Quantum Heterogeneous Distributed Deep Learning Architectures: Models, Discussions, and Applications

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Abstract—Deep learning (DL) has already become a state-of-the-art technology for various data processing tasks. However, data security and computational overload problems frequently occur due to their high data and computational power dependence. To solve this problem, quantum deep learning (QDL) and distributed deep learning (DDL) are emerging to complement existing DL methods by reducing computational overhead and strengthening data security. Furthermore, a quantum distributed deep learning (QDDL) technique that combines these advantages and maximizes them is in the spotlight. QDL takes computational gains by replacing deep learning computations on local devices and servers with quantum deep learning. On the other hand, besides the advantages of the existing distributed learning structure, it can increase data security by using a quantum secure communication protocol between the server and the client. Although many attempts have been made to confirm and demonstrate these various possibilities, QDDL research is still in its infancy. This paper discusses the model structure studied so far and its possibilities and limitations to introduce and promote these studies. It also discusses the areas of applied research so far and in the future and the possibilities of new methodologies.

I. INTRODUCTION

As deep learning (DL) using artificial neural networks has become the state of the art technology in processing data such as images, audios, and videos, a variety of research has been ongoing about the application of DL [1]–[5]. Finance and medicine have shown to be significantly reliant on DL because more complex and sensitive data have to be handled in the respective fields as time passes [6]. Additionally, the classical DL method requires a large amount of data to be collected from the servers because its performance is highly dependent on the input data [7]. As a result, there is a high demand for computational power, and the lack of personal data privacy causes classical DL to be limited. Recently, two methods have arisen as solutions to these limitations: Quantum Deep Learning (QDL) [8] and Distributed Deep Learning (DDL). With more research, quantum computing gradually realizes the theoretical possibilities of utilizing quantum phenomenons such as entanglements and superpositions to increase calculation efficiency. It is also expected to mitigate the limitations of classical DL. More specifically, QDL applies quantum computing to DL by using Variational Quantum Circuit (VQC) [9], which imitates the classical neural networks with lesser parameters. Much research about applying it to data analysis, such as classification and deep reinforcement learning (DRL) to achieve more efficient and scalable training, is already being actively pursued. As demonstrated, QDL is speculated to be an essential part of the future of artificial intelligence. Along with QDL, the DDL method is studied to solve the problems originating from the centralized data and computational structure of the classical DL system [10]. DDL deals with the computational overhead problem and the data security issue at once. It utilizes the computational power of the numerous local devices by operating relatively small models in the devices instead of collecting and training all the data in a central server. Federated Learning (FL) and Split Learning (SL) are the two most used methods [11]. FL involves the clients sending the trained model parameters to the server instead of the data, while SL divides the entire model and distributes the necessary parts to the users. Each user then transmits the latent variable to the server to proceed with the training. By doing so, the two methods both manage to solve the computational overhead and data security problems. Areas like medicine, finance, and facial recognition, which handle sensitive data, are expected to benefit from the advantages of DDL explained above. Research about how it will be applied in the various fields is already ongoing.

In this trend, Quantum Distributed Deep Learning (QDDL), which combines the advantages of the two fields, attracts the attention of many researchers. In addition to the benefits of both QDL and DDL, the QDL can strengthen data security from external attacks by utilizing quantum communication security methods between the server and client. As a result, starting with Distributed Secure Quantum Machine Learning (DSQML) [12] attempting to apply quantum machine learning...
Due to the centralized nature of its structure, the existing centralized DL has suffered from problems like high computational overhead and data security issues. To overcome these challenges, DDL algorithms have been built to either utilize the computational power of local devices or increase data security. Distributed training and Federated training are the most

TABLE I: List of Abbreviations

| Abbreviation | Description                      |
|--------------|----------------------------------|
| CNN          | Convolutional Neural Network      |
| DDL          | Distributed Deep Learning        |
| DL           | Deep Learning                    |
| DNN          | Deep Neural Network              |
| DSQML        | Distributed Secure Quantum Machine Learning |
| FL           | Federated Learning               |
| HC           | Heterogeneous Computing           |
| QCNN         | Quantum Convolutional Neural Network |
| QDDL         | Quantum Distributed Deep Learning |
| QDL          | Quantum Deep Learning            |
| QFL          | Quantum Federated Learning       |
| QML          | Quantum Machine Learning         |
| QNN          | Quantum Neural Network           |
| QRL          | Quantum Reinforcement Learning   |
| VQC          | Variational Quantum Circuit      |
| NISQ         | Noisy Intermediate-Scale Quantum |

A. Quantum Deep Learning

QDL is a training method that is expected to solve some of the limitations of classical DL by replacing neural network calculations with quantum computing [18]. Recently, there have been numerous attempts to replace the classical DL architectures such as Deep Neural Network (DNN), Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN) [19]. This paper is intended to introduce some of the previous attempts.

1) Variational Quantum Circuits: A variational quantum circuit (VQC) is a quantum circuit that has parameters that can be optimized through classical DL [20]. Given datasets are encoded to become quantum states expressed by qubits. These quantum states are fed into the VQCs, which simulate classical neural networks. Then, the output quantum states are measured to collapse the probability distribution into a particular quantum state. Lastly, the output quantum states are converted back into data that we can read and process. VQC can be trained and optimized like any other neural network. VQC, despite its limited size, can be more expressive than classical neural networks while carrying out similar numbers of parameters or with similar learning speeds.

To utilize quantum circuits, a quantum encoder is required. Quantum encoders transform classical vectors into quantum states needed as inputs to the quantum circuits. Therefore, quantum encoders play an essential part in the hybrid quantum-classical model because noisy intermediate-scale quantum (NISQ) devices cannot handle large input datasets. Only a limited number of qubits can be used as inputs. Thus, we need highly efficient quantum encoders to express large datasets with few qubits.

2) Quantum Convolutional Neural Networks: Quantum Convolutional Neural Network (QCNN) [21] [22] is the quantum circuit with the convolution layer and pooling layer and works in the following five steps. 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 acts on the transformed qubit state as classical CNN models. Fourth, the qubit is measured and decoded back into its original classical data form. Finally, circuit parameters are updated by a gradient descent-based optimizer. Through this process, QCNN can process image information like conventional CNN.

B. Distributed Deep Learning

This paper investigates various QDDL techniques, analyzes their advantages and disadvantages, and discusses their limitations and challenges. However, compared to the existing distributed deep learning studies, QDDL research, which is still in its initial steps, lacks width and depth. Therefore, this paper broadens these areas of study and promotes the following research. Furthermore, the application areas of quantum distributed learning that has already been implemented or will potentially be discussed with the direction in which future research field should be headed. The list of abbreviations is presented in Table I.
well-known model structures of DDL. Both structures exploit the computational power of clients’ device to send training results in the form of encrypted datasets or model parameters to the central server. By doing so, the computational overhead and data security problems can be mitigated.

1) Distributed Learning: Distributed learning [23], or split learning (SL), is a method that allows users to use large amounts of data and large models without data sharing. It splits the model and provides it to the user and the server, and the user transmits the latent data to the server through data processing at the edge side of the model. The server should not be able to restore original data using latent data, and the system preserves data privacy through this. In distributed learning, multiple devices participate in the computation, reducing the computational burden on the central server, and each user can use the model trained using the data of all learning participants.

2) Federated Learning: Federated learning is largely composed of two parties which are the central node and the client nodes. The central node contains the global model, and the client nodes contain the shared global model and its own small portion of data. The client model trains the shared global data locally using its portion of data. Then, updated parameters are produced as outputs and they are sent to the central node. The central node then performs aggregation to produce a new global model. This new model is shared to the client nodes to replace the old model. The cycle is repeated until an optimal model is received. There are various ways to perform aggregation and one way used in [24] is to take the mean of the parameters received from the client nodes.

C. Quantum Secure Communication

The current classical security protocols are particularly vulnerable to attacks utilizing quantum computing. For example, the Rivest-Shamir-Adleman (RSA) public-key cryptosystem, which uses the inability of classical computers to factorize large numbers in a short time to defend against attacks, can be easily defeated by a quantum computer using Shor’s algorithm [25]. Therefore, post-quantum cryptography [26] is necessary to protect against quantum algorithm attacks. With this in mind, a quantum communication security protocol that utilizes quantum entanglement and superposition is quickly becoming a suitable communication method of defending against such attacks. This paper will introduce two well-known quantum secure communication systems, quantum key distribution (QKD) [27] and quantum secure direct communication (QSDC).

1) Quantum Key Distribution: Quantum key distribution is a secure communication method based on quantum mechanical phenomena instead of mathematical complexity, and functions as a way to generate a random secret key. In BB84 [28], a representative protocol using QKD, the sender and receiver use polarization filters to generate and measure photons, and verifying the signal in the public channel to use it as a quantum secret key. In communication using QKD, the presence of an eavesdropper is not only known to the sender and receiver, but also the eavesdropper cannot intercept accurate information. This security of QKD is based on the characteristic of photons that are non-replicable and collapse when measured. Therefore, QKD has established itself as the most representative quantum cryptography system, and many studies for practical use are being conducted.
Quantum distributed deep learning is a field that combines quantum computing and distributed learning to solve complex machine learning problems in a secure and efficient manner. This approach leverages the unique properties of quantum systems to enhance the performance and security of traditional machine learning models.

![Diagram of Quantum Distributed Deep Learning](image)

**Fig. 3:** The taxonomy of quantum distributed deep learning.

### TABLE II: Taxonomy on QDDL algorithms depending on the types of tasks.

| Method                  | QDL Structure                      | DDL Structure   | SC Protocol                     | Dataset                      |
|-------------------------|------------------------------------|-----------------|---------------------------------|------------------------------|
| Sheng *et al.*, 2017    | Distributed Secure Quantum Machine Learning | Photonic Quantum Computing | Distributed Learning           | Quantum Secure Direct Communication | - |
| Chen *et al.*, 2021     | Federated Quantum Machine Learning | Variational Quantum Circuit | Federated Learning             | Cats vs Dogs CIFAR10 (Planes vs Cars) |
| Li *et al.*, 2021       | Quantum FL with Blind Quantum Computing | Variational Quantum Classifier | Federated Learning           | Universal Blind Quantum Computation | MNIST WDBC |
| Chehimi *et al.*, 2021  | Quantum FL with Quantum Data       | Quantum Convolutional Neural Network | Federated Learning             | -                            | Proposed Quantum Dataset |
| Yang *et al.*, 2021     | Decentralized Quantum Feature Extraction for Speech Recognition | Quantum Convolutional Neural Network | Vertical Federated Learning    | Random Quantum Circuit        | Google Speech Command V1 |

2) **Quantum Secure Direct Communication:** Besides QKD, quantum secure direct communication (QSDC) \[29\], \[30\] is another important branch of quantum cryptography. In QSDC, secret information can be transmitted through a quantum channel directly without sharing a private key. Since QSDC secures security through coding in quantum terminals, it is known that the communication capacity is more efficient than QKD because there is no need to manage quantum keys \[31\]. There are two types of QSDC, a two-step method that transmits photons for two rounds and a one-step method that transmits photons for only one round. The two-step protocol, which is the original method of QSDC, consists of a checking sequence and a message coding sequence. In this scheme, the receiver directly reads out the encoded message after checking the channel security in the checking sequence. On the other hand, the one-step protocol \[32\] that has recently appeared is a method that combines two steps into one using polarization-spatial hyperentanglement. This method is theoretically known to enable absolute security, and has the advantage of enabling long-distance quantum communication compared to existing techniques.

### III. QUANTUM DISTRIBUTED LEARNING ARCHITECTURES

Quantum distributed learning structure combines QDL, DDL, and quantum secure communication explained above. The main factors considered when building a QDL structure are classical distributed learning structure, compatibility between quantum distributed learning structures, and data security reinforcement via quantum communication.

#### A. Quantum Secure Distributed Machine Learning

This paper proposes a secure QML protocol that allows the client to classify two-dimensional vectors to different clusters and resort to a remote small-scale photon quantum computation processor. This protocol ensures that any third-party entities that attempt to interfere with the learning process will be noticed. Fig. 2 shows the illustration of DSQML. In this paper, two models are proposed in total. We will describe the DSQML protocols next.

1) **Client–Server DSQML Protocol:** The first model is composed of the client and the quantum server and the client wishes to perform quantum machine learning. However, the client does not have the required technology to do so. Therefore, the user utilizes a quantum server remotely to complete
the task instead. During this process, the data possessed by the client should not be accessed by any unauthorized entities.

2) **Client–Server–Database DSQML Protocol:** In the second model, the client possesses neither the data nor the quantum technology. The data and VQC are in other servers, and the client has to perform QML remotely. This model was proposed because, in recent years, the size of the dataset has increased significantly, and it has become impossible for individuals to carry all the required data. Therefore, separating the database from the individual is necessary to portray how quantum machine learning is carried out realistically.

3) **Data Security:** The data used for quantum learning is kept safe by ensuring two things. Firstly, if there is data leakage, the attacker will be exposed, and the client will know that there has been unauthorized access to the data. Secondly, the data seized by the attacker has to be useless and prevent the attacker from extracting meaningful information. In this protocol, after the data has been transmitted from the server to the client, a security check is done by the client and the server by measuring the received data. If the data has been hacked, a faked photon will exist in the data, and this will cause the results produced by the client and quantum server to be different. If there has been no hacking, there will be no faked photons, and the results produced by both parties will be identical. Therefore, this ensures that the client will know whether the data has been hacked or not. Next, if the attacker succeeds in seizing sensitive data, they will not be able to use it because it is expressed in Bell state qubits. There is no information encoded in these qubits. The information can only be known if the client measures the data. After the measurement, the data/qubits collapse into the corresponding states.

### B. Federated Quantum Machine Learning

Chen et al. [13] proposes the first QML model in the federation setting. Specifically, they considered the VQC and Quantum Neural Networks (QNN) coupled with classical pre-trained convolutional neural networks. These hybrid quantum-classical classifiers performed federated training through the FedAvg algorithm [34]. This work is the first case that confirmed that quantum distributed deep learning is possible through practical experiments beyond the existing schematic results.

1) **Variational Quantum Federated Learning:** Although the conceptual possibilities of QDDL have already been confirmed in the previous work, there were difficulties in implementing it practically. In particular, while many quantum communication security protocols are based on quantum photonic computing, the implementation of quantum deep learning is mostly based on ion trapping or superconducting quantum gate operations. Therefore, this model selected learning using VQC instead of quantum communication security protocol to simulate the performance of practical quantum federated learning, and used it for binary classification of the CIFAR image dataset.

2) **Hybrid Quantum-Classical Transfer Learning:** The NISQ device is still limited in processing large-sized data due to limitations in its scale and error correction capability. Therefore, to solve this problem, a method of learning a quantum neural network by transferring the learning results of a pre-trained classical neural network in this work was used. This method is accomplished by first transforming image data into small-dimensional data with a classical CNN and then processing it in a quantum circuit. In this case, classical feature extraction was performed using a pre-trained VGG16 [35] model.

### C. QFL through Blind Quantum Computing

This paper aims to introduce a quantum protocol for distributed learning that can utilize the remote quantum servers without exposing the private data of each device. More than the classical computer, the protocol may have exponential speedups and privacy protection. The blind quantum computing scheme [16] is adaptable to classification problems and other universal problems if used.

1) **Blind Quantum Computation:** Blind quantum computation is a method that allows a client to contract a quantum server to do the calculations without revealing any sensitive information. In this protocol, the client is assumed to prepare single random qubits chosen from a finite set and send them to the server. Other than this, the client does not require any quantum computational power. The quantum server with the client’s qubits may not be trusted because it is vulnerable to attacks. Then, a two-way secure communication channel is set up where the client gives single-qubit measurement instructions to the server. After all the instructions are given, the client will receive the desired output, but the server has received none of the sensitive data from the client. If there is only a single client, privacy is perfectly protected, and the client can safely utilize the quantum classifier. However, suppose multiple clients are using the same quantum classifier. In that case, there is a possibility that an attacker can exploit the information about the quantum classifier and its updated information to retrieve sensitive data.

2) **Single Client:** A single-user system can maintain perfect security even while producing satisfactory results. The quantum server is perfectly ignorant about the client’s quantum classifier from the beginning to the end. Therefore, there is no need for additional security measures for a single-user environment.

3) **Multiple Clients:** If multiple clients use this system, many users share the same quantum classifier model. In transmitting parameters like gradients to the quantum server for computation, there is an unavoidable situation where information becomes vulnerable to attacks. If the updated parameters are leaked, they can be used in a gradient attack. In a gradient attack, the leaked information is reverse engineered to calculate the inputs to the system, which unauthorized entities should not access. To counteract this problem, we use differential privacy, which adds Gaussian or Laplacian noise to the information being transmitted. With noise combined with the information, the attacker will not extract the wanted information. However, the data can be retrieved for clients by...
applying appropriate calculations. The quantum noise from the quantum circuits may further interfere with the attempt to seize the information.

4) Gradient Attack: This paper demonstrates how the attacker might attempt to extract the information in multiple client systems to show that differential privacy is needed. The attacker knows the updated parameters being transmitted from the client to the server. The attacker can then use this information to recover the circuit’s input. The attacker measures the distance between the current gradient and the target to get the information. But if there is differential privacy, the attacker’s gradient attack loss function is interrupted because the noise replaces the target gradient. This decreases the accuracy of recovering the input, but the attacker may still get limited information about the input to the system.

IV. CHALLENGES

A. Quantum Compatibility Problem

Unlike deep learning, quantum machine learning is not a stable application used widely yet. It is still limited by quantum noise without quantum correction when the model exceeds a specific size, as mentioned in [37]. This limitation makes it difficult for quantum deep learning researchers to actually confirm its potential, and various attempts are being made to overcome it. A representative method for this is to use a classical network as an auxiliary role for quantum computation, such as classical-quantum hybrid transfer learning in [13]. In addition, it is recognized as a challenge that most quantum secure communication protocols are difficult to implement in NISQ devices. Therefore, it is considered an important challenge to include a complete QDL and quantum security protocol to implement an ideal QDDL on a NISQ device.

B. Data Privacy Problem

Distributed learning primarily handles financial and medical data, which are sensitive. Thus, it is crucial to prevent unauthorized access and prevent the participants of this training process from accessing each other’s data. In [12], the server and the client used a QKD-based quantum communication to exchange information safely. However, the server could still easily identify the client, which means that this method is not suitable for situations where security is of paramount importance. Additionally, in [13], the client and the server did not exchange any data, but no quantum security protocol was also considered. As a result, this model was especially vulnerable to Byzantine attacks. The model from [33] overcame this challenge by employing differential privacy techniques to block any attacks during data transmission from the client to the server. At the same time, it also proposed a protocol preventing the server from identifying which user transmitted the data. Other possible solutions to the data security issue include SL, first introduced in [23]. Distributing a part of the entire training network to the client allows the client and server to exchange latent data and gradients instead of the actual data. As a result, data privacy is protected. This method generally shows faster algorithmic convergence than Federated Learning, and applying this to QNN will ensure efficient training and data privacy.

C. Data Scalability Problem

It is widely known that the problem of the barren plateau occurs in large-scale QNNs [38], which 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. It is known that this phenomenon is affected not only by the size of the quantum circuit, but also by the quantum calculation error rate, the type of gradient descent method, and the ansatz of the quantum circuit. Therefore, the effective design of quantum circuit ansatz to solve these problems is a big challenge facing whole quantum deep learning research field. To this end, research on efficient quantum encoding [39] of classical information or research
on processing more information inside qubits by constructing a quantum circuit as a tensor network [40] has been conducted.

V. POTENTIAL APPLICATION CASES

A. Speech Recognition

Building new automatic speech recognition frameworks with data privacy issues is necessary. With recent advances in quantum technology, the implementation of QML is expected to bring advancements in parameter encryption and isolation. The author of [14] proposes a novel decentralized framework with QCNN in vertical FL by combining a VQC learning paradigm and deep neural networks to cope with this. The proposed automatic speech recognition system consists of two blocks deployed between local and NISQ servers. The input speech collected from the local users is uploaded to the server and through Mel-spectrogram used for training the system. Then a random circuit is deployed to generate random features from each local QCNN model. The experiment was conducted on Google Speech Command-V1, and Mel-scale spectrogram features are extracted from input speech using the Librosa library [41]. A deep attention RNN model benchmark is used as a baseline setting. The experimental results showed that better performance was achieved from the proposed model when the kernel size of 4 qubits was employed.

B. Medical Data Classification

Analyzing and processing personal medical data is one of the most well-known distributed machine learning method applications. Research about analyzing medical data using classical Distributed Learning techniques such as [42]–[44] have already been thoroughly carried out, and research about using VQC to classify medical data, [45], in the quantum artificial intelligence field is ongoing as well. Considering the outstanding performance in data security and calculation efficiency of QDL, the medical industry must combine these researches and apply QDL in the medical field.

C. Autonomous Mobility

The vast amount of data is occurs from mobility platforms (e.g., autonomous driving or advanced aerial mobility) such as visual data (e.g., image, point cloud, scene graph), communication (e.g., wireless communication, quantum communication), and the positional data (e.g., IMU data, GPS data, SLAM). To achieve automated mobility, *cognition, communication, and control* (C3) should be guaranteed. We present the potential study direction of C3 next.

1) Cognition: For an autonomous mobility platform, a machine should be cognitive to collected data. QCNN has shown successful operation in the image classification task, where the image size is small (e.g., MNIST, FashionMNIST, CIFAR10) [46]. The basis of cognition around circumstances is object detection. Even the author of [47] has suggested object detection using QAOA, the object detection of QDL version is not discussed yet. The VQC-based object detection is an expected topic and it enables QDDL.

2) Communication: Building a low-latency secure communication network is essential in creating an autonomous mobile platform. Quantum communication is expected to play a vital role in making such future networks, and research on terrestrial [48], drone [49], [50] and satellite-based [51] quantum networks has been extensively conducted. Current satellite-drone-terrestrial integrated quantum network research uses a method of transmitting encrypted quantum information using a QKD-based security protocol [52]. Combining such an integrated quantum network and QDDL technology is expected to play a decisive role in autonomous mobile-based distributed learning.

3) Control: Quantum reinforcement learning (QRL) has been actively studied. [53], [54] have proposed the hybrid computing methods, i.e., the controller policy is based on VQC, and the evaluator-side network (i.e., critic) is based on a classical neural network. In addition, [55], [56] have proposed an utterly quantum version of the reinforcement learning regime. Since there are many simulation APIs, e.g., Airsim [57] for aerial mobility CARLA [58] for autonomous driving, the implementation of QRL is expected technology soon. In addition, based on the studies mentioned above, quantum multi-agent distributed reinforcement learning, where the basis is QDDL, is an expected key solution for autonomous mobility platforms.

VI. CONCLUSION

In this work, we first introduced the QDDL studies and their substructures. We also discussed the pros and cons of these studies from multiple perspectives, with a particular focus on data security. We also explored the fields of applications for the research domain and the possibilities of new methodologies. We believe this contribution will definitely help conduct future quantum distributed AI research.

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REFERENCES

[1] J. Koo, J. Yi, J. Kim, M. A. Hoque, and S. Choi, “Seamless dynamic adaptive streaming in LTE/Wi-Fi integrated network under smartphone resource constraints,” IEEE Transactions on Mobile Computing, vol. 18, no. 7, pp. 1647–1660, July 2019.
[2] W. J. Yun, D. Kwon, M. Choi, J. Kim, G. Caire, and A. F. Molisch, “Quality-aware deep reinforcement learning for streaming in infrastructure-assisted connected vehicles,” IEEE Transactions on Vehicular Technology, vol. 71, no. 2, pp. 2002–2017, February 2022.
[3] M. Choi, W. J. Yun, and J. Kim, “Delay-sensitive and power-efficient quality control of dynamic video streaming using adaptive super-resolution,” CoRR, vol. abs/2110.05783, October 2021.
[4] J. Park, S. Samarakoon, A. Elgabli, J. Kim, M. Bennis, S.-L. Kim, and M. Debbah, “Communication-efficient and distributed learning over wireless networks: Principles and applications,” Proceedings of the IEEE, vol. 109, no. 5, pp. 796–819, May 2021.
[5] J. Yi, S. Kim, J. Kim, and S. Choi, “Supremo: Cloud-assisted low-latency super-resolution in mobile devices,” IEEE Transactions on Mobile Computing, pp. 1–1, 2021.
[50] H.-Y. Liu and S.-N. Zhu, “Optical-relayed entanglement distribution using drones as mobile nodes,” Physical Review Letters, vol. 126, no. 2, p. 020503, January 2021.

[51] J. Yin, Y. Cao, Y.-H. Li, S.-K. Liao, L. Zhang, J.-G. Ren, W.-Q. Cai, W.-Y. Liu, B. Li, H. Dai et al., “Satellite-based entanglement distribution over 1200 kilometers,” Science, vol. 356, no. 6343, pp. 1140–1144, June 2017.

[52] A. D. Hill, J. Chapman, K. Herndon, C. Chopp, D. J. Gauthier, and P. Kwiat, “Drone-based quantum key distribution,” Urbana, vol. 51, pp. 61 801–63 003, May 2017.

[53] S. Y.-C. Chen, C.-H. H. Yang, J. Qi, P.-Y. Chen, X. Ma, and H.-S. Goan, “Variational quantum circuits for deep reinforcement learning,” IEEE Access, vol. 8, pp. 141 007–141 024, July 2020.

[54] Y. Kwak, W. J. Yun, S. Jung, J.-K. Kim, and J. Kim, “Introduction to quantum reinforcement learning: Theory and pennylane-based implementation,” in Proc. of the International Conference on Information and Communication Technology Convergence (ICTC). Jeju Island, South Korea: IEEE, October 2021, pp. 416–420.

[55] O. Lockwood and M. Si, “Reinforcement learning with quantum variational circuit,” in Proc. of the AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment, vol. 16, no. 1, Virtual, October 2020, pp. 245–251.

[56] S. Jerbi, L. M. Trenkwalder, H. P. Nautrup, H. J. Briegel, and V. Dunjko, “Quantum enhancements for deep reinforcement learning in large spaces,” PRX Quantum, vol. 2, no. 1, p. 010328, February 2021.

[57] S. Shah, D. Dey, C. Lovett, and A. Kapoor, “Airsim: High-fidelity visual and physical simulation for autonomous vehicles,” CoRR, vol. abs/1711.03938, November 2017.

[58] A. Dosovitskiy, G. Ros, F. Codevilla, A. M. López, and V. Koltun, “CARLA: an open urban driving simulator,” CoRR, vol. abs/1705.05065, 2017.