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On Quantum Deep Learning and Its Applications

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Abstract: *Quantum Deep Learning (QDL) is a specialised direction within QML. It is a new research area that combines quantum computing with deep learning to reduce training time for neural networks. QDL improves feature representation, optimisation, and learning efficiency in complex data-driven tasks. With quantum circuits and quantum neural models, QDL can efficiently handle complex learning problems. In this paper, we describe, among others, the main algorithms of QDL and some of its applications as they are presented in recent studies.*

Keywords*: QDL, QML, QNN, QCNN, VQC, Quantum Computing, Applications, Algorithms.*

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I. INTRODUCTION

Machine learning (ML) is an interdisciplinary subject in the fields of computer science, mathematics, statistics and neuroscience. It has achieved excellent results in recent years. Using ML algorithms are innovated many domains such as speech recognition, visual object recognition, object detection. Deep learning (DL) based on neural network is a branch of machine learning. [2]
DL forms the cornerstone of many modern machine learning techniques.

It has attracted extensive attention for various data processing tasks, such as images, audios, and videos. Basically, the classical DL method requires a large amount of training data, and datasets which are very complicated and privacy-sensitive in some cases. Let us mention, for example, finance and medicine. In these fields, it is difficult to apply the classic DL techniques because they require high computational power. The absence of personal data privacy is another difficulty, as well. [11]

Deep neural networks have led to many innovations in several domains of machine learning, such as computer vision, natural language processing, reinforcement learning , speech recognition, and many others. ([4] - [8], [12], [13]) But simultaneously remarkable progress was found in the quantum computing field. It is focused on fixing classically difficult problems.

Recently it is noticed a significant progress in the physical realization of quantum processes and the features in quantum algorithms. To increase computing efficiency and reduce power consumption, quantum computing utilizes two essential principles of quantum mechanics: entanglement and superposition. The quantum computing and machine learning (ML) synergy has led to many breakthroughs in both of them. For example, it has been eventual research on using the quantum computing features to recover the performance capacity and computational competence of classical ML approaches. (see [3])

Quantum Machine Learning (QML) and Quantum Deep Learning (QDL) are emerging research areas that combine quantum computing with machine learning and deep learning techniques. The goal of these approaches is to improve computational speed, feature representation, optimisation, and learning performance in complex data-driven problems.

Quantum Deep Learning (QDL) is a specialised direction within QML. It connects deep neural architectures with quantum computational principles improving feature representation, optimisation, and learning efficiency in complex data-driven tasks. QDL is a new research area. DL models require substantial computational resources and long training times. With quantum circuits and quantum neural models, QDL can efficiently handle complex learning problems. (see [1])

The most typical technique that applies quantum computing to DL is Variational Quantum Circuit (VQC). It mimics classic neural networks but with lesser parameters. (see [11])

This paper describes the recent developments in QDL. It is concentrated mainly on its algorithms, application areas, implementation approaches, challenges etc.

II. QUANTUM COMPUTING

Quantum Computing (QC) is an emerging field at the intersection of mathematics, physics and computer science. It uses principles of quantum mechanics to perform computations. Quantum computing uses quantum discrete units of information, the qubit (quantum bit) [29]. Qubits represent elementary units of information exchange in quantum computing, similar to the "bits" of classical computing. A bit is always in two basic states, either 0 or 1, while a qubit can be in both bases of these states simultaneously. The characteristic is also known as superposition. Quantum computing normally uses the Dirac notation that represents the two bases of computing of these states $|0\rangle$ and $|1\rangle$. A quantum gate consists of several mathematical operations applied to the qubits that change the amplitude of their probabilities and thus perform the intended computations [27].
In addition to superposition, entanglement allows the manipulation of multiple qubits simultaneously rather than individually. These quantum phenomena provide certain advantages unique to quantum computing over classical approaches, and researchers have been working to integrate them into various algorithms, including those in machine learning and deep learning ([26], [28]). (see [25])

The original idea for a quantum computer is credited to Soviet mathematician Yuri Manin, in 1980 in the introduction of his book "Computable and Uncomputable*".* The american physicist Paul Benioff, working at the French Centre de Physique Theorique, presented a paper in which he described a quantum mechanical model of a Turing machine in 1980, as well. While working on a simulation for quantum physics models, the american theoretical physicist Richard Feynman noticed that the values in his calculations increased exponentially, requiring a computational power that exceeded immensely the capabilities of traditional computers [31]. Benioff and Feynman delivered separate talks on quantum computing at the first Conference on the Physics of Computation at MIT in 1981. In 1985, David Deutsch, a British physicist, formalized the idea of a quantum Turing machine, a theoretical model for a universal quantum computer. His work demonstrated that a quantum computer is capable to solve problems which was impossible using classical computers. In 1994, Peter Shor developed an efficient quantum algorithm for integer factorization [32]. In the early 2000s, researchers built small-scale quantum computers that could run simple algorithms. In 2001, researchers from IBM and Stanford University successfully implemented a small version of Shor's algorithm on a 7-qubit quantum computer, factorizing the number 15. In 2011, D-Wave Systems, a Canadian company, launched its first commercial quantum computing system based on quantum annealing [32]. After 2010, several companies increased considerably their investments in the development of efficient quantum computers. Their objective was to build systems with a greater number of qubits. Currently, large companies such as Google, IBM and Microsoft, along with startups such as Rigetti, D-Wave, and Xanadu, have made many innovations in building quantum computers with greater qubit capacities. Moreover, an active research in developing quantum algorithms and exploring the applications of quantum computers in real-world scenarios, such as finance, machine learning, drug discovery and cryptography is noticed lately. Quantum algorithms have been developed for both NISQ and fault-tolerant devices. For NISQ devices, the most important are variational algorithms, including the Variational Quantum Eigensolver (VQE) [33], the Quantum Approximate Optimization Algorithm (QAOA) [34] and Parameterized Quantum Circuits [35]. A variational quantum circuit is a hybrid approach that combines quantum and classical computation, utilizing the advantages of both. It consists of a quantum circuit with adjustable parameters that a classical computer optimizes iteratively. These parameters function similarly to the weights in artificial neural networks [36]. Just as classical computers rely on classical algorithms for their functionality, quantum computers depend on quantum algorithms. As we mentioned above, the quantum circuit model is the most generally used framework in quantum computing.

Deutsch's Algorithm: After proposing the concept of a quantum Turing machine, Deutsch [38] developed an algorithm to demonstrate faster performance on a quantum computer. It determines whether a given function is

constant or balanced using a single query to the oracle. This algorithm highlights the strength of quantum parallelism.

Deutsch–Josza Algorithm: Deutsch, together with Richard Jozsa, later extended this idea into the more general Deutsch–Jozsa algorithm [39]. Extends Deutsch's algorithm to multiple inputs, identifying whether a function is constant or balanced with just one query, presenting exponential speedup.

Bernstein–Vazirani Algorithm: In 1993, Bernstein and his student Vazirani published a paper [40] introducing an algorithm that outperforms the best-known classical approach to a specific problem. It finds a hidden binary string by querying an oracle only once, providing a polynomial speedup over classical algorithms.

Simon's Algorithm: Following the contributions of Bernstein and Vazirani, Daniel Simon made further advancements in 1994. Simon presented a problem [41] that could be solved exponentially faster by a quantum computer compared to a classical one.
It solves the hidden string problem for functions satisfying $f(x) = f(x \oplus s)$, demonstrating exponential speedup compared to classical methods.

Quantum Fourier Transform: In 1993, Bernstein and his student Vazirani in the same paper [40] contributed by presenting a quantum version of the Fourier transform. This algorithm computes the discrete Fourier transform of a quantum state efficiently, essential for algorithms like Shor's.

Shor's Algorithm: One of the most important breakthroughs in quantum computing was Shor's algorithm [43], developed in 1994. Shor based on earlier works of Deutsch, the Bernstein–Vazirani algorithm and Simon's algorithm created a way for quickly factoring large numbers into two prime factors, which is a very difficult task for the classical computers. Factoring large numbers is fundamental for the Rivest–Shamir–Adleman (RSA) encryption system, which secures most online communication today. This includes protecting credit card info, bank transfers and private messages. [37]

Phase Estimation Algorithm: Estimates the phase of an eigenvalue of a unitary operator, playing a crucial role in many quantum algorithms, including Shor's.

Grover's Algorithm: Lov Grover followed the innovative work of Shor, developing another significant quantum algorithm in 1996. His algorithm [44] focuses on searching through an unsorted database and provides a substantial quadratic speedup compared to classical algorithms for searching an unstructured database.

HHL Algorithm: The last fundamental quantum algorithm proposed by Harrow, Hassidim and Lloyd is called HHL algorithm [42]. This algorithm is designed to solve linear systems of equations providing an exponential speedup for their solution.
These nine quantum algorithms are fault-tolerant. (see [30])

III. QDL

Quantum Deep Learning (QDL) is a specialised direction within QML. It is a new research area that connects deep neural architectures with quantum computational principles improving feature representation, optimisation, and learning efficiency in complex data-driven tasks. [1]

QDL combines quantum computers (which use qubits to process information in superposition) with neural networks (which learn patterns from data). Instead of classical circuits, it uses quantum circuits as trainable layers. This enables exponential speedups for specific tasks like optimization and molecular simulation.

Deep learning, a subset of machine learning, involves complex neural networks with multiple layers (deep neural networks) and has achieved significant successes in areas such as image recognition, natural language processing, and reinforcement learning. The goal of quantum-enhanced deep learning is to leverage the unique properties of quantum computing to improve the training, execution, and optimization of deep neural networks.

Classical deep learning (DL) uses bits (0 or 1) and processes sequentially or in parallel. QDL uses qubits that exist in superposition (both 0 and 1 simultaneously) and leverages entanglement to explore exponentially larger solution spaces. This provides advantages for solving some problems such as high-dimensional optimization which is a very difficult task for the classical computers.

QDL uses the power of quantum computing to create quantum categories of DL algorithms that are used in the associated fields. [3]

So, quantum theories and algorithms inspire and are the basis of different approaches in QDL. In other words, this means that, when a deep learning model with multiple levels or layers of data processing has at least one layer that relies on quantum mechanical concepts, it can be defined as a QDL model. On the contrary, a quantum circuit itself can sometimes imitates a deep neural network, which belongs to the category of QDL, as well. We point out here that the former represents a hybrid architecture, combining classical and quantum elements, while the latter is purely quantum. [25]

The authors in [53] have formulated the following definition of QDL:

Definition: QDL refers to compositional learning architectures and workflows exhibiting hierarchical depth at the level of the overall learning pipeline, in which at least one quantum or quantum-inspired component is functional and architecturally central. Concretely, the learning objective or update rule depends on this component's outputs, and its inclusion nontrivially determines the hypothesis class and/or estimator family under an explicitly stated access and resource model.

Commenting this definition, they have pointed out that it "...distinguishes QDL from broader QML by requiring compositional depth at the pipeline level and by making access models and resource assumptions part of the problem specification. Consequently, QDL includes both hardware-executed and quantum-inspired classical realizations of quantum components. However, it explicitly excludes AI-for-QC studies as well as standalone shallow quantum feature maps, kernels, or single circuit predictors, provided they are used solely as end-to-end models rather than embedded components of a hierarchically deep pipeline. Examples of QDL under this framework include:

(i) a PQC head on a frozen or trainable classical backbone;

(ii) a quantum sampling subroutine used only at deployment within a deep generative pipeline; and

(iii) dequantization baselines embedded in a matched-access evaluation..."

IV. QDL ALGORITHMS

Quantum Deep Learning. QDL performs numerical calculations of the ANN with the help of quantum computing [16]. Lately, the researchers have done much efforts to replace the classical DL architectures such as Deep Neural Network (DNN), Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN) with quantum-based models as follows. ([9], [10], [14], [15]).

Variational Quantum Circuits: Quantum variational circuits are common architectures for quantum-enhanced deep learning. A variational quantum circuit (VQC) is a quantum circuit which uses rotation operator gates with free parameters to perform different numerical tasks such as approximation, optimization, and classification. ([11], [3])

These circuits are composed of alternating layers of qubits and quantum gates, which are optimized to minimize the loss function during training.

In the first step, training datasets are encoded to be expressed as qubits. These quantum states are fed into the VQC, which simulates classic neural networks. Next, the output quantum states are measured and collapsed into one of the basic quantum states. And finally, the collapsed quantum states are converted back into classic data which can be read and precessed by classic computers. Despite their limited model size, VQCs can be trained and optimized like any other neural networks, but they can be more expressive than classic neural networks with similar learning speeds. [11]

The global approximation property of VQC allows it to solve many numerical problems. VQC approximates functions through parameter learning in a similar way to artificial neural networks, but it differs by several properties of quantum computing. All quantum gate operations are linear, reversible operations, so, instead of activation purposes, texture sheets are used for multiple sheet formation. These VQCs are called "quantum deep learning" [3].

Quantum Convolutional Neural Networks (QCNN): QCNN utilizes quantum gates to encode images and to construct convolutional and pooling layers within quantum circuits, closely imitating the architecture of traditional CNN. QCNNs implement convolutional and pooling operations directly on quantum states, inspired by the hierarchical structures of classical CNNs and multi-scale entanglement renormalization.

It operates in the following five steps [16]. First, input data is encoded into its corresponding qubit state and transformed through rotation operator gates. Second, the convolution layer with quasi-local unitary gates filters the input data into a feature map, and the pooling layer with controlled rotation operators downsizes the feature map. Third, this process is repeated, and the fully connected layer performs the same function of a classic CNN model on the transformed qubit state. Fourth, the transformed qubit is measured and decoded back into its original classic form. And in the last step, circuit parameters are updated by a gradient descent-based optimizer. Through this process, QCNN can process image information like a conventional CNN. (see [11])

Cong et al. [49] have proposed a quantum CNN through a quantum circuit model where they modify the ideas of convolutional and pooling layers from classical CNNs. As in the classical CNNs, the general architecture of the quantum CNN is user-defined, while the parameters of the unitaries are learned. The parameters are optimized by minimizing a loss function, for example by using gradient descent with the finite difference method. Cong et al. [49] prove the effectiveness of the proposed architecture on two classes of problems, quantum phase recognition (QPR) and quantum error correction (QEC). Later, Kerenidis et al. [50] identified the relation between convolutions and matrix multiplications. They proposed the first quantum algorithm to compute the forward pass of a CNN as a convolutional product. They also provided a quantum back propagation algorithm to learn network parameters through gradient descent. In an application of CNNs, Zhang et al. [52] and Melnikov et al. [51] proposed special convolutional neural networks for extracting features from graphs, to identify graphs that exhibit quantum advantage. (see [48])

Regardless of its theoretical charm, the quantum convolutional neural network (QCNN) faces several technical challenges, such as sensitivity to hardware noise, limited circuit depth due to decoherence, and poor scalability when applied to high-dimensional or large-scale datasets. They have not demonstrated consistent advantages over classical CNNs with regard to the accuracy or convergence. But, their architectural principles, such as local feature encoding, compact variational circuits, and measurement-driven feature extraction, form a strong basis for quantum deep learning.

Hybrid quantum-classical convolutional neural networks (QCCNNs): To overcome the scalability issues, training instability, and hardware constraints observed in fully QCNNs, hybrid quantum-classical convolutional neural networks (QCCNNs) have been proposed as an extended framework. As we mentioned, QCNNs depend entirely on quantum operations for both feature extraction and pooling. The QCCNNs replace part of the quantum processing pipeline with classical convolutional layers, keeping VQCs as local quantum filters. This hybrid approach reduces quantum resource requirements, improves training stability, and enhances compatibility with NISQ devices. In this architecture, quantum convolutional layers apply parametrized quantum gates to locally encoded input data. The classical pooling and fully connected layers follow to complete the learning pipeline. The QCCNN design has been explored in several studies. For example, Henderson et al. [46], introduced an encoding-decoding scheme to align quantum outputs with classical operations. More recently, Liu et al. [47] further formalized the framework by using VQCs composed of alternating single-qubit rotations and two-qubit entangling gates. QCCNNs apply quantum measurements directly to select qubits following local quantum operations. These measurement outcomes capture localized feature information without explicit summation operations. The extracted quantum feature maps are fed later into classical pooling layers for dimensionality reduction and then into fully connected layers to complete the final classification task. QCCNNs do not yet demonstrate exponential computational advantages, but they offer a more hardware adaptive design utilizing shallow quantum circuits. This hybrid formulation enables more stable training

and reduced quantum resource consumption, making it a practical candidate for near-term quantum computers. (see [45])

V. QDL APPLICATIONS

QDL is an emerging interdisciplinary field that combines quantum computing and deep learning techniques. The possible applications of quantum deep learning are diverse and can provide advantages over classical counterparts in certain scenarios. In this section we present some of these applications:

Image Classification: Quantum convolutional neural networks and variational circuits extract features and sort visual data with fewer parameters than classical models. Using quanvolutional neural networks or hybrid quantum-classical convolutional layers visual data like MNIST datasets can be sorted and categorized. As we pointed out in Section 4, QCNNs have a multiscale convolution-pooling structure [49], which does not allow barren-plateau phenomenon to happen in certain locality-structured settings [54]. But, as it is demonstrated by some researchers, under additional locality or limited-entanglement assumptions, they may also admit efficient classical simulation in broad regimes [55]. Hybrid CNN pipelines insert small PQCs into classical vision stacks ([45], [47], [56]). Closely linked are quanvolutional pipelines [57]. But, until now, it is not demonstrated any adaptable and consistent quantum advantage over the latest classical vision benchmarks and the performance is often limited by data-loading costs, sampling noise, and device errors, as well.

Natural Language Processing (NLP): Natural Language Processing (NLP) involves the interpretation of human language by AI. Quantum algorithms may be applied to tasks such as language modeling, sentiment analysis, and semantic understanding, potentially offering advantages in processing complex linguistic structures. High-dimensional quantum states represent semantic meanings and word relationships more compactly. To handle complex linguistic data structures, models like Bi-Quantum Long Short-Term Memory (BiQLSTM) can be implemented. The authors in [96] compared the performance of QDL with traditional Recurrent Neural Networks (RNNs) and Transformer models, which are commonly used in NLP tasks. In the QDL model, text data is encoded as quantum states in a tensor network representation. The quantum superposition allows for parallel processing of multiple sentence meanings, while quantum entanglement helps in understanding contextual correlations between words, outperforming traditional RNNs and Transformer models in terms of accuracy and training time. [96]

Materials design and quantum chemistry: Materials design and quantum chemistry ([58], [59]) are other two domains where QDL is applied successfully. In materials science it can be used, for example, in discovering new catalysts and batteries. Conventional computational techniques for simulating molecular systems frequently face challenges due to the exponential increase in computational resources needed as the system size expands. Quantum algorithms, like VQE and the quantum phase estimation algorithm, are very promising for efficiently simulating molecular systems on quantum computers. By encoding molecular Hamiltonians into quantum circuits and using quantum parallelism, these algorithms can provide accurate predictions of molecular energies and properties, essential for understanding biochemical processes and drug interactions. Quantum computers naturally operate in multi-dimensional Hilbert spaces, making them ideal for modeling molecular structures and predicting chemical properties. The main scientific difficulty consists in preserving chemical accuracy across high-dimensional configurational and chemical spaces. This is presented, particularly, in strongly correlated regimes where bias and generalization are fragile [58]). Reddy and Bhattacherjee [60] combine latent space compression with a quantum regression module, which functions as a specialized inductive-bias component and should be compared under matched budgets. In some recent works are investigated data-efficient models [61] and early drug-discovery prototypes [62], but large-scale chemically accurate quantum advantage remains unestablished. (see [53])

Scientific Discovery & Physics: Scientific computing is concentrated on data-driven surrogates for accurate but expensive first-principles simulations. QDL approaches include surrogate modeling for quantum mechanical problems, quantum model discovery from sparse data, and operator learning with expensive forward models ([63] - [65]). The variational quantum classifiers can be applied to accelerator physics, such as evaluating the dynamic aperture of storage rings or analyzing quantum many-body states. High-energy physics offers realistic

benchmarking with large structured classical datasets and strict calibration requirements [67]. Quantum pipelines apply in collider-style analyses with circuit feature maps and kernel estimators [66], while quantum-inspired classical methods, including TN classifiers, are strongly competing [68]. These comparisons emphasize the importance of domain-informed inductive bias and careful benchmarking. This domain is a very challenging one for QDL. (see [53])

Quantum Data Processing: Quantum data processing uses the principles of quantum mechanics to encode, manipulate, and analyze information via quantum bits. Thanks to qubits and quantum parallelism, quantum computing can process and encode exponentially more data than classical computing. This capability can be utilized for efficient processing and analysis of large scientific datasets, enabling more comprehensive and accurate data exploration. Quantum-data workflows are distinguished most wisely by the access-and-readout interface: (i) measure-first protocols that map each copy to a classical record and learn by classical postprocessing, and (ii) coherent or collective protocols that retain quantum information (e.g., via quantum memory) to enable joint measurements or coherent processing across copies. Some quantum contribution consist in the use of quantum resources at the interface, including measurement-efficient acquisition protocols with explicit sample-complexity guarantees ([69] - [71]), quantum-native compression ([72] - [74]), or fixed quantum dynamical reservoirs ([75] - [77]). Representative task families that exploit coherent or collective interfaces include collective measurement protocols for learning tasks ([78], [79]), unsupervised classification of quantum states, and separations highlighting limitations of fixed-measurement measure-first pipelines in supervised learning ([80]). Practical impact therefore depends on realistic interface assumptions, including whether quantum memory or only measured outcomes are available, measurement budgets, and rigorous resource-matched benchmarking. (see [53])

Quantum optimal control: Quantum optimal control designs time-dependent controls that direct quantum dynamics toward a target objective, and is traditionally addressed with classical gradient-based methods and, more recently, RL approaches ([81], [82]). The reinforcement learning and hybrid algorithms can be used successfully to steer stochastic quantum dynamics on noisy intermediate-scale quantum (NISQ) devices. Classical optimal-control and RL pipelines define the comparator stack: empirical claims are most interpretable under matched experimental-call budgets, hardware constraints, and evaluation metrics. Standard classical benchmarks include GRAPE ([81]), GOAT ([83]), PEPR ([84]), and Krotov-type updates ([85], [86]) , while RL has been used for robust pulse design in hardware facing settings ([87] - [92]). Hybrid VQAs have also been proposed explicitly for quantum control objectives, providing a direct bridge between VQA methodology and QOC benchmarks. (see [53])

Complex System Modeling: Modeling complex systems often involves dealing with high-dimensional data and complicated correlations. The authors in [96] have compared QDL's performance with traditional Deep Belief Networks (DBNs) in modeling complex systems. By leveraging quantum superposition and entanglement, QDL is capable of effectively processing high dimensional data and apprehending difficult correlations, leading to higher modeling accuracy and faster convergence. In conclusion, they have shown that QDL can outperform traditional deep learning models in various applications, demonstrating the potential of quantum-enhanced deep learning to revolutionize AI.

New domains: QDL has been explored in an expanding number of cutting-edge sociotechnical and engineering domains. The QNN and quantum reinforcement learning algorithms can be used in the research field of communications and networks, as well. QNN can be used, for example, to accelerate the computation in fully distributed platforms, e.g., blockchain [(98], [99]). In addition, various advanced communication technologies such as Internet of Things (IoT) ([100], [101]), millimeter-wave networks ([102], [103]), caching networks ([104] - [107]), and video streaming/scheduling ([108] - [111]) are good applications of QNN and quantum reinforcement learning algorithms. (see [97]) Quantum algorithms are used successfully in finance analyzing volatile market trends, optimizing portfolios, and running risk assessment simulations faster under high uncertainty. Some other important application domains are cybersecurity (post-quantum cryptography),

healthcare (medical imaging, disease prediction), security and privacy constrained inference, logistics (supply chain optimization), robotics ([93], [94]), and distributed learning [95].

VI. QDL CHALLENGES

Some of the challenges that generally impact any QDL algorithm are:

Data Scalability Problem: As in classical neural network knowledge, the vanishing gradient is an essential problem in QDL. In deep neural network computation, the issue of vanishing gradient is considered as a serious problem. In classical neural network models, this problem is solved by using a suitable activation function. The quantum neural networks do not use an activation function, so a specific solution is needed in this case. Former studies called this phenomenon "vanishing quantum gradients" or "barren plateaus". It is well known that the problem of the barren plateau occurs in large-scale QNNs [17]. As we mentioned, it vanishes the quantum gradient and leads to local convergence. This means that even if the size of the VQC is large enough and many parameters become available, its optimal convergence may become difficult. This phenomenon is affected not only by the size of the quantum circuit. The quantum calculation error rate, the type of gradient descent method, and the ansatz of the quantum circuit influence it considerably, as well. Thus, for the researchers of QDL, the effective design of quantum circuit ansatz to solve these problems is a big challenge. A serious attempt to deal with this problem, is the research on efficient quantum encoding [18] of classical information or processing more information per qubits by constructing a quantum circuit as a tensor network [19]. (see [11])

Quantum Compatibility Problem: Unlike deep learning, QDL is not stable and its application is still limited by the quantum noise. This happens because of a large model size and the absence of quantum correction techniques [21]. In [20], is presented a method to overcome this limitation. It primarily utilizes a classic ANN for quantum computation, as shown in classic-quantum hybrid transfer learning. Overcoming this limitation is important because currently, the implementation of most of the quantum secure communication protocols is challenging due to the limitation of NISQ devices. (see [11])

NISQ (Noisy Intermediate Scale Quantum), is now a well-known 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, 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 based completely on VQA and QQ, it is tolerant of environmental constraints, including small circuit depths and qubit requirements which is capable to grow the record processing functionality of the quantum neural community. But, on the other hand, it's all the more crucial to recall near-time period tool compatibility. For instance, the use of many multiqubit 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. Therefore, it's essential to design a set of rules considering those tradeoffs in quantum neural network research.

Data Privacy Problem: When the sensitive data, e.g., financial and medical data, is being handled, it is critical to prevent unauthorized users as well as participants of the training process from having access to other clients' data. In [23], the server and the client use QKD-based or UQBC protocols-based quantum communications to exchange information safely. However, the server could still easily identify each client. Consequently, this method is not enough for situations where the security is of principal importance. On the other hand, in [20], the client and the server did not exchange any data. However, no quantum security protocol is considered, as well. This means that this model is particularly exposed to Byzantine attacks. The model proposed in [22] overcomes this challenge. It applies the differential privacy technique to block any attacks during data transmission from the client to the server. Other possible solutions to the data security problem include SL which is first introduced in [24]. In an SL setting, a part of the entire training network is stored in the client device, and the client and the server exchange latent data and gradients instead of the actual data. As a result, data privacy is protected since no data is exchanged between the two participants. This method generally shows faster algorithmic convergence than federated learning. Therefore, the application of SL to QNN is expected to ensure the efficient training and data privacy. (see [11])

VII. CONCLUSION

Quantum computing and deep learning are two of the most popular fields of research today. Quantum Deep Learning (QDL) is a novel framework which combines quantum computing with deep neural networks to process complex data. [112] A noticeable feature of QDL is its practical implementation using classical computational resources. Furthermore, QDL supports the principles of privacy preservation and energy efficiency. The performance of QDL significantly exceeds that of classical deep learning models, as well. [96]

In this brief summary are described, among others, the main algorithms of QDL, such as Variational Quantum Circuits (VQC), quantum convolutional networks (QCNNs), etc. We have outlined some of the better applications of QDL in different fields of science and industry, as well.

Nowadays, there is a great possibility of collaboration across disciplines - bringing together quantum physicists, computer scientists, and machine learning experts, by applying concepts from one to solve problems in the other. [4] So, researchers and practitioners are making significant progress in developing quantum algorithms and models which can be used more efficiently in real-world problems.

In conclusion, the intersection of quantum computing and deep learning looks very promising, opening new horizons for computational power and algorithmic innovation.

As the exploration in the field of QDL progresses, the integration of quantum-enhanced algorithms into our technological environment has the possibility to revolutionize industries, solve complex optimization problems, and facilitates the groundbreaking advancements in artificial intelligence. The future of QDL is exciting, and traversing through this unexplored territory, it is clear that we are standing at the brink of a modern era in computing and machine learning.

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