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Investigating a Quantum Cloud Paradigm with Quantum Neural Networks

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***Abstract*—In this work, we examine the interactions between an embedded processing board and cloud server performing quantum computing simulations. We examined the trade-offs in performance and complexity between using classical neural networks and quantum-hybrid neural networks on the cloud server. More specifically, we propose the use of quantum hybrid neural network (QNN) for the classification of spoken commands on live audio data acquired at the networks edge. For this application, a compact embedded processor board handles simple operations like data acquisition and pre-processing while a quantum cloud server is used to perform quantum computing simulations. This experimental setup is well suited for quantum computing as it is not feasible to embed a quantum processor at the edge, but practical to interface embedded processor boards to a quantum cloud server for processing massive audio data for a variety of recognition tasks. We found that distributing the task between the embedded processor and quantum sever enabled the application of QNN's to live audio data at the expense of system response time.**

***Index Terms*—Quantum machine learning, voice recognition, quantum neural network, edge computing, quantum cloud.**

I. Introduction

Current investment in quantum computing technologies has led to the rapid development of various quantum systems including, quantum sensors, communication systems, and computers. Currently, these systems are being developed and tested independently with a greater vision of creating things like quantum networks and a quantum internet [6]. Due to the current limitations of quantum technologies, creating a fully realized quantum network using processors, links, and sensors is still on the horizon.

The current generation of quantum processors are known as noisy intermediate-scale quantum (NISQ) devices. These devices have sub-optimal error correction which makes them unreliable for high precision applications [9]. Access to these devices is also incredibly limited and expensive. An alternative to using physical hardware is using a quantum simulation library such as IBM's Qiskit [1], or Xanadu's Pennylane [3]. These tools enable the design and simulation of quantum circuits and provide capabilities to validate software and simulation results. These simulators also provide noise models that allow one to assess the potential effects of quantum errors in NISQ devices [5].

Many consumer smart devices now contain relatively powerful processors and embedded sensors that produce a high volume of data at the *edge* of a network [10]. Edge computing takes advantage of the processors on such devices for important pre-processing tasks at the edge thereby improving response time, bandwidth, and power consumption [11]. Decentralized computing paradigms are well suited to machine learning and AI tasks that require varying levels of computational complexity. Simple machine learning models can be performed on an edge device while more intensive tasks like deep learning can be offloaded to the cloud. Fig 1 shows a block diagram of the edge computing paradigm.

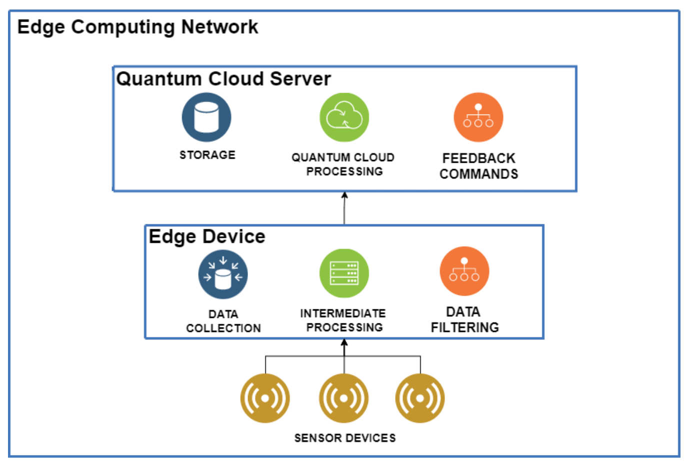

Fig. 1. EDGE-Quantum Cloud Block Diagram with Server, Edge Device, and Sensors.

This paper provides a feasibility study of an edge-quantum-cloud system. At this point, we cannot simulate every component of a distributed quantum network, so we have designed an experimental platform to assess a simple problem using quantum AI. This study was designed to inform us of the challenges and possibilities of connecting real time natural data collection using an edge computer with a quantum computing system. This work does not offer a new high quality speech recognition algorithm but instead focuses on a simple example that can be observed in a classical and quantum environment. By comparing to a similar classical system, we can assess how introducing quantum simulation might impact system accuracy, and response time.

II. Experimental Design

A. Proposed Application

To observe and evaluate a quantum simulator in a quantum-edge environment, an audio machine learning application was selected. Spectral features can be extracted from audio signals in the form of spectrograms which can then be classified using various neural networks. Previous work has used this type of spectral feature [7] for the classification of cough audio data to different pathologies using both classical machine learning and QML approaches.

B. Quantum Circuit Design

The noisy nature of NISQ devices makes them impractical to use with fully quantum neural networks (QNN's). Instead we design hybrid QNN's that can leverage quantum properties to augment classical neural networks. This can be achieved by exchanging traditional neural network layers with a corresponding quantum circuit. This work uses one such quantum circuit called a "quanvolutional" layer [8] as a replacement for a convolutional layer at the front of our neural network.

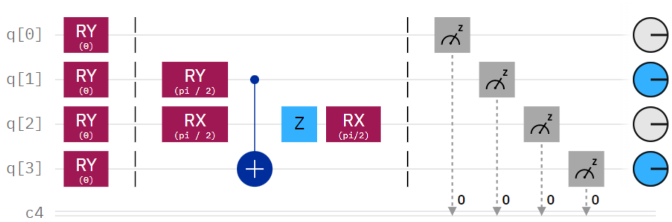

Fig. 2. Pennylane Quanvolutional Layer Quantum Circuit.

Fig. 2 shows the quantum circuit for a *quanvolutional* layer designed using Xanadus quantum simulator Pennylane [3]. In this case, the circuit uses 4 qubits which act as 4 filters through which pixels of an image pass. This circuit allows the user to specify the number of qubits depending on the number of filters desired. Similar applications of hybrid QNN's for audio data have shown increasing the number of qubits in the circuit does not necessarily improve performance [7]. In this application, a 4 qubit circuit was selected to avoid concerns of qubit noise.

The circuit works by phase encoding a 2x2 window of pixels into the 4 qubits. Each qubit corresponds to a single pixel in the window. The four qubits are then passed into a random quantum circuit and subsequently measured into a classical register. Random circuit means that instead of applying a deliberate set of quantum gates we simply exploit the fact that any set of operations produces a unique feature extraction for each qubit. The circuit could also be designed deliberately to search for an optimal feature extractor. Fig. 3 shows an example of spectrograms with the four features extracted by each qubit subsequent rows. This feature extraction was produced using a IBM's quantum simulator qiskit [1].

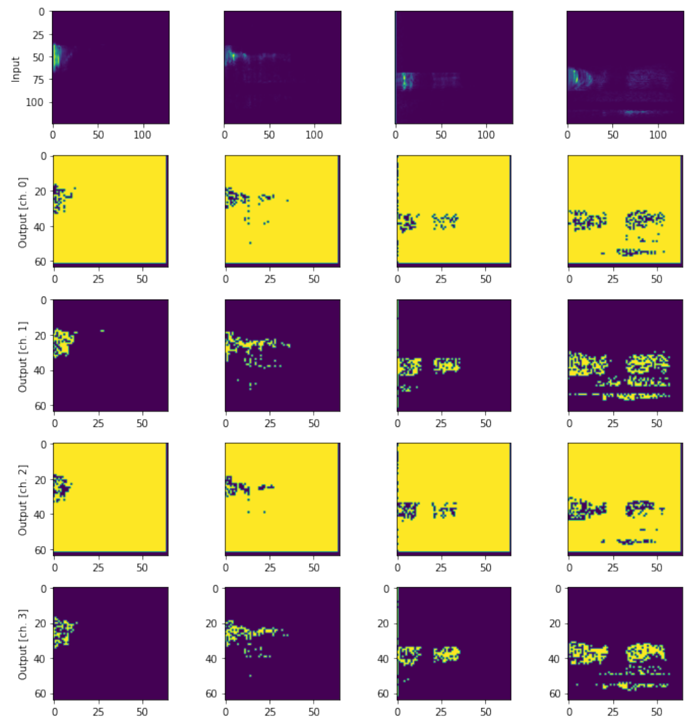

Fig. 3. Spectrograms and Features Extracted by Quanvolutional Circuit.

C. Edge-Quantum Cloud

In our design, we separate the system into a client and server device that communicate over our local WiFi network. The two devices can send data and commands to one another. The client device is our embedded processor at the edge equipped with an external USB microphone. This experimental design allows us to assess how a classical and quantum edge approach differ by observing the same problem using both classical and quantum computing simulations.

To assess how the system performed when communicating between devices, the server waits and listens for spectrogram data from the client. Upon receiving the data the server classifies it using our machine learning models and sends an acknowledgment back to the client. If a specific keyword is detected, in this case the word 'yes', the server responds with a typical acknowledgment and an additional notice that the key word was detected. This basic call and response framework allowed us to observe simple system parameters like response time to assess the feasibility of a quantum cloud system.

D. Classical and Quantum Machine Learning Models

Several machine learning models were trained on the google speech commands data set [13] to classify a set of 8 words. An evenly distributed set of 8000 single second audio files was selected for training and validation data. A split of 80% of the data was used for training and 10% was allocated for both testing and validation. For the training process each 1 second audio file was transformed into a spectrogram using the parameters in table I. Each resulting spectrogram was a

124x129 array where each element can be treated like the pixels of an image.

TABLE I
TABLE OF STFT PARAMETERS

Parameter	*Value*
FFT Size (samples)	256
Frame Step Size (samples)	128
Sample Rate (kHz)	16

Our network performance was compared against an attention recurrent neural network (RNN) that achieved state-of-the-art performance on the command recognition task [2]. Fig. 4 shows the RNN with an optional quanvolutional layer placed at the input. Including the quantum circuit layer makes the network a quantum hybrid neural network (QNN) by training the model on the quantum circuits representation on the input data. The quanvolutional layer is static so it does not update any parameters during the training process. Other QML methods utilize parameters that update during training which are known as variational quantum algorithms. [4] In this case, it is convenient to use an unchanging quantum circuit because it doesn't have to be run each epoch during the training process. Instead we use a quanvolutional circuit as a pre-processing layer a single time on the entire dataset.

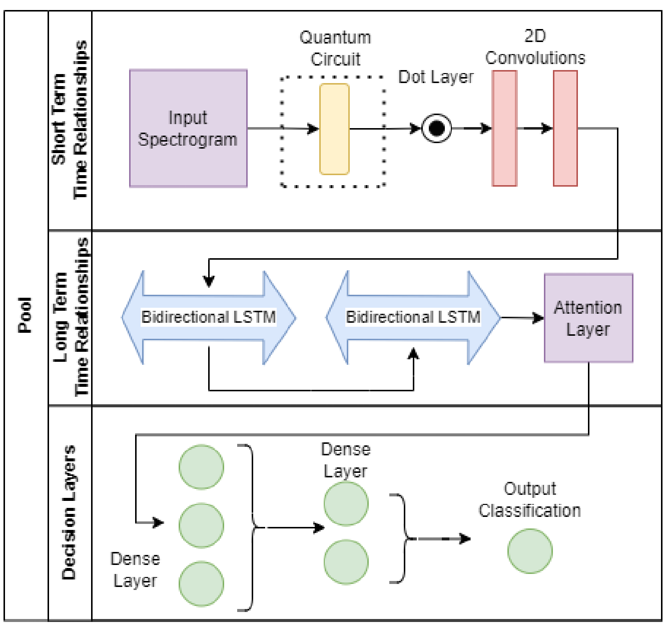

Fig. 4. Diagram of Hybrid QNN Using a Quanvolutional Layer.

E. Hardware

Fig. 5 shows a block diagram of the experimental setup. Audio was captured using the USB microphone at a 16kHz sample rate. A simple voice activity detection (VAD) algorithm [12] was applied to avoid recording and transmitting periods of silence or background noise. The VAD algorithm was a simple energy detector that captured samples above a certain threshold.

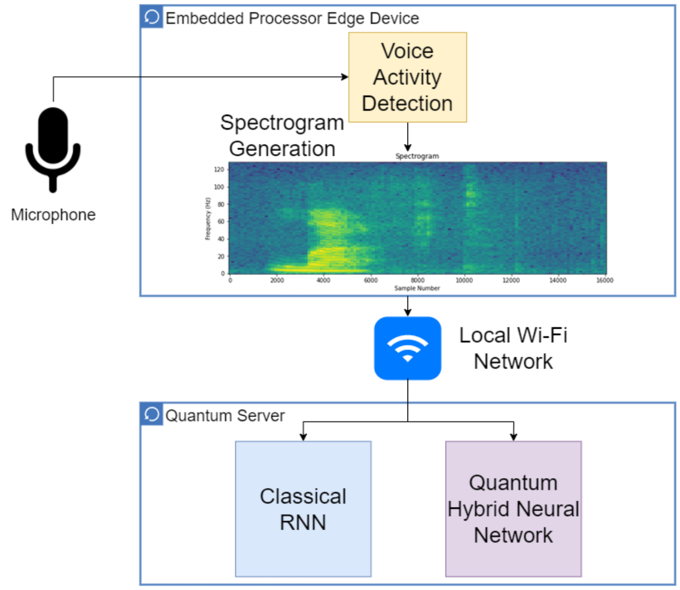

Fig. 5. System Block Diagram Showing Full Process.

F. Audio Features

Audio captured using the VAD algorithm was trimmed or padded to be 1s long and converted to a spectrogram using the short time Fourier transform. After forming a spectrogram on the edge device, it was transmitted over our local WiFi network to the server computer which simulates the quantum circuit. Once the server computer receives a full spectrogram it classifies it using our pre-trained classical RNN and our hybrid QNN design.

III. RESULTS

When observing the quantum edge network in comparison to a classical network several things stood out. Firstly, one challenge in implementing a quantum edge computing network was reduced response times due to quantum circuit simulations. On an Intel i7 processor, using a quanvolutional neural network layer significantly delayed a classification and response from the server. This delay could range from 1-2min whereas a classical system could classify and respond in less than a second. This response time concern could potentially be overcome by using a dedicated quantum device, but no such hardware is currently available. Despite the response time difficulties, the quantum hybrid neural network was able to achieve the same accuracy as the classical one. A simple bit-flip noise model was introduced for the QNN using Pennylanes Qiskit [1] plug-in. This noise model flips the state of a qubit with probability 1% for each logic gate applied. This is meant to more accurately reflect the noise conditions of a real quantum device with a simplified error model.

Table 2 shows the training and validation accuracy of the QNN over 20 epochs and Fig. 6 shows a graph of the training accuracy. The validation accuracy was approximately the same for the classical RNN and hybrid QNN. Introducing the 1% bit flip error reduced the accuracy by about 5%. This demonstrates the quanvolutional circuits efficacy for relevant feature extraction.

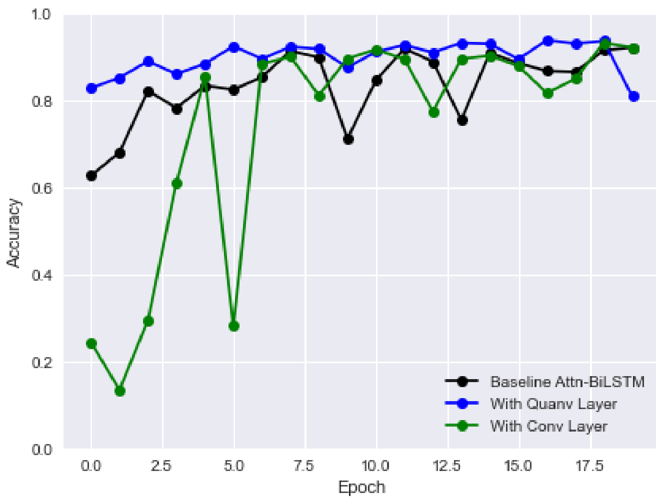

Fig. 6. Plot of Training Accuracy for RNN and QNN.

TABLE II
NEURAL NETWORK ACCURACY AFTER 20 EPOCHS

Network Model	***RNN***	***QNN***	***QNN 1% Bitflip***
Training Accuracy (%)	98.0	98.9	97.6
Validation Accuracy (%)	94.1	94.2	90.5
Training Loss	0.058	0.027	0.068
Validation Loss	0.234	0.254	0.375

IV. CONCLUSIONS

This work has demonstrated the current feasibility of connecting a quantum cloud server device with a remote sensor and edge computer as a building block towards entirely quantum networks. As quantum technology improves classical components can be progressively phased out to avoid switching between the classical and quantum domain. Current limitations in quantum simulation speed drastically reduce the system's response time acting as a bottleneck in the systems capabilities. In future work, this computing paradigm could be tested using real quantum hardware which could mitigate the response time issue but the similarity in model performance suggests that this task should continue to be relegated to classical hardware.

ACKNOWLEDGMENT

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