et el. reported in 2021 as they developed a quantum deep transfer learning model able to achieve higher classification accuracy on small datasets like the popular IRIS dataset than former QML models [33].

After entering the explosion stage, the quantum improvement mode gradually becomes the predominant direction, and most studies are oriented to supervised machine learning tasks. In 2022, Huang et al. proposed a variational convolutional neural network (VCNN) classification algorithm, which could achieve higher accuracy and efficiency compared with other quantum neural network (QNN) algorithms [34]. In 2023, He et al. (the same group as that in [32]) reported another work based on the linear algebra procedure and variational hybrid quantum–classical procedure but focusing on domain adaption (DA) classification in transfer learning, and their classifier could acquire higher accuracy than classical DA classifier as well as two other state-of-art quantum DA classifiers [35]. Very recently, Gong et al. developed a quantum K-nearest neighbor (QKNN) classification algorithm, which achieved higher accuracy and efficiency on the IRIS dataset than other QKNN algorithms, and the accuracy was comparable to classical KNN algorithm [36].

In short, China's QML research has undergone three stages, gradually shifting the model designing mode from the quantum replacement mode to the quantum improvement mode and meanwhile shifting the task type from unsupervised learning to supervised learning.

2.2. Current Status

At present, the QML field in China is undergoing rapid growth, with one of its remarkable features being an increasing internationalization. This is reflected in two main aspects: (1) the development trend of QML in China is gradually aligning with international momentum, demonstrating a high degree of consistency; (2) the overall performance of models proposed in China's cutting-edge QML work has reached internationally advanced levels, and some models can even achieve top-tier performance among all similar models worldwide.

2.2.1. Development Trend

Nowadays, the global QML field primarily focuses on classification tasks, with image classification being the most prevalent among them. Regarding the research modes, most studies follow the quantum replacement mode, aiming to design quantum implementations of classical machine learning algorithms. Meanwhile, there are also quite a few studies based on the quantum improvement mode, which strive to upgrade the circuit implementations of quantum algorithms for the improvement of the QML model performance.

As for China's QML field, as mentioned before, the number of studies focusing on supervised learning tasks is obviously rising nowadays. Supervised learning tasks mainly contain classification and regression, with classification tasks being more popular currently. Therefore, China's QML research is aligned with the global trend in terms of the target task. With regard to the research modes, the number of studies based on quantum improvement is gradually surpassing that of the quantum-replacement-based studies. So, it might be concluded that China's QML investigation holds a leading position internationally in terms of the research mode.

2.2.2. Model Performance

The accuracy performance of the QML models serves as an important benchmark for assessing the sophistication of the QML research. The following examples may showcase the advanced level of China's QML research on the international stage. Gong et al. developed a QKNN model based on a divide-and-conquer strategy, which achieved a classification accuracy of 97.04% on the IRIS dataset, largely outperforming the other typical QKNN models [36]. Song et al. formulated a tensor network (TN) inspired quantum circuit framework and, based on the framework proposed, a parallel quantum tensor network (QTN) for multi-class classification tasks. Their method achieved an average accuracy of over 99% on the MNIST dataset, achieving the highest accuracy not only among all the QTN type methods but also among all the investigated QML methods [37]. Zhang et al. designed a quantum self-attention model (QSAM) based on variational quantum algorithm, which demonstrated performance comparable to other state-of-the-art QSAMs on natural language processing datasets such as Yelp, IMDb, and Amazon and obtained higher classification accuracy than other quantum image classifiers on computer vision datasets like MNIST and Fashion MNIST [38]. Hence, it might be concluded that China's cutting-edge QML models are highly sophisticated regarding performance throughout the international QML field.

3. Algorithms and Applications

In this section, we discuss the algorithms involved in China's QML research and introduce the major application domains of QML algorithms.

3.1. Algorithms

Algorithms are the core component of machine learning (in the classical context), and self-evidently they are also crucial for QML research. For the QML studies in China, various types of algorithms have been established and employed. Most of these quantum algorithms stem from their classical counterparts, e.g., QPCA is inspired by classical PCA [39]; and quantum partial least squares (QPLS) is a quantum version of the classical partial least squares (PLS) [40,41].

The quantum algorithms extensively adopted in China's QML studies include quantum neural network (QNN)-type algorithms [34,42–64], quantum support vector machine (QSVM) algorithms [65–68], quantum K-nearest neighbor (QKNN) algorithms [36,69–71], and so on. Among them, the QNN-type algorithms dominate in terms of the number of papers, mainly consisting of regular QNN [42–50], quantum convolutional neural network (QCNN) [34,51–57], quantum deep neural network (QDNN) [58–60], quantum generative adversarial network (QGAN) [61–64], etc.

For a typical QNN algorithm, there are three main investigation aspects, which will be elucidated below by taking QCNN as a representative example. The first aspect is the pattern of coordination with classical computation methodology. In order to realize efficient coordination between quantum computers and classical computers, most researchers adopt hybrid quantum–classical network architectures [34,51,52,54,55], while there are also a small number of studies in which the network has a principal structure of pure variational quantum circuits and only collaborates with classical computers in the parameter optimization part [57]. The second aspect is the approach to realize the quantization of network architecture. In some studies, researchers have developed efficient quantum convolutional layers that can significantly decrease the computational complexity and, hence, reduce the computational resources [51,53,54]; Cheng et al. have not only designed quantum convolutional layers in PQC but also combined classical fully connected layers with PQC to develop hybrid quantum–classical fully connected layers [52]; Wei et al. have developed a fully quantum version of the classical CNN structure that including convolutional layers, pooling layers, and fully connected layers [55]. The third aspect is the quantum state encoding method. Some studies have employed amplitude encoding [51,53], some studies have employed angle encoding [52], and Gong et al. have developed a tree-structured hybrid amplitude encoding scheme by integrating the advantages of amplitude encoding and angle encoding, hence providing flexibility and stability in adjusting the width and the depth of the quantum circuit [57].

In addition to the hotspot algorithms like QNN, a few studies utilizing less popular algorithms have also achieved good results. Zhang et al. improved a quantum support matrix machine (QSMM) algorithm by leveraging a quantum matrix inversion (QMI) technique. Compared to a former version of QSMM, the dependence on the precision of the upgraded QSMM is exponentially improved, showing strong potential for applications in image classification [72]. Cao et al. proposed a linear-layer-enhanced quantum long short-term memory (QLSTM) model, which adopts the linear layers before and after the variational quantum circuit (VQC) of QLSTM to extract features. This model can effectively reduce the number of qubits required while amplifying quantum advantages, showing promising prospects for price forecast applications [73]. Other quantum algorithms include quantum canonical correlation analysis (QCCA), QSAM, quantum autoencoder (QAE), quantum multi-classification classifier (QMCC), quantum continual learning (QCL), quantum capsule network (QCN), variational shadow quantum learning (VSQL), quantum state clustering (QSC), quantum linear discriminant analysis (QLDA), quantum hierarchical agglomerative clustering (QHAC), quantum support vector regression (QSVR), quantum neighborhood preserving embedding (QNPE), and so on [74–90].

All these QML algorithms can generally be categorized into supervised learning and unsupervised learning based on their learning modes. Supervised learning includes classification and regression tasks, while unsupervised learning mainly involves tasks such as clustering, dimensionality reduction, data generation, and correlation analysis. The different types of machine learning tasks, the corresponding QML algorithms, and the associated references are summarized in Table 1.

Table 1. The different types of machine learning tasks, the corresponding QML algorithms, and the associated references.

Learning Mode	Task	Algorithm	References
Supervised	Classification	QNN	[42–50]
		QCNN	[34,51–57]
		QSVM	[65–68]
		QKNN	[36,69–71]
		QDNN	[58–60]
		QTN	[37,77]
		QDA	[35]
		QSAM	[38]
		QMCC	[78]
		QEL	[79]
		QCL	[80]
		SQC	[81]
		QCN	[82]
		RQC	[83]
		QDTL	[33]
		QSMM	[72]
		QAB	[84]
		VSQL	[85]
	Regression	QPLS	[40,41]
		QCNN	[57]
		QLSTM	[73]
		QSVR	[89]
Unsupervised	Clustering	QKMM	[90]
		QSC	[86]
		QHAC	[87]
	Dimensionality reduction	QAE	[75,76]
		QNPE	[91]
		QFS	[30]
		QLLE	[32]
		QPCA	[41]
		QLDA	[88]
	Data generation	QGAN	[61–64]
	Correlation analysis	QCCA	[74]

3.2. Applications

The application fields of China's QML research are diverse, with the several popular areas including computer vision, cybersecurity, physical science, and natural language processing, as shown in Figure 3.

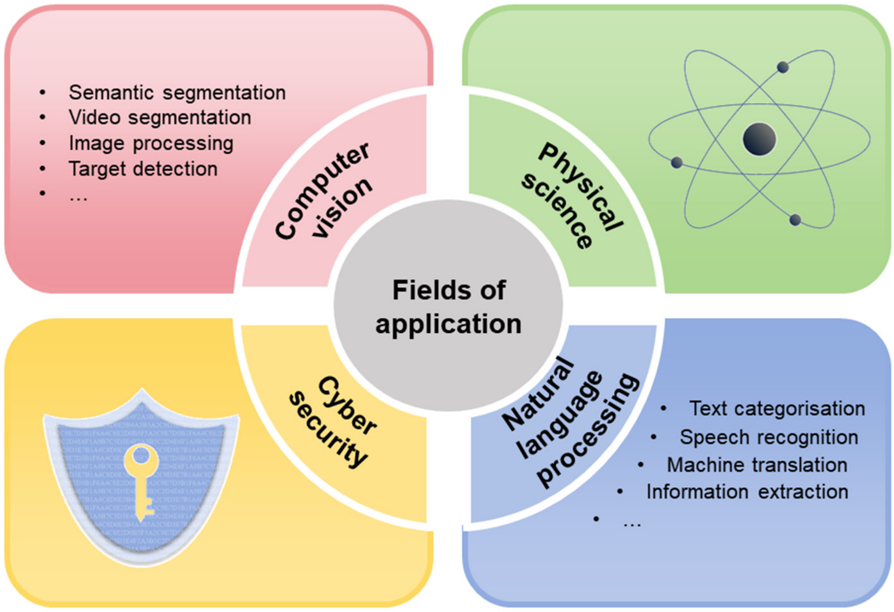

Figure 3. Application fields involved in China's QML research, such as computer vision [38,42,51,52,54,55,58–60], cybersecurity [29,45,50], physical science [49,67,92–94], and natural language processing [38,53].

In the field of computer vision, the relevant studies mainly cover applications like image processing, object detection, semantic segmentation, etc. For example, Bai and Hu proposed two image superposition methods, i.e., quantum state superposition and angle superposition. The superposition-enhanced quantum neural network (SEQNN) based on angle superposition could outperform two other similar QML models in classification accuracy on the MNIST dataset [42]; Wang et al. proposed a quantum–classical hybrid deep neural network (QHDNN) model for image anomaly detection. They explored multiple quantum layer architectures and designed a VQC-based QHDNN solution, which could surpass the classical counterpart on both the MNIST and Fashion-MNIST datasets [58].

With regard to cybersecurity, intrusion detection for preventing network attacks has been a key research direction. For example, a protocol for distributed secure QML was designed to detect eavesdroppers attempting to intercept or interfere with the learning process [29]; Gong's team developed two intrusion detection systems in succession based on QNN [50] and QCNN [45], respectively.

Some representative QML applications in the physics field include Liang et al.'s work on the ground-state preparation of a Hamiltonian system [92]; Wang et al.'s investigation into the role of entanglement in QML [93]; and Liu et al.'s study on quantum state tomography [94].

In the area of natural language processing, the relevant studies mainly cover applications like text classification, speech recognition, machine translation, etc. For instance, Zhang et al. proposed a novel QSAM based on variational quantum algorithms for binary and multiple classification on natural language processing datasets, and their model could outperform its classical counterpart and was as good as the state-of-art QSAM [38]; Chen et al. developed a novel QCNN model based on multi-scale feature fusion for text classification, and their model was able to surpass a wide range of state-of-art QNN models [53].

4. Innovation Aspect Analysis

Based on the compilation and categorization of the various creative QML studies in China, it can be found that there are mainly three innovation aspects, namely, algorithm/model design, strategy selection, and application scenario.

4.1. Algorithm/Model Design

Innovation in model design refers to either the proposal of originally innovative QML algorithms or the development of new frameworks or structural components for a certain QML algorithm model. These new algorithms/models can outperform the conventional ones in terms of computation accuracy and/or efficiency. Some relevant research cases are shown below.

In an original innovation work, Hou et al. first proposed a QPLS regression algorithm as a quantum version of classical PLS algorithm. By investigating time and space complexity, they have theoretically demonstrated that the QPLS can realize exponential speed-ups over classical PLS on the independent variable dimension, the dependent variable dimension, and the number of variables [41].

Song et al. proposed a computationally resource-efficient QCNN model, which employed amplitude encoding and quantum alternating operator ansatz to construct the quantum convolutional layer. The complexity of either the forward or the backward propagation process in such a quantum convolutional layer is much lower than that of the convolutional layer in a classical CNN model, and hence the computational resources required for the convolutional layer can be significantly reduced [51].

In the QSAM model proposed in the aforementioned study [38], the three important model components, namely, query, key, and value, were obtained by a method based on amplitude phase decomposition measurement. This new framework can lead to fewer parameters in the model while achieving high performance on different datasets. Upon two natural language processing datasets, Yelp and IMDb, this new QSAM model can acquire accuracy values of 91.03% and 88.35%, surpassing both classical self-attention neural network and quantum self-attention neural network models. Upon the MNIST dataset, the new QSAM model can acquire a classification accuracy of 82.22%, higher than that of a QCNN model.

Also, in the field of natural language processing, the authors of the work [53] mentioned above designed a novel quantum depth-wise convolution structure in their QCNN model. The new QCNN model can integrate word-level and sentence-level features while reducing the number of parameters in the model and the computational complexity. On the RP dataset, this QCNN model achieved an accuracy of 96.77%, significantly higher than that of a normal QSANN model.

Li et al. proposed a novel hybrid quantum classical framework called variational shadow quantum learning (VSQL). This framework used variational shadow quantum circuits to extract classical features in a convolution way and then utilized a fully connected neural network to complete classification tasks. This method can greatly reduce the number of parameters to facilitate the training process of quantum circuits. For a classification testing on the MNIST dataset, a single-layer classical neural network obtained an accuracy of 86.36% with nearly 8000 parameters, while the VSQL model achieved an accuracy of 87.39% with only about 900 parameters [85].

4.2. Strategy Selection

Innovation in strategy selection refers to the introduction of computational strategies that have not been previously applied to a certain QML algorithm. By selecting appropriate computational strategies and integrating them into QML models, researchers can acquire new QML models with better performance. A few study examples are presented as follows.

Li et al. creatively applied particle swarm optimization (PSO) algorithm for the training of QNN models. As a collective intelligence-based optimization strategy, PSO was able to outperform conventional gradient descent-based optimization strategy (such as Adam) when dealing with certain problems such as 2D Hamiltonian ground state solution and many-body system quantum phase classification in terms of fewer optimization iterations and higher classification accuracy [44].

For the SEQNN model developed in the aforementioned work [42], the innovative scheme was based on the combination of superposition strategy and one-vs.-all strategy. For the multi-class image classification task on the MNIST dataset, the SEQNN model achieved an accuracy of 87.56%, higher than other QML models like HQNN-Quanv and QNet.

Lin et al. first applied game theory strategies to privacy protection in QML and proposed a privacy game model of user–server–attacker in a hybrid classical quantum back-propagation neural network. Unlike previous studies, this model can set game strategies based on users' privacy requirements in practical applications to maximize the interests of users with different roles [46].

4.3. Application Scenario

Innovation in application scenarios refers to the effective application of a certain type of QML algorithm to a new scenario ("effective" means that the application should achieve good performance). Two typical research instances are introduced as follows.

Jing et al. proposed two types of quantum convolutional circuits for classifying images with RGB three-color channels. Many previous studies have adopted quantum convolution circuits for grayscale image classification, while this is the first work that applies quantum convolutional circuits in the scenario of RGB image classification and achieves effective results. The designed quantum convolutional circuits were able to achieve higher classification accuracy on the CIFAR-10-small dataset compared to classical CNN models [54].

For the aforementioned study [73], it is not the research that originally proposed QLSTM algorithm, but it is the first research that applies QLSTM in the scenario of carbon price forecast. Additionally, the designed linear-layer-enhanced scheme enabled their QLSTM model to achieve as good a performance as the classical LSTM model on the European Union carbon market price dataset.

In Table 2, we summarize the typical research examples of the three innovation aspects mentioned above and provide model performance comparison regarding accuracy on various benchmark datasets.

Table 2. Typical research examples of the three innovation aspects and accuracy comparison of the relevant models.

Innovation	Datasets	Algorithms	Accuracy	References
Algorithm/ modeldesign	Yelp	CSANN	83.11%	[38]
		QSANN	90.09%	
		QSAM	**91.03%**	
	IMDb	CSANN	79.67%	
		QSANN	87.28%	
		QSAM	**88.35%**	
	MNIST	QCNN	74.30%	
		QSAM	**82.22%**	
	RP	QSANN	67.74%	[53]
		QNN-MSFF	**96.77%**	
Strategy selection	MNIST	NN	86.36%	[85]
		VSQL	**87.39%**	
	MNIST	HQNN-Quanv	67.00%	[42]
		QNet	81.00%	
		SEQNN	**87.56%**	
	Quantumphase	QCNN-Adam	53.00%	[44]
		QCNN-PSO	**84.00%**	
Application scenario	CIFAR-10-small	CNN	95.83%	[54]
		HQconv	**99.45%**	

5. Challenges and Prospects

In the QML field, many creative studies have been carried out, and significant achievements have been made. At the same time, however, there are also quite a few unresolved problems and thorny challenges. In this section, we will discuss the current challenges faced by QML researchers and provide some prospects for the future development.

5.1. Challenges

The current challenges in QML mainly involve noise interference, hardware limitation, barren plateaus, catastrophic forgetting, circuit structure optimization, and input–output bottleneck.

5.1.1. Noise Interference

To genuinely implement QML algorithms, real quantum computing devices are indispensable despite the existence of classical platforms for simulating quantum computing. A core technology of quantum computing devices is the preparation of qubits. At present, there are several kinds of physical qubits, mainly including semiconductor quantum dot qubits [95,96], spin qubit [97], superconducting qubits [98], trapped-ion qubits [99], and photonic qubits [100], named after the preparation methods.

For quantum computation, we are now in a so-called NISQ era (noisy intermediate-scale quantum) [101]. In quantum systems, noise refers to the interaction of qubits with uncontrolled degrees of freedom in the environment. There are different kinds of quantum noises, mainly including depolarizing noise, amplitude damping noise, phase damping noise, bit-flip noise, phase-flip noise, and others. Taking depolarizing noise as an example, its mathematical representation is $\epsilon(\rho) = (1-p)\rho + pI/2^n$, where ϵ denotes the noise channel, ρ is the density matrix, p is the probabilistic error rate that depends on both the device and the circuit, and n is the number of qubits [102]. This noise can cause qubits to decohere, transitioning from superposition/entanglement states to classical mixed states, thus resulting in quantum information loss.

In this era, quantum devices are inevitably affected by noise, hence bringing negative impacts to QML models [34,40,42,78]. To address the issue of noise interference, some feasible approaches include developing noise suppression techniques, quantum error correction techniques, and models with noise-resistant quantum circuits [89,103]. Taking noise-resistant quantum circuits as an example, the VCNN model designed in [34] exhibited excellent noise resistance since a new hybrid quantum–classical circuit framework was formulated; the VSQL model designed in [85] based on a variational shadow quantum circuit could introduce less noise by using fewer quantum gates.

5.1.2. Hardware Limitation

In the current NISQ era, quantum devices only allow the employment of a small number of qubits to represent data and perform simple quantum calculations. Hence, it is challenging to encode large-scale data into quantum state data and execute QML algorithms in quantum computers [34,38,60]. Therefore, it is necessary to implement feature extraction or other kinds of dimension reduction operations on high-dimensional datasets before executing the algorithms [65]. For instance, Wu et al. proposed a scalable QNN system based on the collaborative utilization of multiple small quantum devices. The multiple quantum devices play the roles of quantum feature extractors and are independent of each other. Hence, researchers can flexibly combine quantum devices of different sizes to extract local features in a more efficiently way [43].

5.1.3. Barren Plateaus

The so-called "barren plateaus" problem in QML refers to the phenomenon that in quantum circuits with randomly initialized parameters, the gradient of the objective loss function decreases exponentially with the increase in qubit number [50,104]. The vanishing of gradient means the QML model becomes frozen and the optimization training process can no longer continue. Although it has been demonstrated that the barren plateau problem would not appear in QCNN models [105], this problem widely exists in those QNNs without convolutional structures [49,82]. Some studies have tried to provide solutions by designing special algorithm models, such as variational shadow quantum circuits [85], QGAN model based on Rényi divergences [62], and variational QNN model based on PSO strategy [44].

5.1.4. Catastrophic Forgetting

Catastrophic forgetting is a common problem in machine learning, especially for deep learning neural network models. During the optimization process of a neural network, the model may quickly forget the already-learned knowledge in the updating of neural network weights. In application scenarios that require incremental learning or continual learning to accumulate long-term knowledge, this problem will bring significant negative impacts to the models. In QML, the catastrophic forgetting problems also exist, and a few studies aiming to address this issue have been carried out. As an instance, Situ et al. designed a quantum continual learning scheme based on gradient episodic memory strategy that is able to well overcome catastrophic forgetting and realize knowledge backward transfer for quantum state classification tasks [80].

5.1.5. Circuit Structure Optimization

For QML models based on quantum variational algorithms, the designed architecture of the parameterized quantum circuit is crucial to the model performance [35,83]. At present, it is still a challenging problem to optimize the quantum circuit structure. Some researchers have tried to develop an elaborate variational layer to replace the normal variational layer for better model performance, such as the strongly entangled controlled-Z variational layer in the linear-layer-enhanced QLSTM model described in [73].

5.1.6. Input–Output Bottleneck

The input–output bottleneck is a common problem for those QML algorithms that deal with classical data. For input, most QML algorithms need to encode classical input data into quantum states in advance; and for output, most algorithms can only offer the quantum states corresponding to the classical solution, unable to directly provide the solution itself. These non-computing processes will consume additional time and cancel out the acceleration effect of quantum algorithms. Hence, it is worth exploring how to design algorithms to break through the input–output bottlenecks. As a research example, Situ et al. proposed a QGAN model with a special quantum classical hybrid architecture, which was able to directly receive classical inputs and output classical solutions [63].

5.1.7. Unsatisfactory Performance and Fair Comparisons

While QML research continues to evolve at an exciting pace, current QML algorithms may sometimes underperform on basic machine learning tasks. In [106], Raubitzek and Mallinger compared the performance of two quantum algorithms, i.e., VQC and quantum kernel estimator (QKE), with various classical methods, i.e., LASSO/ridge, multilayer perceptron, support vector machines, and gradient-boosting machines, on six benchmark classification datasets and two artificially generated classification datasets. It has been found that the aforementioned QML models currently cannot outperform properly trained and/or sophisticated classical machine learning models in terms of accuracy and runtime performance. Furthermore, they have noted that challenges related to "fair comparisons" may exist in QML model design. Specifically, when constructing and training classical machine learning models, some researchers may not have used randomized search cross-validation to fully optimize the hyperparameters. Therefore, the performance of classical machine learning models may seem relatively poor, and hence the significance of quantum supremacy is likely to be overstated.

5.2. Prospects

The future development of the QML field can be roughly divided into two stages. In the near future, we may have the opportunity to witness the transition of QML from theoretical research to practical applications and from specific-problem-oriented to general-problem-oriented. As for the distant future, we may enter an era of quantum data, and, at that time, QML methods would comprehensively replace classical machine learning methods and become mainstream solutions.

5.2.1. Practical Applications

At present, most QML studies are theoretical analysis of algorithms, and the numerical experiments are only conducted on a few standard datasets (e.g., MNIST, IRIS, etc.). However, there is hardly research that tests the performance of the QML algorithms on complicated real-world datasets. In order to enhance the practical value of QML algorithms, we need to make improvements in both hardware and software aspects. As for hardware, it is necessary to address the technical issues of how to increase effective qubits in the system and reduce noise interference. Regarding software, it is important to design better core algorithms and/or quantum circuit structures to alleviate problems such as barren plateaus, catastrophic forgetting, and so on.

5.2.2. General Problems

For quantum computing, many current studies are aimed at a few specific quantum-related problems rather than facing general scientific or engineering problems, both in China and internationally. For example, Pan's team has made use of quantum computing in molecule ground-state energy solution [25], sequential multiphoton entanglement generation [107], etc.; the Google AI team has utilized quantum computing in isomerization reaction Hartree–Fock simulation [108], topologically ordered state realization [109], and so forth.

Specifically for QML research, as stated above, most studies are limited to a few certain fields, such as physical science and image processing, and the numerical experiments are usually conducted on special standard datasets. In the future, QML or other quantum computing algorithms may be able to deal with more general problems in various real-world scenarios and play a broader role in promoting the progress of science and technology.

Here, we would take another important China's national strategic area outside of quantum computing, namely, lunar and planetary exploration, as an example to make further descriptions. In China's Tianwen-1 Mars exploration mission, a payload on Zhurong Mars rover called MarSCoDe has adopted laser-induced breakdown spectroscopy (LIBS) to detect and analyze the chemical composition of the substances on Martian surface [110]. The LIBS spectrum is a kind of high-dimensional data, e.g., each MarSCoDe LIBS spectrum contains over 5000 pixel data points [111]. Additionally, to promote the accuracy of LIBS analysis, it is helpful to integrate other relevant physical parameters into the chemometrics model, such as the plasma temperature and density, the images of plasma, the images of laser ablation crater, and so on [112,113]. Such data fusion strategies would be beneficial for relieving common problems in LIBS detection, including matrix effects, spectral fluctuation effect, varying-distance effect, dusty surface effect, etc. [114,115]. Furthermore, the joint use of data from different detection techniques is another trend, e.g., combining LIBS and Raman spectroscopy [116], combining LIBS and remote sensing data [117], etc. These data fusion strategies can improve analytical accuracy, while they would also lead to drastic increase in data dimensionality and volume. For the current data processing scheme (i.e., the on-orbit payloads transmit data back to the Earth laboratory, and the analysts perform subsequent processing in the laboratory), classical computing methodology can meet the requirement of computing speed. However, in application scenes requiring real-time mass data processing (e.g., China's future manned lunar landing mission [118]), classical computing may be hardly competent, and quantum computing may play a shining role at that time. In fact, besides constructing QML models able to efficiently analyze high-dimensional LIBS data and/or different kinds of fused data, quantum computing may also provide key supports for the numerical simulation of laser–plasma evolution dynamics (so that underlying mechanisms of LIBS processes can be better understood and spectral quality can be improved) and for the accurate characterization of LIBS spectral feature differences between Earth lab data and Mars in situ data (so that transfer learning technique can be better utilized and data analysis accuracy can be promoted).

5.2.3. Application Popularity

At present, most of the datasets used in QML research are classical ones on which the supremacy of quantum computing cannot be really achieved, as indicated by Kübler et al. in [119]. Therefore, for the current era in which quantum datasets are still very scarce [120,121], most quantum algorithms can only serve as alternatives to mainstream classical algorithms. If we enter the quantum information era in the future, the various detection and sensing techniques might directly acquire, store, and transmit mass data in quantum form. At that time, quantum algorithms will have great potential to replace classical ones and own much broader application popularity.

6. Conclusions

As an intersection of quantum computing and machine learning, QML has gradually flourished in the past decade. Despite a relatively late start, China's QML research has developed rapidly in recent years, and many excellent achievements have emerged. This article provides an overview of the QML development in China. As far as we know, this is the first comprehensive review that focuses on QML studies within Chinese research institutions.

Based on the number of published papers, we divide the development of QML research in China into three stages, i.e., the preliminary stage, transition stage, and explosion stage. In the developing process, the model designing mode has gradually shifted from the quantum replacement mode to the quantum improvement mode, and the learning task type has gradually shifted from unsupervised learning to supervised learning.

Among China's QML studies, popular algorithms include QSVM, QKNN, and various kinds of QNNs. The applications of QML mainly involve the fields of computer vision, cybersecurity, physical science, and natural language processing. By systematically inspecting the creative QML studies, we have found that there are three major innovation aspects, namely, algorithm/model design, strategy selection, and application scenario. Through these innovations, excellent model performance can be acquired. It is worth noting that in China's cutting-edge work, the overall performance of the proposed QML models has reached worldwide advanced levels, and some models can even achieve top-tier performance among all the analogous models reported globally.

Finally, we have discussed the major challenges in current QML research and offered some prospects for the future development. Although focusing on the QML work within China, this review is expected to provide inspiration for both China's and global QML-domain progress.

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Glossary

Adam	adaptive moment estimation
APDM	amplitude-phase decomposition measurement
AS	angle superposition
CNN	convolutional neural network
CSANN	classic self-attention neural network
DA	domain adaptation
DNN	deep-learning neural network
DSQML	distributed secure quantum machine learning
FS	feature selection
HQNN	hybrid quantum neural network
KNN	k-nearest neighbor
LIBS	laser-induced breakdown spectroscopy

LLE	locally linear embedding
MSFF	multi-scale feature fusion
NN	neural network
NPE	neighborhood preserving embedding
PCA	principal component analysis
PQC	parameterized quantum circuit
PSO	particle swarm optimization
QAB	quantum AdaBoost
QAE	quantum AutoEncoder
QAOA	quantum approximate optimization algorithm
QCCA	quantum canonical correlation analysis
QCCNN	hybrid quantum–classical convolutional neural network
QCL	quantum continual learning
QCN	quantum capsule network
QCNN	quantum convolutional neural network
QDAC	quantum domain adaptation
QDNN	quantum deep-learning neural network
QDTL	quantum deep transfer learning
QEL	quantum ensemble classifier
QFS	quantum feature selection
QGAN	quantum generative adversarial network
QHAC	quantum hierarchical agglomerative clustering
QKE	quantum kernel estimator
QKMM	quantum k-means based on Manhattan distance
QKNN	quantum k-nearest neighbor
QLDA	quantum linear discriminant analysis
QLLE	quantum locally linear embedding
QLSTM	quantum long short-term memory
QMCC	quantum multi-classification classifier
QMI	quantum matrix inversion
QNN	quantum neural network
QNPE	quantum neighborhood preserving embedding
QPCA	quantum principal component analysis
QPLS	quantum partial least squares
QSAM	quantum self-attention model
QSANN	quantum self-attention neural network
QSC	quantum state clustering
QSMM	quantum support matrix machines
QSS	quantum state superposition
QSVM	quantum support vector machine
QSVR	quantum support vector regression
QTN	quantum tensor network
RQC	re-uploading quantum classifier
SEQNN	superposition-enhanced quantum neural network
SQC	succinct quantum classification
SVR	support vector regression
TN	tensor network
VCNN	variational convolutional neural network
VQA	variational quantum algorithms
VQC	variational quantum circuit
VSQL	variational shadow quantum learning

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