Wireless Sensing in Artificial Intelligence of Things: A General Quantum Machine Learning Framework

Peng Liao, Xuyu Wang, Yingxin Shan, Lingling An, and Shiwen Mao

Abstract

With the emergence of the 5G and beyond, wireless networks have transformed from a simple communication medium to ubiquitous versatile platforms. This trend has enabled numerous device-free and non-contact applications. As computing power and machine learning algorithms continue to improve, deep learning techniques are increasingly used in wireless sensing applications. However, the limits of deep learning-centered wireless sensing approaches are still being explored. Concurrently, research in quantum computing is advancing rapidly, prompting researchers to explore the burgeoning field of quantum machine learning, which combines quantum computing and machine learning, for its boundless potential. In this article, we propose a general quantum machine learning framework for wireless sensing applications in the Artificial Internet of Things (AIoT). The proposed framework provides a systematic approach for designing deeply interpreted wireless sensing models based on quantum machine learning. We then present several representative applications and case studies, and conclude this article with a discussion of the challenges and future research directions in this exciting area.

Introduction

With the rapid development of wireless communication, numerous edge devices can now be connected to the Internet of Things (IoT) with their intelligent wireless sensing modules, which opens up the era of Artificial Intelligence of Things (AIoT) [1]. Wireless sensing plays a vital role in AIoT, and has thus received significant attention recently. Unlike traditional device-based sensing, wireless sensing is contactless, pervasive, low-cost, and non-invasive, making it highly suited for many IoT applications. While being reflected, blocked, and scattered by objects such as walls, furniture, vehicles, and human bodies, wireless signals are essentially sampling the surrounding environment. Useful information can be extracted from the received wireless signals, such as Received Signal Strength Indication (RSSI), Channel State Information (CSI), and Range-Doppler Matrix (RDM). By processing such information with machine/deep learning techniques [2], [3], target events in the environment can be sensed, such as human activity recognition, indoor localization, and vital sign monitoring. Moreover, all of these applications can be realized through a pervasive wireless infrastructure without the need for dedicated sensors.

Machine learning, specifically deep learning, provides a data-driven approach that has been widely utilized for developing wireless sensing applications [4]. This approach allows the extraction of relevant features without explicitly modeling the underlying physical processes, thus eliminating the need for manual model tuning. Despite its undeniable effectiveness, it is important to note certain phenomena that arise during the development process, such as the increasing number of parameters in deep learning models, the growing volume of wireless datasets for pre-training, and the connection of more edge devices with limited computing power to the AIoT. Hence, lightening and generalizing these intelligent sensing models are core areas of future AIoT research. On the other hand, traditional computers are approaching their limits, which promotes researchers to explore quantum technologies and quantum computers. Unlike classical computers, quantum computers use quantum bits as the basic unit and are not bounded by the laws of classical physics, enabling parallel and simultaneous processing of multiple inputs. Therefore, quantum machine learning, which combines quantum computing and machine learning, is a promising and emerging field with tremendous potential [5].

Quantum machine learning [5], [6] has stronger expressive power and higher computational power than classical machine learning, with great potential to overcome the limits of classical machine learning. First, counter-intuitive patterns in quantum systems help obtain statistical features that classical systems cannot effectively produce. This means that quantum systems can recognize patterns that are difficult for classical systems to recognize. Additionally, a quantum computer with 30 quantum bits has a comparable computational power to a classical computer with trillions of floating-point operations per second.

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Thus quantum machine learning is able to process large datasets to learn complex and subtle patterns. Although the deployment of quantum machine learning techniques in wireless networks is still at its infancy stage, some recent works have attempted to address common problems in the field, such as a proposed quantum fingerprint-based localization algorithm by Shokry and Youssef [7] or applying reverse quantum annealing to 5G wireless networks to alleviate explosive growth of wireless network traffic [8]. Despite these promising advances, a systematic framework of quantum machine learning in wireless sensing is still missing, which is a crucial link for quantum machine learning based wireless sensing.

In this article, we present a quantum machine learning framework for wireless sensing in the AIoT, along with several experimental case studies, and a discussion of challenges and future directions. We first present the general system architecture, followed by a discussion of various wireless sensing technologies, such as WiFi, millimeter-wave radar, radio frequency identification (RFID), and acoustics. Second, three representative quantum machine learning algorithms are introduced. These algorithms will be applied in the several case studies for two typical wireless sensing applications (i.e., activity recognition and gesture recognition). We then discuss the challenges and future research directions for wireless sensing based on quantum machine learning. These include the design of classical quantum hybrid structures, lightweight quantum circuits, and quantum entanglement encryption and the related privacy security issues.

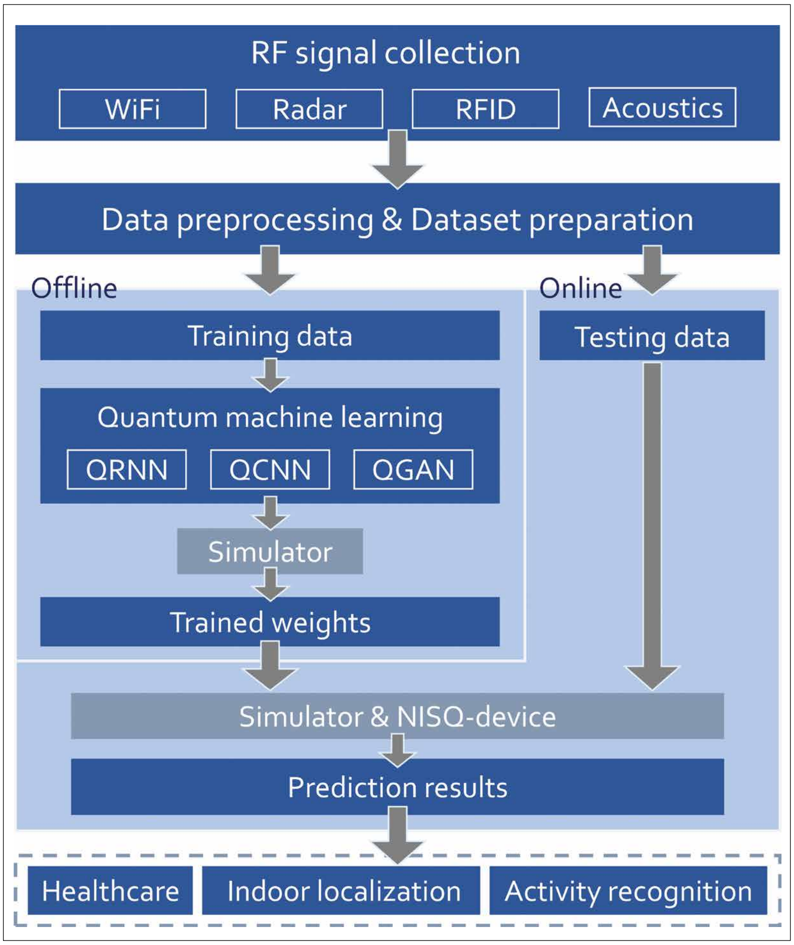

FIGURE 1. A general quantum machine learning framework for wireless sensing.

General Quantum Machine Learning Framework for Wireless Sensing

System Architecture

This section presents the general framework for applying quantum machine learning techniques in wireless sensing applications. Fig. 1 illustrates various types of wireless signals, such as WiFi, RFID, Radar, and acoustics, which can be leveraged to develop various applications (e.g., healthcare, indoor localization, activity recognition). During the sensing process, the presence and movement of an object can alter the reflection of wireless signal, resulting in changes in properties such as amplitude, phase, angle of arrival (AoA), and time of flight (ToF). We can extract such changing patterns of signals and predict target states by employing signal processing or quantum machine learning algorithms. Data pre-processing and dataset preparation are essential steps before conducting analytics. Data pre-processing includes calibration, denoising, and well-designed signal enhancement. For example, in WiFi sensing, calibration usually involves calibrating the phase or phase difference between the two antennas. Denoising aims to remove noise and irrelevant background information from the environment. Filtering and principal component analysis (PCA) are two commonly used denoising methods. Additionally, well-designed signal enhancement techniques are used to solve the sparsity of wireless data for different downstream tasks. High-quality wireless datasets can be obtained through the above pre-processing methods, which are then processed by the quantum machine learning network.

The proposed framework comprises two phases, namely, an offline training phase and an online inference phase. Given the current limitations in the availability of Noisy Intermediate-Scale Quantum (NISQ) resources, the former is commonly carried out using pre-approved quantum circuit simulators, while the latter can be executed on both simulators and actual quantum devices. During the offline training phase, the quantum machine learning model will use the superposition and entanglement states of qubits to encode and extract features from wireless signals more efficiently. For example, *Quantum Convolutional Neural Network* (QCNN) architectures have shown promise in addressing pattern recognition tasks, which can be effective for spectral representation in wireless sensing. It follows the characteristics of CNN that emulate the natural visual perception mechanism, ensuring the ability to effectively process complex data patterns. Furthermore, *Quantum Recurrent Neural Network* (QRNN) models are effective in handling variable-length input sequences, making it highly suitable for processing temporal data from wireless sensors with non-linearities. Additionally, *Quantum Generative Adversarial Network* (QGAN) can be leveraged for addressing issues such as wireless data augmentation. Specifically, QGAN can mitigate the pattern collapse problem by leveraging quantum properties, which is a main challenge in traditional Generative Adversarial Networks (GAN). These models can provide a comprehensive solution to the complex data processing challenges in wireless sensing applications. In the online phase of quantum network testing, the correlation network's output can be utilized as direct prediction results for various applications, including recognition and detection. Additionally, the framework can facilitate transfer learning, i.e., updating the weights with small measurement datasets when the surrounding environment undergoes changes. This enables domain adaptation to new environments.

Wireless Sensing Techniques

WiFi, Radar, RFID, and acoustic signals have gained widespread use in the realm of wireless sensing. Specifically, wireless sensing allows real-time monitoring and data collection of various environmental parameters at low costs. It can also be easily implemented in smart homes, smart cities, and smart healthcare, to enhance convenience and efficiency in people's daily lives and professional endeavors.

1) WiFi: is a wireless local area network technology that employs wireless signals at 2.4GHz or 5GHz to facilitate connection and data transmission between devices. Environmental changes (e.g., a walking person) can be captured by WiFi signals in diverse settings, both indoor and outdoor. WiFi is also useful in detecting the location of individuals or objects, by measuring the signal strength and CSI. WiFi has been playing an crucial role in indoor positioning, intelligent transportation, smart homes, and many other areas.

2) Radar: The Radar technology enables the acquisition, monitoring, and alarming of various status parameters, including distance, speed, and position of target objects. However, radar signals may overlap with the frequency bands used for wireless communications, making potential interference with wireless communication signals. To mitigate such interference effects, band allocation, power control, and antenna orientation control are commonly used. And the application of radar technology extends beyond traditional fields, which include intelligent transportation systems, smart homes, smart offices, military, and security fields. With the continued advancements in wireless sensor networks, the joint design of communications and sensing has become an active research area.

3) RFID: The RFID system comprises two main components, namely a reader and tags. The RFID tags, which are equipped with a dedicated wireless sub-module, can function as wearable sensors for detection of various events, including temperature, humidity, and light intensity, from the object to which they are attached. These tags are capable of communicating with the reader through radio waves, enabling collection of radio data for analysis and control. Significantly, RFID tags possess the advantage of not requiring batteries to power them. This attribute makes RFID tags ideal for certain long-term monitoring applications.

4) Acoustic: Acoustic sensing generally leverages a speaker and a microphone or microphone array to sense or recognize objects in the short-range. For example, acoustic sensing can be used for vital sign monitoring or gesture recognition. In addition, acoustic sensing has been used to detect the moisture content in the surrounding environment, enabling real-time monitoring and control of plants and objects. Although acoustic signals are more susceptible to interference from other sound sources and lack the strong penetration capability of WiFi and RFID, their low power consumption, low cost, high capacity, and high accuracy make them prevalent in many smart home applications.

Quantum Machine Learning Techniques

Quantum computing is an emerging field that combines quantum mechanics with computation theory, which leads to a novel computing model that operates on quantum bits (qubits) of information through the fundamental laws of quantum mechanics. Compared with classical computing models, quantum computing is generally believed to offer superior information processing capabilities. Recently, the integration of quantum computing and artificial intelligence, known as *quantum machine learning*, has gained increasing attention. Researchers aim to leverage the information processing power of quantum computing to advance the development of artificial intelligence, and conversely, to utilize the existing artificial intelligence technologies to overcome the challenges of quantum computing. The application of quantum machine learning to wireless systems is of particular interest, as it is supported by the computational power of quantum hardware and the high potential of quantum computing. In this study, we present a comparison of the architectures of three representative quantum machine learning models, i.e., QRNN, QCNN, and QGAN, as summarized in Table 1.

Researchers aim to leverage the information processing power of quantum computing to advance the development of artificial intelligence, and conversely, to utilize the existing artificial intelligence technologies to overcome the challenges of quantum computing.

	Potential applications	Implementation details	Methodology superiority
QRNN	Natural language processing, speech recognition, time series analysis	Sequential data, internal memory of previous inputs, quantum decoherence	Backpropagation through time, better suited for sequential data
QCNN	Image classification, object detection, video analysis, activity recognition	Quantum convolutional layers, feature extraction. quantum teleportation	Standard backpropagation, normalization, better suited for image data
QGAN	Image synthesis, text-to-image generation, data compression, signal denoising	Generator creates fake data, discriminator distinguishes between real and fake data.	Adversarial loss, quantum state tomography, quantum optimization algorithm

TABLE 1. Features of Three Representative Quantum Machine Learning Techniques.

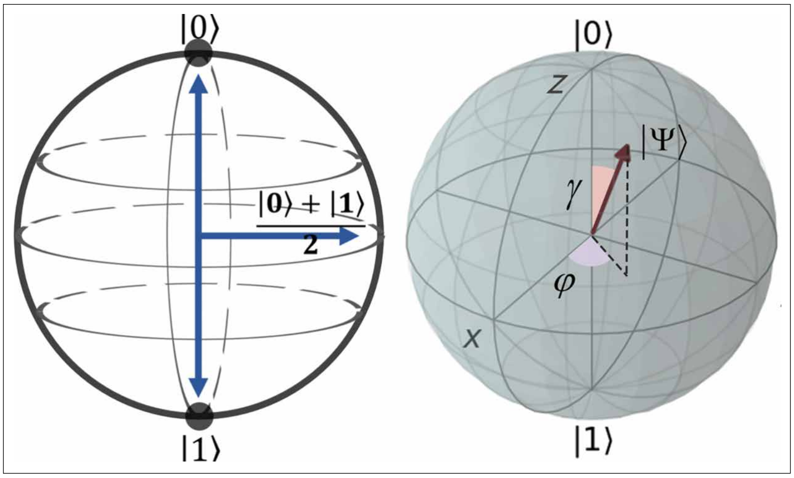

FIGURE 2. Bloch sphere. Left: Superposition illustrated. Right: Visualizing quantum state in the Bloch sphere.

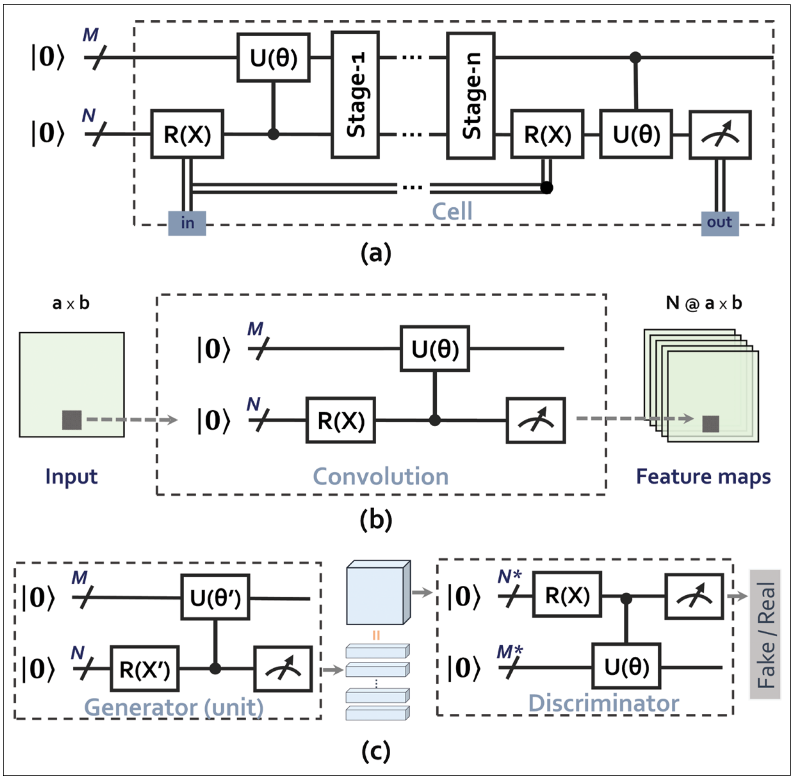

FIGURE 3. Three popular quantum machine learning networks: QRNN (top), QCNN (middle), QGAN (bottom). a) The same QRNN unit is applied repeatedly to input data, reusing qubits for auxiliary data and parameters. b) A novel transformation layer locally alters input data using random quantum circuits, similar to a random convolutional filter. c) The QGAN mechanism samples potential states from a space and feeds them into a quantum generator with multiple sub-generators.

1) Universal Quantum Computing: Classical computers rely on bits to store and manipulate information. A bit can represent either a "1" or a "0," but not both at the same time. In contrast, quantum computing is based on the concept of *qubit,* which can be in a coherent superposition of two states simultaneously due to the principles of quantum mechanics. This idea is illustrated in Fig. 2 (Left). Each quantum state has an associated probability magnitude, and when a qubit is measured, its state collapses to either a $|0\rangle = [1, 0]^T$ or a $|1\rangle = [0, 1]^T$ state based on the probability associated with each state. The collapse probability of a qubit is influenced by quantum interference, which affects the state of the qubit and thus the likelihood of a specific measurement outcome. The probabilistic nature of quantum computing is a key advantage over classical computing.

A general single-qubit state can be represented as their linear combination (data): $|\psi\rangle = \alpha\,|0\rangle + \beta\,|1\rangle = [\alpha, \beta]^T$, where α and β are complex numbers and $|\alpha|^2 + |\beta|^2 = 1$. In the measurement of qubits, $|\alpha|^2$ and $|\beta|^2$ represent the state probability of the qubit being "0" or "1," respectively. There is also another representation of $|\psi\rangle$, i.e., $|\psi\rangle = \cos(\gamma/2)\,|0\rangle + e^{i\varphi}\sin(\gamma/2)\,|1\rangle$, where γ is the angle between $|\psi\rangle$ and the z-axis, and φ is the angle between $|\psi\rangle$ and the x-axis after the projection onto the horizontal plane. The quantum state of a single qubit with (γ, φ) can be mapped into a point on a Bloch sphere [9] with three dimensions. Fig. 2 (Right) shows an visualization example.

In the realm of classical computing, basic logical operations like "NOT," "AND," and "OR," along with other more complex operations, are performed on classical bits. In contrast, quantum computing employs a unique logical operation called a *quantum gate*. Specifically, quantum neural networks can be implemented through the use of parametric quantum circuits built on quantum gates, which can encode variational parameters via the rotation angle of specific quantum gates. This method enables the establishment of a quantum state by adjusting these parameters, which can then be refined on a classical computer to address a given problem.

2) Quantum Recurrent Neural Network: Recurrent Neural Networks (RNNs) have served as the foundation for various sequence-to-sequence models in machine learning, such as machine translation and speech synthesis. As the field of quantum computing continues to advance, QRNN has been proposed as shown in Fig. 3 [10], and its performance has been demonstrated for complex tasks such as learning and classification of sequential data. Consequently, QRNN appears to be a promising solution for analyzing wireless sensing data with long-range dependencies. QRNN units are constructed from parameterized quantum neurons; nonlinear activation of polynomials of their inputs and unit states is employed to extract probability distributions of prediction classes at each step. By iteratively applying the same QRNN unit to the input data, the qubits used for the auxiliary data X and parameters $\boldsymbol{\theta}$ can be reused throughout the process. The design of QRNN guarantees the effectiveness of the gradient-based optimization method in training, requiring $N + M$ qubits where M qubits are used to construct the variational quantum circuit, and N qubits are used to facilitate data uploading.

3) Quantum Convolutional Neural Network: Convolutional neural networks (CNNs) have gained popularity in various machine learning applications, particularly in image recognition, due to their emulation of the natural visual perception mechanism of living creatures. CNN learns and extracts features from data in a layered manner, which has attracted the attention of researchers in wireless sensing. We present a novel transformation layer, QCNN, which locally transforms input data using random quantum circuits, similar to the transformation performed by a random convolutional filter layer. Fig. 3 depicts a complete network stack with a quantum convolutional layer. Unlike classical CNNs that use elementary matrix multiplication, QCNN transforms input data using quantum circuits, which can be structured or random. The QCNN architecture transforms input data into multi-channel output feature maps, which are well-suited for spectral map recognition in wireless sensing. The recent work [11] has demonstrated the higher accuracy and faster convergence of QCNN over CNNs.

4) Quantum Generative Adversarial Network: Generative Adversarial Network (GAN) has garnered significant attention in wireless sensing applications with promising results. GAN's high flexibility and scalability render it suitable for a diverse range of wireless sensing scenarios. For example, GAN can generate synthetic signals similar to real signals, thereby expanding the data set and improving the performance of the model. Furthermore, GAN can acquire signal features through adversarial learning, improving signal recognition and classification accuracy. GAN's potential wireless applications include signal classification, spectrum sensing, localization, and wireless sensing. Recent theoretical advances [12] suggest that QGAN could offer exponential advantages over classical GAN, paving the way for advanced applications in wireless communications, radar systems, and spectrum monitoring.

As shown in Fig. 3, the QGAN scheme comprises a quantum generator and a quantum discriminator. The QGAN mechanism involves sampling potential states X' from the potential space, which is then fed into a quantum generator consisting of multiple sub-generators (units). The generated image X is produced by concatenating the generated states output from the measurement function in each sub-generator. The stitched-generated image and the real image are subsequently fed into the quantum discriminator in turn, trying to distinguish them. Finally, the generator and discriminator's trainable circuit parameters are updated by the optimizer, following the classification results with the relevant objective functions.

Implementation Details

Quantum and conventional learning frameworks differ significantly in the neural nodes and the learnable layers of the network. These differences stem from quantum entanglement, which empowers learning architectures to deeply analyze data and extract features from a novel quantum dimension. Combining more advanced deep learning methods, such as contrastive learning and diffusion models, with quantum technologies presents an appealing vision.

1) Advantages: The unique advantages of integrating quantum networks with machine learning algorithms are as follows: *Privacy Protection*. Quantum communication mechanisms inherently ensure robust security through principles such as quantum no-cloning and quantum key distribution. Mapping wireless data with quantum features enhances security, making it highly resistant to inversion or inference by attackers seeking sensitive information. *Enhanced Computational Efficiency*. While quantum systems are currently more complex and expensive to construct than classical systems, this challenge is a natural phase in the evolution of new technologies. As quantum technology becomes more widespread, the associated overheads will be significantly reduced. Quantum entanglement and distributed quantum processing enable efficient computation, accelerating the convergence of large-scale learning tasks and achieving substantially lower computational overheads compared to classical systems. *Scalability*. Quantum entanglement enables efficient management of interconnected quantum systems, making quantum networks particularly suitable for multi-node learning scenarios. As quantum resources become increasingly accessible, these networks will be applied to a broader range of scenarios, with our work serving as a foundational reference for their continued development.

> Specifically, quantum neural networks can be implemented through the use of parametric quantum circuits built on quantum gates, which can encode variational parameters via the rotation angle of specific quantum gates.

2) Challenges: Realizing this vision begins with the structural design of the model. For example, the convolutional layer in a CNN extracts features using a sliding window, which depends on the sequential storage and processing flow of data in traditional computing architectures. In contrast, quantum computing relies on quantum gate operations to manipulate qubit states. Currently, quantum gates cannot precisely replicate the sliding window functionality of convolutional layers. Next, adjustments to the algorithmic logic must be addressed. Deep learning algorithms frequently use methods like gradient descent for parameter optimization, requiring numerous iterative computations and intermediate result storage. However, the intrinsic nature of quantum computation prevents intermediate states from being measured and reused for gradient computation. Finally, the implementation plan is adjusted to align with hardware constraints. Deep learning model training currently relies heavily on high-performance clusters optimized for floating-point and parallel computing. However, quantum hardware remains at the NISQ stage, lacking stability for long-term and large-scale data processing. Addressing these challenges is essential as deep learning and quantum computing converge, and overcoming them could elevate the field to a new stage of advancement.

3) Solutions: Our proposed framework leverages the principles of quantum mechanics to enhance the efficiency of solving sensing problems. The quantum algorithms integrated into the framework are specifically designed for wireless sensing tasks, rather than relying on off-the-shelf solutions. The key innovations are outlined below: *Quantum Feature Mapping*. Quantum circuits are employed to transform classical data into a high-dimensional quantum Hilbert space, enabling more expressive feature representations. To address the limitation of qubit availability, we propose

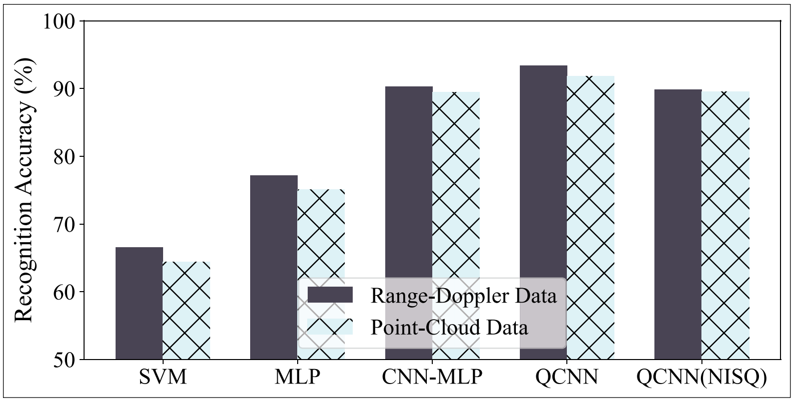

FIGURE 4. Activity recognition performance of quantum convolutional neural networks.

an efficient quantum coding approach. *Hybrid Quantum-Classical Optimization.* The framework combines quantum subroutines with classical optimizers, enabling efficient optimization while mitigating the limitations of quantum hardware. This integration is achieved through operations such as defining optimization objectives based on quantum states, effectively solving the training problem of quantum algorithms. *Task-Specific Quantum Layers.* Unlike generic quantum models, our framework integrates task-specific quantum layers tailored to leverage problem-specific structures. We present various quantum scenarios applicable to advanced deep learning paradigms, providing a foundation for future advancements in the field.

Case Studies and Results

Wireless Sensing Applications

1) Activity Recognition: Activity recognition represents a crucial element in numerous applications of wireless sensing. By exploiting the ability of wireless sensors to capture electromagnetic waves surrounding the human body, valuable information regarding movement and posture can be gathered. The acquired data can be analyzed to facilitate the identification of different human activities, such as walking, running, sitting, or standing. It thus allows for the deployment of motion recognition, fall detection, and health monitoring applications. Researchers have dedicated to exploring various models for feature extraction and classification for these applications. Typically, wireless signals are represented as spectrograms, and the potential of QCNN for feature extraction of spatio-temporal features from wireless signals has been proved, which can subsequently be used for training activity classifiers.

2) Gesture Recognition: In the absence of traditional input methods such as touch screens, gestures offer a promising alternative that allows users to interact with and control machines and devices in a more natural and convenient manner. Wireless sensing-based gesture recognition has emerged as a viable solution, offering several advantages, including high accuracy, resistance to light interference, no requirement for direct contact with the sensor, applicability to objects of various materials, and real-time monitoring. This technology has broad applications in fields such as smart home, intelligent transportation, medical health, entertainment, and others, thereby offering a more convenient and intelligent life experience to users.

Different from activity recognition, gesture recognition imposes fine-grained requirements on the state information of the target, specifically in terms of suppressing the interference of the body torso and capturing the subtle movements of the hand. Furthermore, gesture recognition necessitates high accuracy to ensure that user actions are accurately recognized and executed. In this regard, the greater representational power of quantum neural networks makes them a promising solution to build a gesture recognition classifier for extracting micro-motion features of the target hand.

Experiments and Results

In our subsequent experiments, we employ a commercially available TI millimeter wave radar, augmented with a corresponding data acquisition board and a laptop to implement our proposed system. Through the application of optimized radar configuration parameters, we were able to achieve distance and velocity resolutions of 4.3 cm and 0.14 m/s, respectively. To streamline the signal processing in MATLAB, we developed an automated script in LUA, which can be readily invoked. Our system leverages the Pennylane [13] open-source quantum machine learning software library to construct quantum neural networks. The experimental validation is performed on the NISQ hardware provided by the IBM Quantum Computer Laboratory, which hosts multiple quantum computers. The resulting quantum circuits can be executed on both quantum simulators and real quantum computers.

In this study, we conducted quantum verification (QCNN) for an activity recognition task using the Radar device. This task involves the use of various spectral representations as a pre-processing step of radar data, which includes two-dimensional range-doppler maps and three-dimensional point cloud data. To evaluate the applicability of our approach on classical data of different dimensions, we processed our own collected radar dataset into the aforementioned 2D and 3D data. The data was collected in an office scenario, and we simulated different environments by changing the position of objects in the environment. Specifically, our dataset comprises three distinct environments, two volunteers (one male and one female), and five target activities. To minimize the impact of temperature and humidity, volunteers were performing the activities at different times during the data collection process.

The radar data collected from three different environments are divided into training and test datasets in a 7:3 ratio. The pre-processed data containing activity information serves as the baseline input for several advanced classification models. The performance of activity recognition accuracy is presented in Fig. 4. The classical CNN coupled with Natural Language Processing (NLP) architecture and the QCNN architecture exhibit recognition accuracy rates of 89.87% and 92.63%, respectively. The accuracy deviations of the QCNN circuits trained on the simulator and subsequently loaded onto the real NISQ hardware are 3.59% and 2.88%, respectively.

The findings suggest that the proposed QCNN achieves precise activity recognition on both simulator and quantum device. Additionally, the proposed framework is utilized to perform gesture recognition, using a comprehensive dataset [14] in a large scene comprising five different gestures, namely, left swipe, right swipe, tap, rotation, and some unexpected actions. Out of the 600 samples selected, the detection rates of the five gestures are 91.62%, 91.67%, 92.30%, 90.91%, and 85.59%, respectively, as given in Fig. 5. The results demonstrate that the quantum machine learning-based wireless sensing framework can effectively detect the differences in gestures.

Additionally, we evaluated the training overhead using our self-collected dataset. The input for each model, with a size of 256×128, consists of micro-Doppler features obtained through our classical data preprocessing module. We ran the three classical machine learning methods on an NVIDIA GeForce GTX 1660 SUPER and trained the latter two QML methods on IBM's quantum simulator, testing them on both a quantum computer and a classical computer. For the classical training, CNN-MLP requires 12 million parameters. In the hybrid quantum-classical architecture of QCNN, the number of model parameters can be reduced to less than a million using only four qubits. In terms of training time, quantum computing does not yet show clear advantages over classical approaches, as the IBM quantum simulator we used only simulates the quantum circuit and does not possess the computational power of a true quantum computer.

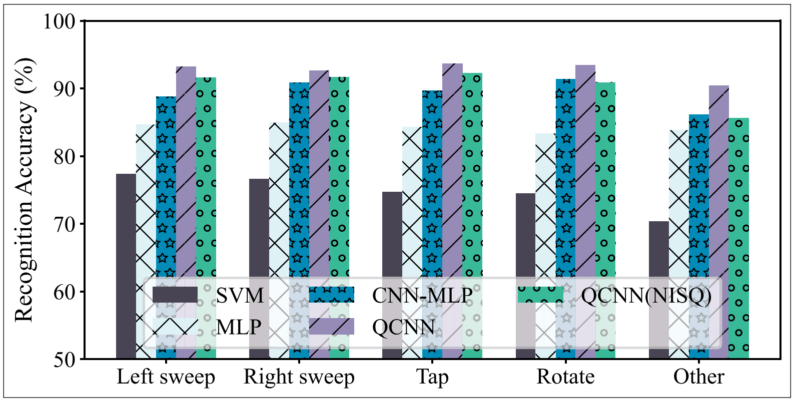

FIGURE 5. Gesture recognition performance of quantum convolutional neural networks.

Future Directions

Design of Hybrid Quantum-Classical Structures

Deep learning faces a fundamental challenge of requiring a substantial amount of training data to learn the underlying features. However, labeling a large volume of wireless data incurs significant efforts and costs. To overcome this issue, future research should focus on efficiently utilizing all the existing data, such as unlabeled data in the same domain or same-labeled data in different domains [15]. Classical deep learning methods, e.g., semi-supervised, self-supervised, and few-shot learning, have proven to be effective solutions to this challenge. The powerful characterization capability of quantum circuits to accomplish the target task using less data motivates the exploration of a framework, which combines classical machine learning and quantum machine learning, known as hybrid quantum-classical architecture.

Designing this framework presents a significant challenge in combining classical and quantum computing to achieve more efficient computation and superior performance. This requires a deep understanding of the unique properties of quantum computing. Current related work primarily focuses on modeling quantum layers in hybrid structures as classical layers, which is suitable for the current era of quantum scarcity but ignores potential error and noise issues in real quantum hardware. Thus this approach may not be favored in the future quantum era. In this article, we present a complete quantum computing-based wireless sensing framework that can be implemented in real quantum computers. However, the exploitation of the advantages of classical computing is absent. Therefore, subsequent work shall focus on making a breakthrough in the design of hybrid structures to fully realize their potential.

Quantum Circuit Lightweighting

Due to the limited hardware resources of current quantum computers, quantum circuit lightweighting techniques have emerged as a means to reduce resource requirements. Nonetheless, precise control and calibration of the quantum gates in the circuit are necessary, and lightweighting may compromise the achievability of quantum gates. Furthermore, with the rise of the Internet of Everything, basic devices with insufficient computing power are increasingly being utilized as access nodes in the AIoT. Consequently, even in the future when universal quantum resources are available, the quantum computing power deployed on such devices must be restricted, and lightweight quantum circuits remain a focus and challenge of future research on quantum machine learning. In this article, we propose a generic quantum architecture that adjusts the circuit structure automatically based on the input data characteristics, thereby minimizing the number of unnecessary gates. We have successfully validated the architecture in Radar-based wireless sensing applications and plan to extend this system to different types of wireless sensors (e.g., RFID, LoRa, WiFi, acoustic) to validate the performance of the quantum system further and provide targeted lightweighting solutions for various sensing tasks.

Quantum Entanglement Encryption and Privacy/Security Issues

Untraceable wireless sensing systems offer a non-intrusive and non-obtrusive approach to sensing in real-world applications. However, these systems also present several concerns related to privacy and security. Specifically, the various applications of sensing daily activities, vital signs, human postures can be vulnerable to information leakage and unauthorized access by malicious individuals, leading to harm to the victims. These issues require urgent attention and effective solutions to ensure safe and secure deployment of wireless sensing systems.

The proposed general architecture was first presented, followed by an overview of existing wireless sensing techniques and quantum machine learning algorithms.

Quantum entanglement is a fundamental aspect of quantum information theory and quantum technology. It arises when two particles are created with identical quantum states at the same time and location. Consequently, measuring one particle instantaneously determines the properties of the other particle without any exchange of information. Quantum entanglement encryption and privacy security is a crucial field of quantum cryptography that employs quantum states as information carrier. This approach enables secure transmission and protection of information, with benefits such as unbreakability and unforgeability. Any attempt to intercept the communication will alter the quantum state of the particle, which will be detected by both parties in a timely manner. Furthermore, the properties of entanglement are ideal for multimodal sensing systems in AIoT applications. For instance, existing systems often cater to a specific sensor, and cannot be generalized to other heterogeneous sensor modalities. Therefore, research on quantum entanglement can significantly advance the development of AIoT security in the future.

Conclusion

This article presented a general quantum machine learning framework for wireless sensing in the AIoT. The proposed general architecture was first presented, followed by an overview of existing wireless sensing techniques and quantum machine learning algorithms. We also reviewed canonical wireless sensing applications and presented two experimental studies that utilize the proposed framework. The article was concluded with a discussion of the challenges and open problems that emerge in this field.

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