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Quantum Deep Learning: A Review

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Abstract

Quantum computing is described as a process by which a system calculates output. Quantum physics usually refers to the smallest discrete unit of any property; the basic unit of data in quantum is the qubit; this qubit unit is equivalent to the bit unit in classical neural networks. Quantum deep learning combines quantum computing with deep learning to reduce training time for neural networks, which has proven effective in solving some intractable problems on classical computers. Quantum deep learning has proven effective in solving some intractable problems on classical computers. A quantum network can benefit from quantum information flow because it is a more efficient framework than classical systems. Each quantum deep learning consists of a quantum gate. In this review, we provide a comprehensive review of recent studies that include different quantum deep learning applications, including healthcare, handwriting, and many others. Also, methodologies, problems, main datasets, results, strengths, limitations, and challenges are included in this review.

Keywords: Quantum, Deep Learning, Quantum Deep Learning, Quantum Circuit, Quantum Computing, Quantum Neural Network, Quantum Algorithm.

التعلم العميق الكمي: مراجعة

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الخلاصة

توصف الحوسبة الكمومية بأنها عملية على النظام لحساب المخرجات. عادةً ما تشير فيزياء الكم إلى أصغر وحدة منفصلة من أي خاصية، والوحدة الأساسية للبيانات في الكم هي كيوبت، ووحدة الكيوبت هذه تعادل وحدة البت في الشبكات العصبية الكلاسيكية، ويجمع التعلم العميق الكمي بين الحوسبة الكمية والتعلم العميق لتقليل وقت التدريب للشبكة العصبية، والتي أثبتت فعاليتها في حل بعض المشكلات المستعصية على أجهزة الحاسوب التقليدية. لقد أثبت التعلم العميق الكمومي فعاليته في حل بعض المشكلات المستعصية على الحاسوب التقليدي. يمكن لشبكة الكم أن تستفيد من تدفق المعلومات الكمومية لأنها إطار عمل أكثر كفاءة من الأنظمة التقليدية. يتكون كل تعلم عميق كمي من بوابة كمومية. في هذه الدراسة، نقدم مراجعة شاملة للدراسات الحديثة التي تتضمن تطبيقات مختلفة للتعلم العميق الكمي بما في ذلك الرعاية الصحية والكتابة اليدوية وغيرها الكثير. كما تم تضمين المنهجيات والمشكلات ومجموعات البيانات الرئيسية والنتائج ونقاط القوة والقيود والتحديات في هذه المراجعة.

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1. Introduction

The expanding significance of neural networks in the industry will require extraordinary computational control as the complexity of these algorithms and database sizes are anticipated to increase [1], [2]. Deep neural networks have led to breakthroughs in several domains of machine learning, such as computer vision [3], natural language processing [4], reinforcement learning [5], speech recognition [6], and many others [7]. Deep learning [8] forms the backbone of many modern machine learning techniques and has become one of the most active research areas in computer science, spurred on by the increased availability of data and computational resources [7].

Equally, noticeable progress was found in the quantum computing field, which concentrated on fixing classically difficult issues through computationally moderate techniques. Quantum computers are a good source to answer this challenge; the latest progress in the physical realization of quantum processes and the features in quantum algorithms increase more than ever the need to recognize their limits and abilities. Eventual research has been aimed at developing poly-time alternatives to classical algorithms to get the core idea of quantum texture and overlap [7].

Quantum computing surely supplies its thoughts to the field of machine learning (ML), and then there has been eventual research on using the quantum computing features to recover the performance capacity and computational competence of classical ML approaches [9]. Quantum neural networks, issues of making quantum circuits that recover the operations of deep learning, and some research results into quantum deep learning support the idea that completely quantum deep learning will not be carried out effectively [10].
In this work, we summarize the different ideas presented in the domain of quantum deep learning, which include quantum analogues to classic deep learning networks and quantum-inspired classic deep learning algorithms.
This work is structured as follows: a review of deep learning, quantum computing, and quantum neural networks is presented in Sections 2, 3, and 4, while Section 5 provides a detailed review of quantum deep learning as explained in several publications. A summary of QNNs is also shown in Section 5. And Section 6 included quantum deep learning challenges. Finally, in Section 7, conclusions and some future directions are provided.

2. Deep Learning

Deep learning (DL) is playing an increasingly important role in our lives. It has already made a huge impact in areas such as cancer diagnosis, precision medicine, self-driving cars, predictive forecasting, and speech recognition. The painstakingly handcrafted feature extractors used in traditional learning, classification, and pattern recognition systems are not scalable for large datasets. In many cases, depending on the complexity of the problem, DL can also overcome the limitations of earlier shallow networks that prevented efficient training and the abstraction of hierarchical representations of multi-dimensional training data. Deep neural networks (DNN) use multiple (deep) layers of units with highly optimized algorithms and architectures. Deep learning algorithms seek to exploit the unknown structure in the input distribution in order to discover good representations, like CNN [11] and [12].

A convolutional neural network (CNN) is one of the most significant networks in the deep learning field. The Convolutional Neural Network (CNN) has been making brilliant achievements. It has become one of the most representative neural networks in the field of deep learning. Computer vision based on convolutional neural networks has enabled people to accomplish what had been considered impossible in the past few centuries, such as face recognition, autonomous vehicles, self-service supermarkets, and intelligent medical treatment, to better understand modern convolutional neural networks and make them better serve human beings [13].

3. Principals of Quantum Computing

Qubits are the important computational units in quantum computers, which perform a superposition state between |0⟩ and |1⟩[14] [15]. It is possible to represent a single qubit state as a complex two-dimensional vector, i.e., as shown in eq. 1 [16] [17],

$$|\psi\rangle = \alpha\ |0\rangle + \beta\ |1\rangle\ , \left||\alpha|\right|^2 + \left||\beta|\right|^2 = 1 \tag{1}$$

Here, |ψ⟩ is the state vector representing a quantum system. This system is in a superposition of two basis states, represented by |0⟩ and |1⟩. The coefficients α and β are complex numbers that determine the probability amplitudes of the system being in each of the two basis states, and ||α||2 and ||β||2 are the probabilities of observing |0⟩ and |1⟩ from the qubit, respectively. It can also be represented geometrically using the polar coordinates θ and φ, as shown in eq. 2 [16].

$$|\psi\rangle = cos\ cos\ \left(\frac{\theta}{2}\right)\ |0\rangle + e^{i\emptyset}\ sin\ sin\ \left(\frac{\theta}{2}\right)\ |1\rangle \tag{2}$$

Here, |ψ⟩ is the state vector representing a single-qubit quantum system. This system is in a superposition of two basis states, represented by |0⟩ and |1⟩. The coefficients are determined by the angles θ and ϕ. θ is the polar angle, which ranges from 0 to π, and ϕ is the azimuthal angle, ranging from 0 to 2π. Both angles are expressed in radians. The term eiϕ is a complex exponential representing the phase of the quantum state, where 0 ≤ θ ≤ π and 0 ≤ φ ≤ π. A single qubit state is represented by the surface of a three-dimensional unit sphere, referred to as the Bloch sphere. A multiqubit system can be performed as the product of n single qubits, which is equivalent to a superposition of n basis states from |00...00⟩ to |11...11⟩. In this system, quantum entanglement connects different qubits. In quantum circuits, these systems perform quantum computations by means of quantum gates [18].

It is well known that a quantum gate transforms a qubit system into another, and as a matter of classical computing, it can be combined with several classical operators, such as rotation operator gates and CX gates [8]. Rotation operator gates Rx(θ), Ry(θ), Rz(θ) rotates a qubit state in the Bloch field around the corresponding axis by θ and CX gate entangles two qubits by overturning a qubit state if the other is |1⟩. Those quantum gates use quantum overlap and entanglement to add utility to classical computing, and it is familiar that quantum algorithms can add a rapid computational gain to the current algorithms in specific functions such as major factorization [19].

4. Quantum Deep Learning

Quantum neural networks have been developed recently as a subfield of quantum computing that explores how quantum computers are used for neural network missions. That is, quantum deep learning is an integrative field that consolidates quantum physics and deep learning; it uses the power of quantum computing to create quantum categories of deep learning algorithms that are used in the associated fields.

Some quantum connotations that help in understanding quantum neural networks are below:

- Linear superposition is like the mathematical principles of the linear combination of vectors [20] [21].

● Coherence and decoherence have similarities with linear superposition. A quantum computer is consistent when linear superposition is in basis states and if it is not incoherent [22].
● Operators work on the transformation of states in the wave functions on a Hilbert space [23].
● Interference works on wave appearance, and it is calculated in capacity [21].
● Entanglement is a special quantum state that does not occur in classical computers [21].

The two main kinds of quantum deep learning are [15] and [19]:

4.1 Variational Quantum Circuits (VQC)

A variational quantum circuit (VQC) uses rotation operator gates with free parameters to perform different numerical tasks such as approximation, optimization, and classification. As its parameters are often optimized by a classical computer, the variational quantum algorithm (VQA) is a hybrid algorithm of classical and quantum circuits. Numerous numerical problems are solved using VQC because its global approximation property allows it to solve many different problems [14] [24]. Several applications of VQA in machine learning resulted from this flow, and it was used to replace the artificial neural network of the existing model with VQC in many cases. VQC approximates functions through parameter learning in a similar way to artificial neural networks, but it is distinguished by several properties of quantum computing. All quantum gate operations are linear, reversible operations, so texture sheets are used for multiple sheet formation instead of activation purposes. These VQCs are called “quantum deep learning” [19].

4.2 Quantum Neural Networks

In this section, the basic quantum neural network (QNN) will be revealed. QNNs process data according to the following method: Initially, input data is encrypted into corresponding qubit states of a relevant number of qubits. Afterward, the qubit state is transformed via parameterized rotation gates and texture gates for a given number of sheets. Transfigured qubit states are then calculated through the application of a Hamiltonian administrator, such as Pauli gates. Decryption of these evaluations results in proper output data. Developers like Adam Optimizer then update the parameters. Various parts can be produced by a neural network assembled as a VQC, which will be investigated as quantum deep learning [19].

Quantum convolutional neural networks (QCNNs) were proposed, utilizing the complication layer and linking layer of quantum circuits. As reported by the research results in [7] and [15], QCNN circuits are computed in the following manner: The first step in applying any QNN pattern is the encoding of input data into qubit states using rotation operator gates. The complication layer then filters the input data into an aspect map using quasi-local unitary gates. This aspect map is then reduced by the linking layer with controlled rotation operators. Essentially, this process repeats until the fully associated layer is able to deal with the qubit state as a classical CNN pattern. Finally, the assessment of the qubit state is decrypted into output data with the desired sizes. The circuit parameters are updated by descent-based developers after each assessment. Unfortunately, in the current quantum computing conditions [25], QCNN is tougher to achieve than the current classical CNN. Anyhow, it is anticipated that the QCNN will be capable of carrying out adequate computational gains over the classical ones in future quantum computing conditions in which larger-size quantum calculations are achievable [15].

There are two various techniques for quantum neural networks for health protection image category and execution: the first one uses quantum circuits to help the training and deduction of classical neural networks by modifying the network to be adjustable to current quantum hardware; the second builds on the recent work on quantum rectangular neural networks, where quantum parameterized circuits are trained to enforce orthogonality of weight forms. Orthogonality is an essential stuff of quantum procedures, which are expressed by unitary forms, and it has been revealed that it can raise the performance of deep neural nets and help to avoid vanishing or exploding gradients, such as the dying ReLU, which is a kind of vanishing gradient that occurs when the neurons in the ReLU become inactive and only output zero for any input. Dying ReLU is known to be among the biggest obstacles in the training of deep feedforward ReLU neural networks [26].

5. Techniques and Methods of Quantum Deep Learning

The quantum deep learning network has been most popularly modeled through many applications like healthcare, handwriting classification, and other applications:

5.1 Healthcare

Healthcare is one of the most important areas in which image processing procedures can be usefully applied. Processing images is an important step in improving an operation's accuracy and accuracy in diagnosis. COVID-19 detection is one of those fields.

L. Parisi et al. [27] proposed Leaky ReLU (RLE) as a starting point for the proposed Quantum ReLU (QReLU) and Modified Quantum ReLU (m-QReLU) activation functions, based on the two quantum principles of entanglement and superposition. However, the results indicate an overall higher classification accuracy, indicating its potential to replace the gold standard activation functions (AF) in CNNs for image classification tasks such as medical diagnosis of COVID-19 and Parkinson’s Disease (PD) without facing the issue of vanishing gradients [27].

Detecting a disease early is crucial to medical diagnosis and clinical practice, as it lessens stress on the healthcare system and achieves high degrees of accuracy, although neural networks and classical computers have limitations. The work in [28] used quantum algorithms for linear algebra and quantum neural networks. Quantum deep learning techniques have been proposed as a way to enhance the performance of machine learning applications. Using quantum circuits for training classical neural networks and developing and training quantum orthogonal neural networks for medical image classification, they developed two different quantum neural network techniques. Their techniques were tested on chest X-rays and retinal color fundus images. Although QNN provides similar accuracy to classical NN, quantum accuracy drops for more challenging tasks.

For improving accuracy when processing difficult tasks, the researchers in [29] developed a prototype system for classifying COVID-19-related pneumonia signals in computed tomography (CT) images by comparing them with non-COVID pneumonia signals. This simulation work determines the efficacy of deep learning algorithms for image classification problems while also evaluating quantum computations, thus establishing the performance quality necessary to improve prediction rates when dealing with complex clinical image data exhibiting high biases. On specific classification tasks, the proposed model performed better than conventional deep learning models. They evaluated quantum algorithms for complex problems and found them to be very efficient in classifying large, biased images. The quantum model runs faster than classical neural networks. The simulation shows QNN to be superior to DNN, CNN, and 2D CNN.

Houssein et al. [30] used a hybrid quantum-classical convolutional neural network (HQCNN) to detect COVID-19 patients with CXR images using random quantum circuits

(RQCs). In the first dataset, this study used 6952 CXR images [30], including 1161 COVID-19 images, 1575 normal images, and 5216 pneumonia images. Compared to other available models, the proposed HQCNN model achieves higher performance and accuracy. The model is tested on a binary and multiclass dataset, with confirmed COVID-19 cases in the first dataset. But this model has a more complex architecture. Moreover, on the second dataset, the researchers [31] obtained a higher degree of sensitivity and accuracy. Furthermore, it reached an accuracy and sensitivity of 88.6% and 88.7%, respectively, on the third multiclass dataset. There are 5445 images [31] in the second dataset, including 1350 COVID-19, 1350 normal, 1345 viral pneumonia images, and 1400 bacterial pneumonia images. In addition, the proposed model shows greater ability to predict positive COVID-19 cases when compared to the second HQCNN model. But the method worked in [30] and [31], which were complex; the disease was diagnosed in these two cases only and was not tested to diagnose new cases of the disease.

The researchers in [32] proposed “Quantum ReLUs” (QReLU) and modified QReLUs (m-QReLUs) that are derived by mathematically exploiting the quantum principles of entanglement and superposition. As part of classification tasks that involved detecting COVID-19 and PD, the proposed AFs were tested in conjunction with a CNN using seven image datasets. CNN was compared with nine classical AFs, including variations based on the ReLU model, for out-of-test classification accuracy and reliability. Based on five of the seven datasets evaluated, the results indicate higher accuracy and reliability for the CNN with QReLU or M-QReLU and avoid the “dying ReLU” problem with quantum AFs [32].

The mutated SARS-CoV-2 RNA sequences have led to the emergence of new epidemic strains of COVID-19, like Delta and Omicron, that cause high mortality while spreading rapidly. Yu-Xin Jin et al. [33] proposed a hybrid quantum-classical model that achieved blurred convolution like classical depth-wise convolution while also successfully implementing quantum progressive training with quantum circuits. These features simultaneously guarantee that their model is the quantum counterpart to the well-known style-based GAN. According to the results, the percentages of the randomly generated spike protein variation structure are always over 96% for Delta and 94% for Omicron. In the HQNN model, by using the quantum algorithm, they have contributed to predicting mutant strains effectively, and the training loss curve is more stable and converges better than conventional methods. The generated images generated by ProGAN cannot be controlled, and the random parameter inputs have slight changes.

The current hardware used to train neural networks’ size, control, and utility are still greatly limited. Physical limitations of conventional computers are causing performance improvements to be slowed in the coming years, and therefore, these concerns have become increasingly pressing. The work in [34] introduced a quantum-classical hybrid neural network architecture where each neuron is a variational quantum circuit. A simulation of a quantum computer and a state-of-the-art quantum computer are used to evaluate the performance of this hybrid neural network. Compared to a variational quantum circuit set up in isolation, the hybrid neural network achieves roughly 10% higher classification accuracy and 20% better cost minimization. Each quantum hardware model can only perform well when the qubit and gate counts are small enough. However, VQC is cheaper and more robust, so adding more parameters does not guarantee better results. In tests on the iris, bars, and stripes datasets, HQNN and quantum hardware performed poorly.

Emmanuel Ovalle et al. [35] used a hybrid transfer-learning paradigm in which a quantum network drove and enhanced a classical network trained for stenosis detection. In an intermediate step between classical and quantum networks, the classical features are transformed into a hypersphere of a fixed radius using a hyperbolic tangent function. Following normalization of these features, these probabilities are computed in the quantum network using the SoftMax function. Further, rather than a single quantum circuit, multiple quantum circuits are used to divide the training data within the quantum network to improve training time without compromising stenosis detection performance. A small dataset of 250 images was used to evaluate the proposed method. Hybrid classical-quantum networks outperform classical networks significantly; this method has very complex operations.

To overcome the complexity in the above works, Viraj Kulkami [36] created a hybrid neural network to detect pneumonia from chest radiographs using a classical neural network. It combined a variational quantum circuit with a layer of a classical convolutional neural network. On a chest radiograph image dataset, they train both networks and benchmark their results. Multiple rounds of network training are used to minimize the effects of different sources of randomness. According to the study, hybrid networks outperform classical networks on various performance measures, and these improvements are statistically significant. As a result of their work, they show that quantum computing has the potential to improve the performance of neural networks in real-world applications relevant to society and industry. However, the work was expensive in terms of time and depended on a number of factors. Table 1 summarizes the previous work that has been done in the healthcare sector.

Table 1: Summary of quantum deep learning in healthcare

	Authors, Year	***Problem***	***Dataset***	***Method***	***Strength***	***Weakness***
[27]	L. Parisi, D. Neagu, R. Ma, and F. Campean (2020) [27]	- Limited NN in healthcare - Dying ReLU problem	- Covid-19 dataset - MNIST	Quantum ReLU & m-QReLU	- Higher classification accuracy, without facing the issue of vanishing gradients	-Takes a long time. In the results were different for the other than Covid-19 data
[28]	N. Mathur et al (2021) [28]	- Limitation of NN for medical image classificati on	- MedMNI ST	Two methods QNN (Quantum Circuits and Quantum orthogonal NN)	- Used two image models, retinal color image and chest x-ray	- QNN Provide similar accuracy to NN. - For more difficult tasks, Q accuracies drop
[29]	K. Sengupta and P. R. Srivastava (2021) [29]	- Limitation of NN for medical image classificati on	CT image	Quantum neural network	- It better, and faster than CNN -evaluated Q algorithms for complex problems - Found it to be very efficient in classifying large images.	- Need a development area on edge-quantum computing
[30]	E. H. Houssein, Z. Abohashima, M. Elhoseny, and W. M. Mohamed (2021) [30]	- Limited NN for image classificati on - Binary & multiclass dataset	- Two CXR covid-19 image,	HQCNN used RQCs	- Enhance performance, model is evaluated on binary & multi-class dataset with confirmed COVID-19 cases	-HQCNN is more complexity
[31]	E. H. Houssein, Z.	- Limited NN for	- Collectio	HQCNN using random	-Tested on high dimensional	-This method similar to ref [28],

	Abohashima, M. Elhoseny, and W. M. Mohamed (2022) [31]	image classification - High dimensional images	n 5445 X-RAY image	QC	images & achieved higher performance	but tested on different dataset
[32]	L. Parisi, D. Neagu, R. Ma, and F. Campean (2022) [32]	- Limited NN in medical applications -Dying ReLU problem	- Covid-19 dataset - MNIST	QReLU & M-QReLU	- Avoid the 'dying ReLU' problem with quantum AFs	- Method is very difficult
[33]	Y.-X. Jin et al (2022) [33]	- Limited NN for image classification - Detected new strains of COVID-19	- SARS-Cov-2 RNAs	Deep Quantum, Hybrid quantum-classical model with QC	-Training loss curve is more stable and converges better with multiple loss function - Effectively predict the mutant strains are strong	-ProGAN is not have ability to control the specific features of the generated images -Random parameter inputted has slight modification
[34]	D. Arthur and P. Date (2022) [34]	- Their size, control and utility are still greatly limited	- Iris Bars stripes	HQNN architecture where each neuron is VQC	- In simulated hardware, HQNN achieve 10% higher classification, 20% better minimization of cost than individual VQC - Quantum hardware, only performs well when qubit & gate count is sufficiently	- Network more expensive than VQC - Increase number of parameters do not guarantee better results - When used quantum hardware & HQNN both performed poorly on iris, bars, and stripes datasets
[35]	E. Ovalle-Magallanes, J. G. Avina-Cervantes, I. Cruz-Aceves, and J. Ruiz-Pinales (2022) [35]	- Pre-trained classical network - Limited CNN in image classification	- 250 images	Hybrid classical-quantum networks	- It improved the training time without compromising the stenosis detection performance, HQNN outperform classical networks significantly	- Very complex operations
[36]	Viraj Kulkarni (2022) [36]	-The limitation is still in NN, and complexity	- 5856 chest radiographs	VQC integrated into classical NN to detecting pneumonia	- Improve NN performance for real-world, non-trivial problems	- Expensive in terms of time - Depended on many considerations

5.2 Handwriting Classification

A long time ago, the intractable challenges were the memory requirements and the time efficiency tolerance. The work in [37] introduces a quantum deep convolutional neural network (QDCNN) model based on the quantum parameterized circuit. A comparison of the proposed model with the classical deep convolutional neural network (DCNN) indicates an exponential speedup compared with its classical counterpart based on variational quantum algorithms. Furthermore, the MNIST and GTSRB datasets are simulated numerically, and the quantitative experimental results are used to verify the validity and feasibility of the model. However, there is a lack of information about network complexity.

Based on quantum and classical computing, the researcher in [38] proposed an image classification model that uses a hybrid approach. By replacing classical filters with variational quantum filters, the method leverages the potential of convolutional networks. The aim of this work is to compare the system's performance on different servers with other classification methods. The quantum feasibility of the algorithm is modeled and tested on MNIST and Amazon Braket Notebook instances. In this study, various strategies were tested to approach hybrid programming problems that were longer than usual. Despite the increase in operations, the results obtained are satisfying given the experiments performed, especially considering the low number of images used for training to reduce time and costs.

Ali Mohsen et al. [39] used quantum machine learning techniques where images are encoded in quantum states and inferences are made by a quantum neural network. Quantum machine learning techniques are particularly useful for classical image classification. Unfortunately, input images have been limited to extremely small sizes, no more than 4*4. Using larger input images has proven problematic due to the need for more qubits than are physically feasible in the existing encoding schemes. Their proposal is to use quantum systems to classify larger, more realistic images. Rather than requiring more qubits than prior work, their approach involves embedding images in quantum states. The framework is able to distinguish images up to 16*16 for the MNIST dataset on a laptop computer and is accurate enough to compete with classical neural networks with the same number of learnable parameters, and we also proposed a technique for reducing the number of qubits needed to represent images, which may lead to less computing power but better performance in the end, but the challenges remain in high-dimensional data.

In the NISQ (Noisy Intermediate-Scale Quantum) era, quantum machine learning is one of the most compelling applications of quantum computing. The work in [40], which introduced quantum CNN, has been used to reduce computing complexity by using logarithms. Image recognition tasks can be handled with this model, which is robust to noise and independent of input sizes. With O((log2M)6) basic gates and O(m2+e) variational parameters, this model can perform image recognition tasks with high precision even when the input size changes. It is therefore well suited for near-term quantum devices. The machine learning model can produce operands that correspond accurately to a specific classical convolutional kernel when compared to previous work. This creates a direct path to converting CNN to QCNN and opens the possibility of utilizing quantum power to process large amounts of information as the era of big data continues.

Historically, classical neural networks were limited in efficiency, cost, and performance due to limitations in runtime and efficiency. The work in [41] used quantum dilated convolutional neural networks (QDCNNs), which first combated between dilated concepts and VQCs, which could reduce computational costs. Comparing the QDCNN models to existing quantum convolutional neural networks (QCNNs), they generally perform better in terms of both accuracy and computation efficiency. However, classical CNN achieves higher accuracy than QDCNN, and QDC with a higher dilation rate performs better than QDCNN [41].

The training phase takes a long time and consumes a lot of resources in classical NN. Therefore, according to Y. Jing et al. [42], developing QCNN models that can efficiently process massive data sets is a possible solution using quantum computing. The QRAM algorithm allows us to design new QCNN models. A more resource- and depth-efficient model is presented for large input data and multiple output channels using a QRAM algorithm to extract features as efficiently as possible; for that, it took a long runtime [42].

Scientists tend to focus on processing input data through randomized quantum circuits; for example, in J. Orduz et al. [43], the proposed model acts as quantum convolutions and produces new representations that can be applied to a convolutional network. Quantum convolutions can speed up convergence and enhance stability in learning higher-dimensional problems as well as compute performance like classic convolutional neural networks, and they reduce runtime.

The work in [44] proposed quantum neural networks, which handle high-dimensional spatial data. On the popular MNIST image dataset, the influence of encoding type, circuit depth, bias term, and readout is examined. The results of experimental work show a wide range of interesting findings regarding different QNNs' learning behaviors. To the best of their knowledge, the present work is the first to address various aspects of QNN for image data. Performance can be improved by creating a separate qubit. As a result, the fewer the training sessions, the more challenging the classification. Circuit depth and bias helped improve performance as well. It can be considered optimal for a circuit to have 8 qubits and an 8-qubit depth when depth and width are set appropriately. Yet the circuit is extremely complex. Table 2 summarizes the previous works that were done in the handwritten classification.

Table 2: Summary of quantum deep learning in handwriting classification

	Authors, Year	***Problem***	***Dataset***	***Method***	***Strength***	***Weakness***
[37]	Q. Science (2020) [37]	- Memory requirements and the time efficiency tolerance	MNIST	QDCNN based on Q parameterized circuit for image recognition	- Provides exponential acceleration comparing with classical NN - Results verify feasibility, and validity	-The network is complexity analysis - Lack of information about network complexity
[38]	P. Atchade-Adelomou and G. Alonso-Linaje (2021) [38]	- NN limited in efficiency, cost - Long time	MNIST	Hybrid approach. By replacing classical filters with variational quantum filters	- Reduce time and costs	-The increase in operations
[39]	Ali Mohsen (2021) [39]	Input images limited to small sizes, no more than 4*4	MNIST	Framework to classify layer realistic image using Q systems	- Reduce number of required qubits. - Could imagine that invoking 3 or more qubit gate to layer circuits would improve learning outcomes	- Compress black & white images only. - Did not a comprehensive survey of space of all possibly unitary operation
[40]	S. Wei, Y. Chen, Z. Zhou, and G. Long (2022) [40]	- Noisy Intermediate-Scale Quantum	MNIST	Quantum convolutional neural networks	- Suited for near-term quantum devices - Process large amounts of	- Takes long time - Use dataset low dimensions and QCNN hard

					information as the era of big data continues	representation
[41]	Y. Chen (2022) [41]	- Classical neural networks limited in efficiency, cost	MNIST	HQ algorithm called QDCNN	- Reducing computational cost, better accuracy & computation efficiency, combine dilated with variational QCs.	- Classical CNN achieve high accuracy compared to QDCNN
[42]	Ya Jing et-al (2022) [42]	- Training takes a long time, lot of resources in NN	MNIST	Used two types of QC Ansatz to simulate convolutional operations on RGB image	- Improves predicative performance in multiclass classification tasks	- Used quantum for small dimensions dataset
[43]	Javier Orduz (2022) [43]	- Pr ocessing input data through RQC	MNIST	Randomized QC act as Q convolutional producing	- Performance is comparable to CNN in reconstruction ability & accelerate convergence -Stability in learning higher-dimensional	- Results is similar in classical NN - Long time
[44]	Tuyen Nguyen et-al (2022) [44]	- Hi gh dimensional spatial data	MNIST	Hybrid Quantum & classification system	- Various interesting finding different of QNN obtained through experimental results	- Difficult architecture for small dataset

5.3 Other Applications

Because deep quantum circuits for noisy intermediate-scale quantum (NISQ) are intractable and difficult to apply, and traditional quantum computing platforms are hard to simulate classical neural network models or problems, Samuel Yen-chi Chen [45] proposed the design of quantum neural networks for NISQ devices. It becomes necessary to devise a feasible algorithm. For deep reinforcement learning, researchers investigated variational quantum circuits. This research reshapes classical deep reinforcement learning algorithms into variational quantum circuit representations. They use these circuit representations as parameters for deep reinforcement learning. In a near-term NISQ machine, the VQC will be deployed.

In an existing CNN model, when the learning scale grows large, the learning speed and resource usage become problematic. Furthermore, quantum computers are limited in the number of usable qubits. To deal with these limitations, the researchers in [46] used the concept of quantum together with CNN (QCNN). As a technique for processing large amounts of data at once, quantum random access memory (QRAM) uses superposition and entanglement to store large amounts of data. The model is more efficient on the resource side, the computational capacity side, and the depth side. The QRAM method is used to extract features and is more efficient on the resource side. But it is time-consuming and difficult to apply.

In contrast to quantum neural networks, which require repeated computations to achieve their desired level of accuracy, Bayesian neural networks consider sampling from posterior distributions rather than using point estimation. For this problem, the work in [47] proposes a quantum Bayesian neural network (QBNN). In empirical experiments, they discovered that for a small number of qubits, their model approximated the true posterior well, and they did not require repeated computations, meaning that they could fully realize quantum speedups by replacing the classical inner product of two vectors with quantum estimates. Increasing the number of qubits will provide better accuracy in the inner product estimate.

Currently, QNNs are difficult to train because quantum resources are limited, so the researchers in [48] developed an unsupervised method of learning quantum classical convolutional networks by combining multiple quanvolutional filters in a hierarchy, followed by a pooling layer. Quantum circuit arrangement was optimized using K-means clustering. It was tested on a bearing fault detection dataset, which demonstrated its effectiveness. Nonetheless, it appears to be difficult to stack enough layers to generate useful higher-level representations.

This work [49] combines quantum and classical processing blocks in order to perform image classification and segmentation in a systematic manner using both methods of quantum computing. Surface crack dataset segmentation illustrates its efficacy and utility. Our in-house Cognitive Model Management framework orchestrates the functionalities of the software engineering task, so it can be used across multiple domains. Weakness: the image dataset was very limited.

In [50], proposed parameterized quantum circuits with three layers (convolution, pooling, and unsampling) can be distinguished by their generative one-qubit and two-qubit gates. It performed well on many platforms, including NSIQ devices. While Hue et al. [51] propose a model that only uses two-qubit interactions for all interactions in a convolutional neural network, a variety of QCNN models were tested using MNIST datasets, differentiating them according to the structures of parameterized quantum circuits, quantum data encoding schemes, and classical data preprocessing schemes. Even with a limited number of free parameters, QCNN was able to achieve excellent classification accuracy. With the QCNN algorithm presented in this work, it is possible to develop NISQ devices with fully parameterized quantum circuits and shallow layers.

Digital image processing requires edge detection as the amount of data required to be processed grows rapidly, pushing even the most powerful supercomputers to their limits. Comparing the number of qubits in quantum computing to the number of classical bits, the number of qubits will consume exponentially less memory. The researchers in [52] used an artificial quantum neuron concept in this work for quantum edge detection. Methods like these can be practically implemented on quantum computers, including the current noisy intermediate-scale quantum computers. The objective of this study is to compare six variants of the method to reduce the number of circuits and the time needed to detect quantum edges. Because our method can be scaled, edges can be detected in images that were much larger than previously possible.

Because of the limitations of a standard neural network, image classifiers for remote sensing are a challenge for classical neural networks. As an Earth observation (EO) use case, the researchers in [53] applied the quantum concept with CNN to land-use/land-cover classification and tested it using the EuroSAT dataset as a benchmark. By demonstrating that the QCNN performs better than its classical counterpart, the multiclass classification results demonstrate the effectiveness of the presented approach. Additionally, the best classification scores are achieved by circuits that exploit quantum entanglement. Using quantum systems as a lens to study EO, this study highlights the possibilities of applying quantum computing to a real-world case study and lays the theoretical and experimental groundwork for further investigations. There is, however, a lack of quantum processing in more complex quantum circuits.

A major goal of economic analysis is the precise forecasting of macroeconomic conditions, since it facilitates a timely assessment of future economic conditions and can be used for monetary, fiscal, and economic policy purposes. The macroeconomic situation has been extensively studied and forecasting models developed. Nevertheless, despite the limitations of existing models, David Alaminos [54] proposes new forecasting models that are capable of accurately estimating future scenarios worldwide. Quantum computing with deep learning techniques was compared to producing a high-accuracy model by means of deep neural decision trees, which demonstrated excellent prediction results in large-scale processing with mini-batch-based learning and can be integrated with any neural network model. The model offers tools that help achieve macroeconomic and monetary stability globally, as well as methods for predicting GDP growth at the global level, and can have a major impact on the adequacy of macroeconomic policies. Table 3 summarizes the previous work that has been done in the other applications.

Table 3: Summary of quantum deep learning in other applications

Ref	***Authors, Year***	***Problem***	***Dataset***	***Method***	***Strength***	***Weakness***
[45]	Samuel yen-chi Chen (2020) [45]	Unfeasible machine learning for noisy intermediate scale quantum (NISQ) devices	Real-world dataset	Variational QC for reinforceme nt learning	- Reduce number of parameters - it is fast compared to classical NN - Applicable in different scenarios - QC based DRL is robust against noise in current machines - Less memory consumption	- Intractability of deep quantum circuits
[46]	Seunghyeok oh And et-al (2021) [46]	It is a relatively burdened model in terms of learning speed and resource usage	Massive data	Design QCNN a potential solution using quantum computer to handle problem	- More resource and depth efficient model for larger-sized input data - Number of output channel suing QRAM and efficiently extracting features	- Difficult method and takes long time.
[47]	N. Berner, V. Fortuin, and J. Landman (2021) [47]	QML requires repeated computations to achieve a desired level of accuracy for its point estimates	UCI dataset	Quantum algorithm for Bayesian NN inference	- Found small number of Qubits - Reducing asymptotic of inference & prediction in BNN using QA	- Need speed up the inference even further
[48]	T. Dou, K. Wang, Z. Zhou, S. Yan, and W. Cui (2021) [48]	the lack of quantum resource, it is costly to train QNNs	Dataset has 299 samples	Unsupervise d method for QCNN to hierarchy Q feature extraction and used K-means	It achieves competitive results on bearing fault detection dataset	It seems that is not easy to stack as many layers as needed to get useful higher-level representation
[49]	S. Pramanik et al (2021) [49]	NN limited to solve different problems, but face those of applied nature, together with	Surface Crack dataset	Hybrid quantum and classical processing block	- Can be of great use across domains	- Few images are used

		classical computers.				
[50]	Y. Chen, W. Hu, and X. Li, (2021) [50]	Unfeasible classical NN architecture on noisy intermediate-scale quantum devices	Real-world dataset	Quantum architecture	It performed well on many platforms, including NSIQ devices	Training time may be required increase
[51]	T. Hur, L. Kim, and D. K. Park (2022) [51]	Several quantum-analogue of convolutional neural network unfeasible	MNIST	QCNN	QCNN was able to achieve excellent classification accuracy	Cost functions
[52]	A. Geng, A. Moghiseh, C. Redenbach, and K. Schladitz (2022) [52]	Digital image processing requires edge detection as the amount of data required to be processed grows rapidly	USC-SIPI image database	QNN	- The number of qubits will consume exponentially less memory. - Reduce the number of circuits and the time needed to detect quantum edges	- Limited Computer devices
[53]	A. Sebastianelli, D. A. Zaidenberg, D. Spiller, B. Le Saux, and S. Ullo (2022) [53]	Image classifiers in the context of remote sensing.	EuroSAT	Quantum layer within standard NN	- HQCNN has proven to be effective in terms of multiclass identification & computing efficiency - QC shows achieve best classification score	- More complex quantum circuits - Few proportion of quantum processing
[54]	D. Alaminos, M. B. Salas, and M. A. Fernández-Gámez (2022) [54]	Precise macroeconomic forecasting has limitations, and the accuracy of the models is still poor	1980-2018 sample of 70 countries	Quantum computing and deep learning	- Achieve a high accuracy - Provided excellent predication to large scale processing - Help to achieve macroeconomic & monetary stability at global level	- Required long runtime

6. Quantum Deep Learning Challenges

There are several challenges that generally impact any QDL algorithm, and those are:

1. Gradient Vanishing: As in classical neural network knowledge, the vanishing gradient is a crucial issue in quantum deep learning. In deep neural network computation, the issue of gradient disappearance has been regarded as a constant hassle. In the same way that classical neural networks train their parameters through a gradient descent approach, quantum neural networks have the same problem. The problem is remedied in classical neural network models by using a suitable activation function, but quantum neural networks do not use an activation function, so ultimately a specific solution is needed. Former studies called this phenomenon "vanishing quantum gradients" or "barren plateaus," as well as proving that as the number of qubits increases, the probability of barren plateaus occurring will also increase exponentially. This may be averted by putting the top initial parameters in small-scale quantum neural networks; in designing quantum neural networks, dealing with this hassle is unavoidable. It's an open problem for which there is no clear solution at the moment [55].

2. Near-Term Device Compatibility: NISQ, which stands for Noisy Intermediate Scale Quantum, has already become a familiar term in the quantum field because fewer qubits and

various computational errors are involved. It is predicted that many algorithms developed for quantum computation will not work at all in this NISQ context and will not be implemented for several decades. As an example, even without the blunder's correction procedures, a practical implementation of Shor's method would require tens of qubits, while modern quantum devices only have a few tens of qubits with non-zero computational errors. Because QNN is surprisingly based entirely on VQA and QQ, it is tolerant of environmental constraints, including small circuit depths and qubit requirements. Though that allows you to grow the record processing functionality of the quantum neural community, it's far more important to recall near-time period tool compatibility. For instance, the use of many multi-qubit controlling gates for quantum entanglement is theoretically thought to boost the performance of QNN, but it includes a big error fee and a complex error correction system. Consequently, it's essential to design a set of rules regarding those tradeoffs in quantum neural network research [55].

3. The Quantum Advantage: The term "quantum supremacy" can also result in the illusion that quantum methods are continually better than classical methods, appearing to perform the same function. However, due to quantum computing's inherent barriers, its benefits can only be discovered through well-thought-out algorithms under certain circumstances [19]. In particular, only a few variational quantum-based algorithms have proven their quantum advantage in a confined scenario. Because of the generic approximation assets of QNN, it's widely recognized that quantum deep learning can carry out the maximum of the computations accomplished in classical deep learning [56]. Nonetheless, if one technique is certainly primarily based on this truth without the attention of quantum benefit, the result may be significantly less efficient than the existing classical set of rules. Therefore, when designing QNN-based deep mastering rules, it is vital to articulate their advantages over corresponding classical models in order to justify their inclusion.

7. Conclusions and Future works

Deep learning and quantum computing are two of the most popular fields of research today. In this study, we presented a comprehensive and easy-to-read overview of quantum deep learning. This paper reviews a variety of quantum neural networks (QNNs), their variants, quantum convolutional networks (QCNNs), and recent developments in quantum-inspired deep learning algorithms. There is tremendous potential for collaborative research at the intersection of the two fields by applying concepts from one to solve problems in the other. For example, demonstrating deep networks' ability to entangle and therefore their use in applications such as healthcare, handwriting classification, and quantum many-body physics.

In the future, it will be exciting to extend these studies to more realistic prediction tasks using efficient methods and potentially speed up the inference even further through the use of quantum deep learning techniques.

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