Exploration of Quantum Neural Architecture by Mixing Quantum Neuron Designs

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Abstract—With the constant increase of the number of quantum bits (qubits) in the actual quantum computers, implementing and accelerating the prevalent deep learning on quantum computers are becoming possible. Along with this trend, there emerge quantum neural architectures based on different designs of quantum neurons. A fundamental question in quantum deep learning arises: what is the best quantum neural architecture? Inspired by the design of neural architectures for classical computing which typically employs multiple types of neurons, this paper makes the very first attempt to mix quantum neuron designs to build quantum neural architectures. We observe that the existing quantum neuron designs may be quite different but complementary, such as neurons from variational quantum circuits (VQC) and QuantumFlow. More specifically, VQC can apply real-valued weights but suffer from being extended to multiple layers, while QuantumFlow can build a multi-layer network efficiently, but is limited to use binary weights. To take their respective advantages, we propose to mix them together and figure out a way to connect them seamlessly without additional costly measurement. We further investigate the design principles to mix quantum neurons, which can provide guidance for quantum neural architecture exploration in the future. Experimental results demonstrate that the identified quantum neural architectures with mixed quantum neurons can achieve 90.62% of accuracy on the MNIST dataset, compared with 52.77% and 69.92% on the VQC and QuantumFlow, respectively.

Index Terms—Quantum Machine Learning, Variational Quantum Circuits, QuantumFlow, Deep Neural Network

I. INTRODUCTION

Neural networks have shown its great power on machine learning applications such as image classification [1], speech recognition [2] and visual question answering [3]. With the growing demand on high accuracy, the size of neural networks consistently grow: from 60 million parameters in the very first image classification task model (i.e., AlexNet [4]) to over 175 billion parameters in the latest speech recognition model (i.e., GPT-3 [5]). The growing model size gradually sets a gap between the requirements/demands and supplies in classical computing. Quantum computing [3–8], on the other hand, is evolving rapidly in recent years: from 5 quantum bits (qubits) back to 2016 to 65 qubits in 2020, and IBM plans to develop a quantum processor with 1,121 qubits in 2023 [9]. In consequence, there emerge recent works on putting neural computation to quantum computing [10–18], and it is expected that neural networks on quantum computers (or quantum neural networks, QNNs) can achieve exponentially speedup, compared with the classical version.

When the neural network comes to quantum computing, a fundamental question arises: what is the best neural architecture for quantum computing and can we directly apply the ones designed for classical computing? Limited by the computation can be performed and the data can be retained by the quantum computer, not all classical neural operations can be directly applied to quantum computing. For example, N qubit can represent $2^N$ data items, but their value is limited by the range from -1 to 1. As a result, directly applying the neural network architecture designed for classical computing cannot work.

In recent years, different quantum neurons (e.g., quantum perceptron, quantum non-linear neurons, variational quantum circuit) are proposed [10–22]. On top of the basic quantum neurons, the architecture of QNN needs to be explored for complicated machine learning tasks. Although the QNNs built with the proposed quantum neurons achieve good results on a small dataset, for example, over 90% accuracy on a subset of MINST (e.g., only 3 and 6 digits), they will perform much worse for a larger dataset (say 52.77% on a full MNIST dataset using VQC). It is, therefore, at most of importance to optimize the neural network architecture for quantum computing.

The experience from the neural architecture design [23–32] on classical computers can shed light on the design of QNN to improve performance. One way in the design of classical NN is to mix the basic neurons in existing networks to explore a better neural architecture, which is typically used in neural architecture search (NAS) [33–43]. For example, the dilated depthwise-separable convolution from ESPNet [27] and depthwise-separable convolution from MobileNets [25] are commonly used in NAS. With the exiting designs of quantum neurons, it seems straightforward to mix them together for QNN architecture exploration; however, new questions and challenges are posed in connecting different quantum neurons: it is unclear (1) whether different quantum neuron designs can be complementary to each other by mixing them, instead of being canceled out by others; (2) whether we can connect any types of quantum neurons, considering that quantum neurons may have different data encoding; and (3) whether we can avoid use measurement operation at the joint point of quantum neurons, since the measurement incurs classical to quantum communication which may easily become a performance bottleneck.

In this paper, we make the very first attempt to investigate the potential of mixing different quantum neurons.
More specifically, we develop the design principles of mixing quantum neurons, which can be applied to a wide range of quantum neuron designs using different data encoding methods. This will be a guidance for the future exploration of quantum neural architectures using different quantum neurons and connecting them seamlessly. Follow the developed design principles, we identify a mixed neural architecture, namely QF-MixNN, which incorporates both VQC [13] and neurons in QuantumFlow [12] such that they can be complementary for each other and no measurement is needed during the execution. To evaluate the proposed QF-MixNN in terms of network performance (e.g., accuracy) and the building cost, we further provide an exploration tool for connecting quantum neurons, namely QF-Mixer.

The contribution of this paper is three-fold as follows.

- We investigate the connection of quantum neurons with different encoding methods and propose the design principles for mixing quantum neurons. It gives the insight and guidance for mixing different quantum neurons.
- We seamlessly connected by VQC-based QNN and neurons in QuantumFlow to construct a new quantum neural network, QF-MixNN, which can outperform the existing QNNs.
- QF-Mixer\(^1\) is developed for designers to easily mix the quantum neuron designs in different ways and evaluate the produced quantum neural architecture during the exploration phase.
- Experimental results show that QF-MixNN can achieve 90.62\% of accuracy on MNIST, compared with 52.77\% and 69.92\% on VQC and QuantumFlow, respectively.

The remainder of the paper is organized as follows. Section II reviews the detailed design of neurons from VQC-based QNN and QuantumFlow and presents the motivation of mixing them for quantum architecture design. Section III provides a detailed description of our proposed quantum neural architecture. Section IV discusses all the possible connection between different neurons and points out the critical principles to follow for the connection. Experimental results are shown in Section V and the concluding remarks are given in Section VI.

II. PRELIMINARY AND MOTIVATION

Neural architecture is constructed based on artificial neurons. To understand what is the best neural architecture, different quantum versions of artificial neuron (a.k.a., quantum neuron) designs were proposed recently. For example, quantum perceptron neurons are proposed by (a) [7], (b) [11], and [12], which can utilize quantum computing to realize the perceptron. Authors in [10], [19] proposed the quantum non-linear neurons based on the boolean functions, so that non-linear function (e.g., ReLU) can be realized. In [12], the authors proposed the quantum normalization neuron to adjust the outputs of quantum neurons. In addition to these implementations having analogue on classical computing, variational quantum circuit (VQC) [13]–[18], [20]–[22] is proposed to be a basic neuron

\(^1\)Accessing at https://github.com/Jqub/QF-Mixer

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Fig. 1. Illustration of QNN and quantum neurons: (a) general framework of a QNN, where \(\theta\) is the adaptable parameters of the QNN; (b) V-NEU with \(2n\) adaptable parameters and \(n\) input qubits, which is reused as \(n\) output qubits; (c) N-NEU for normalization; (d) P-NEU with \(n\) input qubits and a single output qubit; (e) U-NEU with \(n\) input qubits and a single output qubit.
Although the VQC-based QNNs have been widely applied to machine learning tasks \cite{13}, it lacks the universal approximability because quantum gates are intrinsically linear operations, which are difficult to construct non-linear operations within the quantum circuits. Therefore, it could not handle the dataset that is not linearly separable. For example, this kind of QNN could not approximate an XOR operation, whose input is not linearly separable.

Inserting the measurement components between the basic circuit blocks (e.g., VQC in Figure 1(b)) within the VQC-based QNNs is a potential solution to implement the non-linear function (i.e., quadratic function). However, it will bring the communication overhead between the quantum-classical interface during the computation. Such overhead can easily dominate the overall performance, and cancel out the benefit brought by quantum computing further.

An alternative solution to achieve universal approximability is to add extra neural network layers which will be executed on the classical computer. Similar to the previous solution, we cannot avoid the quantum-classical communication overhead. Moreover, this solution will offload part of neural computations to classical computers, which mitigates the advantages brought by quantum computing.

**B. QuantumFlow**

Quantumflow \cite{12} is a co-design framework to optimize quantum neurons and quantum circuits simultaneously, such that quantum advantage can be achieved. In terms of different quantum circuit implementations, two types of quantum neurons were proposed, including P-NEU and U-NEU.

**P-NEU** implements a probabilistic model-based neural computation. For P-NEU, the state-preparation component should encode the original real-valued input data to the quantum states $|\phi_i\rangle (i = 1, 2, ..., n)$ through probability encoding, which is then used as the input for P-NEU. More specifically, each data item will be encoded to the probability of a qubit’s $|1\rangle$ state, which will be illustrated in Section IV. P-NEU embeds the adaptable weights $\theta$ to the input qubits by using X gates (denoted by the dashed box in Figure 1(d)), followed by a circuit to complete the weighted sum operation of inputs through Hadamard gates and Control-X gates as shown in Figure 1(d). The single output qubit $|O\rangle$ will be measured to extract the output data and perform post-process, which corresponds to $M$ in Figure 1(a).

**U-NEU** is based on the input qubits encoded with amplitude encoding (see details in Section IV), which maps an input data item to the amplitude of a basis state (e.g., $|0\rangle$ or $|1\rangle$ for one qubit). As a result, for a quantum computer with $k$ qubits, it can encode $2^k$ input data items. U-NEU encodes the adaptable weights $\theta$ to the input qubits by using $Z$ gate and Control-Z gates (denoted by the dashed box in Figure 1(e)). Next, similar to P-NEU, we apply a circuit to complete the weighted sum operation of inputs through Hadamard gates and Control-X gates and store the output to an ancillary qubit. Last, the output qubit $|O\rangle$ is measured and we perform post-process on the output, which corresponds to $M$ in Figure 1(a).

In addition to P-NEU and U-NEU, QuantumFlow further devises N-NEU for normalization, shown in Figure 1(c).

In the circuit implementations of P-NEU and U-NEU, the multiplication between inputs (i.e., $x_k$ for P-NEU and $u_k$ for U-NEU) and weights (i.e., $w_k$) are realized by maintaining or flipping amplitudes of a quantum state. As a result, adaptable weight $\theta$ has to be binary, which degrades the representation capability of the model compared with real-valued weight.

The networks devised by QuantumFlow (referred as QF-Net) apply the above three neurons, which shows the potential advantage to have different quantum neurons when designing a QNN; however, both neurons have the same limitation on data representation, i.e., binary weights. In this work, we aim to provide a more general framework to incorporate different neuron designs to form a QNN. And we investigate the requirements and overhead in connecting different neurons.

**C. Motivation: VQC and QuantumFlow are complementary**

We observe that VQC-based QNN and QF-Net are complementary to each other, and it is meaningful to mix them in a holistic neural network for better neural model performance.

**VQC-based QNN enhances QF-Nets.** The weights of VQC-based QNN are real numbers while the weights of QF-Net are restricted to binary numbers. It is obvious that real-valued weights have higher representation ability since binary-valued weights are just the special case of the real-number ones. Thus, there exists great potential to improve the model performance (i.e., accuracy for classification tasks) by taking VQC as a complement to QF-Net.

**QF-Nets enhances VQC-based QNN.** VQC-based QNN has difficulties in integrating non-linear function into the quantum circuit without measurement, which may not have universal approximability, resulting in low neural model performance. On the other hand, QF-Nets provide flexibility in realizing quadratic function in-between layers. In consequence, mixing the VQC and QF-Net provide the potential to make the network having universal approximability, and in turn, improve model performance.

**Challenge.** It seems straightforward to mix different quantum neurons to build up a network; however, arbitrary connecting different neuron designs may bring heavy overheads, posing new challenges. More specifically, if measurement operation is inserted at the joint point of quantum neurons, it can become the performance bottleneck and diminish the benefits brought by quantum computing. However, it is unclear whether or not we can avoid use measurement operation in a neural network with mixed quantum neurons.

**III. QF-MIXNN: A QUANTUM NEURAL ARCHITECTURE WITH MIXED QUANTUM NEURONS**

Although connecting different quantum neurons arbitrarily seems feasible when they are implemented on quantum circuits, mixing them without any rules could cause problems that make the built quantum architecture difficult to be used
Goal 1: The entire quantum neural architecture is able to be executed on quantum processor without measurements. In this way, we can avoid the expensive quantum-classical communication overheads.

Goal 2: The same type of neuron should be consistent regardless of the location of the neuron. For example, if a neuron as the first layer applies amplitude encoding to the input data, then this neuron in the other layers, its encoding method for input should still be amplitude encoding. In this way, we can build neural blocks to support QNN.

Goal 3: The quantum architecture could be trained on classical computers correctly and efficiently. Although training DNN on classical computers is expensive and inefficient [46–48], we still have to train QNN on classical computers because the near-term quantum computer (NISQ) has a limited number of qubits and high noise on each qubit, resulting in the QNN training on quantum computers being unstable and not scalable. A straightforward way to achieve the equivalent training on classical computers is to formulate each quantum gate as a unitary matrix. However, since most of layers apply quantum gates that entangle the input qubits, the output qubits of each layer are coupled with the output qubits of all the preceding layers. For example, assume that layer \( i \) has \( p \) output qubits and the number of output qubits from all of the previous layers are summed to \( m \). Then the size of unitary matrix to formulate the quantum gate in layer \( (i+1) \) is \( O(2^{m+p}) \times O(2^{m+p}) \). It is obvious that when the QNN goes deeper, the size of the unitary matrix for the last layer of the QNN will be increased dramatically, which incurs expensive training overhead on memory and computation. Fortunately, the output qubits of layer \( i \) could be regarded as decoupled with the output qubits of previous layers in some cases, which will be illustrated in Section [IV]. If this is the case, then the size of the unitary matrix for the quantum gate in layer \( i+1 \) will be decreased to \( O(2^p) \times O(2^p) \), which is only related to the number of output neurons of the current layer and thus reduces the training overhead by a large margin. Besides, the first and third goals are also naturally achieved if mixture is conducted between the quantum neurons of layer \( i \) which is decoupled with its preceding layers, and the quantum neurons of layer \( i+1 \).

To achieve all of the above goals, we propose QF-MixNN, a novel design mixing VQC (called V-NEU in the following for consistency), U-NEU, P-NEU, and N-NEU together. Figure 2 shows the structure of QF-MixNN: After data preprocessing, an input data with \( N \) data items will be encoded as the corresponding quantum state with \( \log N \) qubits through amplitude encoding. It will be sent to V-Layer, which is implemented by V-NEU. V-Layer could be repeated by \( R_1 \) times, where \( R_1 \geq 1 \). By increasing \( R_1 \), the number of real-valued weights are increased.

Then, \( R_2 \) of U-Layer (\( R_2 \in \{0, 1\} \)) will be added. Note that if \( R_2 = 0 \), we skip U-Layer and connect V-Layer with other layers to add flexibility. The U-Layer will take the output from the previous V-Layer as input, execute the neural computations implemented by U-NEU, and output the quantum state encoded as probability. The next block is made up of N-Layer and P-Layer, where N-Layer and P-Layer consist of multiple N-NEUs and P-NEUs, respectively. Such a block could be repeated by \( R_3 \) times, where \( R_3 \geq 0 \). The quantum states produced by the last layer of QF-MixNN will be measured in the data post-processing stage and the quantum state of each output qubit will be interpreted as the probability of its corresponding class, which is used for classification.

Assume \( N_i \) denotes the number of output qubits of the \( i \)-th layer. If the layer is V-Layer, since V-NEU reuses the input qubits as its output qubits, \( N_i = N_{i-1} = \ldots = N_1 = \log N \). For U-Layer and P-Layer, \( N_i \) equals the number of neurons (i.e., U-NEU and P-NEU, respectively), which is manually defined. For N-Layer, since it always follows either U-Layer or P-Layer, \( N_i \) should be the same as the number of neurons of its previous layer, i.e., \( N_{i-1} \). Note that for the last layer in QF-MixNN, its number of neurons has to be set to the number of classes defined by the classification tasks regardless of the type of its neurons.

**IV. QF-MIXER: DESIGN PRINCIPLES**

QF-Mixer is developed to help designers in exploring different quantum neural architectures. The key component in QF-Mixer is to check whether or not two types of quantum neurons can be connected without violating the design goals presented in Section [III], if yes, what is the cost? The above question is non-trivial, because the neuron designs may apply different data encoding methods. In this section, we will investigate two most commonly used data encoding methods: (1) amplitude encoding, and (2) probability encoding, a.k.a., angle encoding. We will provide 5 design principles to cover all possible situations for mixing quantum neurons applying the above encoding methods.

Before introducing the design principles, we first introduce two data encoding methods. Amplitude encoding (A) is to encode \( N \) data items to \( N \) amplitudes of quantum state composed of \( \log_2 N \) qubits. For example, the given dataset is \[\{a, b, c, d\}\], amplitude encoding will operate 2 qubits \( |q_0q_1\rangle \), such that \( |q_0q_1\rangle = a|00\rangle + b|01\rangle + c|10\rangle + d|11\rangle \). Probability
encoding (P) is to interpret the given data d as a probability and apply a rotation gate (e.g., $R_y$ gate) with an angle $\theta$ on a qubit (say $|\psi\rangle = |0\rangle$), such that the qubit has the probability of d to be state $|1\rangle$, i.e., $R_y|\psi\rangle = \sqrt{1-d^2}|0\rangle + \sqrt{d^2}|1\rangle$. To better study the connection of different neurons, we give the data encoding method for different neuron designs. Note that the input and output may apply different encoding methods.

- U-NEU: Input (A) and Output (P).
- V-NEU: Input (A) and Output (A/P).
- P-NEU: Input (P) and Output (P).
- N-NEU: Input (P) and Output (P).

As we can see from the above list, we need to investigate all possible combinations of data encoding, which helps us to formulate the design principles.

Figure 3 shows all 8 combinations/paths when two different neurons are connected. Specifically, we have two separate graphs since the output of the neurons in the first layer (denoted as QN-1) can be either P or A encoding. For each case, there are two paths in terms of whether or not the output qubits are entangled after the neuron computation in QN-1. Furthermore, the input of neurons in the second layer (denoted as QN-2) has two possible encoding methods. As a result, there are 8 paths in total.

Given two types of neurons, QF-Mixer not only needs to identify the path for these neurons, but also need to tell whether such path is feasible. Here, a path is feasible, if a combination can achieve the design goals mentioned in Section III. In the paper, the paths that are feasible if the node in QN-2 is marked in green, and it is not feasible, if it is in red, and it is conditional feasible for that in orange color.

QF-Mixer figures out 5 design principles, listed as follows.

**Principle 1. (Paths 1-4)** If the output qubits of QN-1 are not entangled, then it is feasible to be directly connected to QN-2 regardless of the encoding method of QN-2’s input.

Without quantum entanglement, the output qubits from QN-1 are decoupled with the output qubits of its previous layers. Therefore, the direct connection between QN-1 and QN-2 is feasible. In the following, we will discuss the situation that the output qubits of QN-1 are entangled.

**Principle 2. (Path 5)** If output qubits of QN-1 are amplitude encoding and entangled, and the input of QN-2 is amplitude encoding, then it is feasible to connect QN-1 and QN-2.

**Principle 3. (Path 6)** If output qubits of QN-1 are amplitude encoding and entangled, and the input of QN-2 is probability encoding and having independent requirement, then it is infeasible to connect QN-1 and QN-2.

The neuron designed using probability encoding commonly assume that the input data are independent, so that the rotation gate can be applied for the angle encoding. According to the third design goal in Section III, QN-2 also has such requirement. However, the output qubits of QN-1 are entangled, which violates such requirement. Thus, we have the above principle. This principle is obvious.

**Principle 4. (Path 7)** If output qubits of QN-1 are probability encoding and entangled, and the input of QN-2 is amplitude encoding, then it is feasible to directly connect QN-1 and QN-2 if the output qubits of QN-1 are the same with its input qubits.

If QN-1 reuses its input qubits and output qubits, the direct connection between QN-1 and QN-2 is feasible. Otherwise, such a connection is infeasible.

The above principle indicates that if QN-1 reuse the qubits for inputs and outputs, we can connect QN-1 and QN-2. This is because in such a situation (like V-NEU), its output qubits could be interpreted as amplitudes directly and thus becomes the case in Principle 2. Otherwise, since the output qubits of QN-1 are entangled with the input qubits, the change of the amplitude of one output qubit will affect the amplitude of another output qubit. As a result, we cannot independently compute two neurons in the inference phase, leading to high computation complexity. This is violate to the second design goal mentioned in Section III.

**Principle 5. (Path 8)** If output qubits of QN-1 are probability encoding and entangled, and the input of QN-2 is also probability encoding, QN-1 and QN-2 can be connected if the design in QN-2 (1) uses outputs of QN-1 as control end without phase kickback, or (2) operate on the outputs of QN-1 rotates around X-axis only (i.e., using RX gate) or the combine of (1) and (2).

Due to the limited space, the detailed proof is omitted here.

As an example, in QF-MixNN, it connects V-NEU and U-NEU (Path 5, Related to Principle 2), U-NEU and N-NEU (Path 8, related to Principle 5), N-NEU and P-NEU (Path 8). V-NEU and P-NEU will also be connected if $R_z = 0$. To make the connection between V-NEU and P-NEU feasible, V-NEU has to encode its output as probability (Path 8). Since the implementation of P-NEU shown in Figure 1(d) does not introduce phase kickback at the end and also not use any rotation gate, the condition of Principle 5 is satisfied. Therefore, all of these connections are feasible, and thus QF-MixNN could achieve the design goals listed in Section III.

V. NUMERICAL EXPERIMENTS

This section reports the related evaluation results of QF-MixNN on MNIST dataset and its different sub-datasets. Results demonstrated that the state-of-the-art VQC and QuantumFlow can only obtain 52.77% and 69.92% accuracy on MNIST dataset, while QF-MixNN can achieve over 20% accuracy gain, reaching 90.62%.


A. Experimental Setting

Dataset. We employ different sub-datasets of MNIST dataset to evaluate the performance of different quantum neural architectures for classifying the handwritten digits. A sub-dataset with $X$ classes is denoted as MNIST-$X$, where $X \in \{2, 3, 4, 5, 10\}$. For MNIST-2, we select digits 3 and 6 for the classification, which is denoted as $\{3, 6\}$. Moreover, $\{0, 3, 6\}$, $\{0, 3, 6, 9\}$, $\{0, 1, 3, 6, 9\}$ are the specific chosen sub-datasets for MNIST-3, MNIST-4, MNIST-5, respectively. MNIST-10 represents the original dataset, abbreviated as MNIST. Before training and inference, images within the dataset should be downsampled to a smaller resolution to reduce the number of input qubits. Specifically, the original image is downsampled from the resolution of $28 \times 28$ to $4 \times 4$, $8 \times 8$, $16 \times 16$ for different datasets, shown in Table I.

Quantum Neural Architectures. For the intermediate layers in quantum neural architecture, we need to specify the number of neurons in U-Layer and P-Layer. In the experiments, we set the value to be 4, 8, 16, 16, and 32 for MNIST-2, MNIST-3, MNIST-4, MNIST-5 and MNIST, respectively.

Baselines. The baseline QNNs contain (1) the QNNs from Quantumflow [12] and (2) a variant of the VQC in [13], whose circuit implementation is shown in Figure 1(b).

B. Evaluation of QF-MixNN

Table I reports the performance comparison among VQC-based QNN, QuantumFlow, and QF-MixNN. In this table, notations V, U, and P represent V-Layer, U-Layer, and P-Layer, respectively. Note that we do not show N-Layer in QF-MixNN explicitly here for simplicity. For each architecture, we tried multiple configurations of N-Layer and report the best results. For VQC-based NN, $V \times R_1$ represents that the same VQC block is repeated by $R_1$ times to construct the entire VQC, as shown in Figure 2. We tried the value of $R_1$ from 1 to 5, and report the best results in Table I.

We have several observations from the results, for MNIST-2 (requiring binary classification) a linear decision boundary might be sufficient for classifying, which explains why VQC-based QNN achieves the best result that is 0.55% higher than the best architecture from QF-MixNN. On MNIST-$\{3,4,5,10\}$ that are more complicated than MNIST-2, the best architecture from QF-MixNN always outperforms VQC-based QNN. More specifically, on MNIST, QF-MixNN can achieve 37.85% higher accuracy over the VQC-based QNNs, which shows that for complicated dataset that is usually not linear separable, increasing the number of linear layers without non-linear function cannot achieve good performance. Therefore, it is important to build a deep QNN with nonlinear function following each linear layer. Besides, the best architecture from QF-MixNN outperforms QF-Net on all the evaluated datasets consistently. It proves that by adding more real-valued weights to QF-Net, the resulted neural architecture can achieve better performance. Therefore, we can conclude that VQC-based QNN and QF-MixNN are complementary to each other. By mixing the neurons from them carefully, QF-MixNN could produce better quantum neural architecture.

C. Sensitivity Analysis of Number of V-Layer

We conduct sensitivity analysis on MNIST-4 and MNIST-5 to explore the impact of the number of V-Layer ($R$) on the performance of QF-MixNN-1 (i.e., $V \times R + U$) and QF-MixNN-2 (i.e., $V \times R + U + P$). Figures 4(a)-b) show the results of QF-MixNN-1 and QF-MixNN-2, respectively. As we can see in Figure 4 when $R$ increases, the accuracy of the model has a trend to improve.

An interesting observation is obtained for QF-MixNN-2 on MNIST-4. Along with the increase of $R$, the accuracy starts to drop when $R$ is greater than 3. Since we use the same training setting for different value of $R$ for fair comparison, this result might indicate that for QNN with more layers like QF-MixNN-2, we should pay more attention to tune the training parameters if we want to obtain accuracy gain by increasing the number of V-Layers. But even for QF-MixNN-2 on MNIST-4, we can achieve 2.19% accuracy gain when $R$ increases from 1 to 3.

In summary, we can conclude that the performance of the neural architectures from QF-MixNN could be further improved if we increase its total number of real-valued weights by adding more V-Layers.

VI. CONCLUSION

In this paper, we propose to mix different quantum neuron designs to explore a better quantum neural architecture. A set of general principles to mix different quantum neurons are developed, which can be as a foundation for the future research on quantum neuron mixture. Based on these design principles, we mix the quantum neurons from VQC-based QNN and QuantumFlow, and identify the QF-MixNN to take advantage of both design. As a result, the newly explored QF-MixNN can achieve 90.62% of accuracy on MNIST, which outperforms the neural architectures without our method of mixture by a large margin.

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