# Performance Evaluation of Hybrid Quantum-Classical Neural Networks

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***Abstract*—Quantum machine learning provides an essential paradigm in developing next-generation intelligent systems. Classical neural networks can leverage quantum computational power to enhance their performance. However, such hybrid architectures require detailed benchmarking to be implementable in noisy intermediate-scale quantum devices. In this regard, we provide a comparative study for two different quantum circuit variations to determine the best quantum circuit design for binary classification.**

## I. Introduction

Superposition and entanglement are unique features of quantum systems that have been used for the development of quantum computing, quantum metrology, and quantum communication [1], [2]. Advances in quantum computing hardware have created the need for developing quantum algorithms to solve classically intractable problems for the noisy intermediate-scale quantum (NISQ) era [3]. Quantum machine learning (QML) utilizes quantum computation to provide a quantum speed-up in learning tasks as compared to classical machine learning techniques. However, most of these techniques require significant quantum circuit depth, which remains a big challenge on the hardware side [4]. One way to counter this problem is to create hybrid quantum-classical neural networks (HQCNNs).

The idea behind HQCNN is to use a classical neural network layer that optimizes a parameter value and feeds it into the quantum layer comprised of a parameterized quantum circuit. The quantum state created in the circuit is controlled by rotation operators that act on the qubits and rotate them around the $x$, $y$, and $z$ axis of the Bloch sphere, respectively. The measurement result of the qubits determines the predicted class of the input.

This paper analyzes the performance of the HQCNN for a binary classification problem. We compare the performance of quantum layers composed of two different types of quantum circuits on the MNIST data set to classify images labeled "0" and "1". One circuit is a resource-efficient circuit labeled as Type-1 and another that employs additional gate operations, Type-2. We evaluate the training convergence of HQCNN created using either one of the circuits and plot the result.

## II. Hybrid quantum-classical neural networks

We use our HQCNN for binary classification of image data of two types of digits, "0" and "1". Its structure consists of two parts; the classical layer is made up of a convolutional neural network (CNN) with two fully connected layers at the end, and the quantum layer consists of a parameterized quantum circuit. As the quantum circuit takes in one input, we condense the output of the classical layer to a single value, $\theta$. The output of the quantum circuit defines the label assigned to the input data, which is the final measurement result.

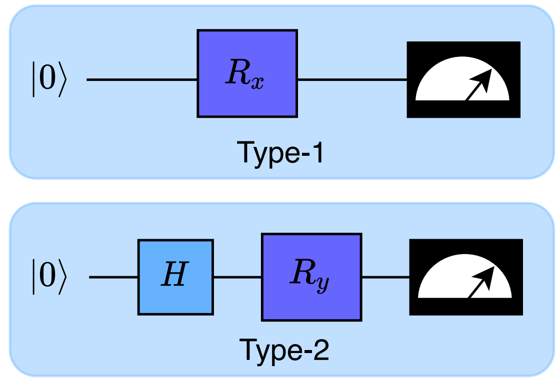


Fig. 1. Type-1 and Type-2 quantum layers. Type-1 rotates the input by $\theta$ around the $x$-axis. Type-2 circuit requires a Hadamard transformation of the input before rotating it around the $y$-axis by $\theta$.

### A. Quantum Layer

The parameterized quantum circuit can be controlled by one of the following unitaries that serve as rotation operators

$$R_x(\theta) = \begin{bmatrix} \cos(\theta/2) & -i\sin(\theta/2) \\ -i\sin(\theta/2) & \cos(\theta/2) \end{bmatrix},$$

$$R_y(\theta) = \begin{bmatrix} \cos(\theta/2) & -\sin(\theta/2) \\ \sin(\theta/2) & \cos(\theta/2) \end{bmatrix},$$

and

$$R_z(\theta) = \begin{bmatrix} e^{i\theta/2} & 0 \\ 0 & e^{-i\theta/2} \end{bmatrix}.$$

For our experiment, we use two different types of quantum layers as shown in Fig. 1. Type-1 circuit uses a computational basis state as input and applies an $R_x$ rotation by a parameter value $\theta$. Type-2 circuit uses a Hadamard gate before applying the $R_y$ gate. We evaluate the result of the quantum layer by measuring the $\sigma_z$ observable given as

$$\sigma_z(\theta) = \sum_j z(\theta)_j p(z(\theta)_j), \tag{1}$$

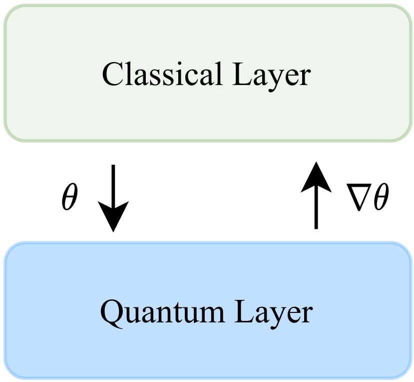


Fig. 2. The HQCNN consists of a classical and quantum layer. The parameter value is passed by the classical layer to the quantum layer. $\nabla\theta$ passed back to the classical to optimize the weights of the classical neural network to arrive at the optimal $\theta$ value.

where $z(\theta)_j$ is the measurement result after the qubit is measured in the $z$-basis and $p(z(\theta)_j)$ represents the probability of the outcome.

### B. Backpropagation :

To compute the gradient descent for the optimization of $\theta$ in our quantum layer, we evaluate the gradient of the quantum layer using the parameter shift rule. The gradient is defined as

$$\nabla_\theta \sigma_z = \sigma_z(\theta + \delta) - \sigma_z(\theta - \delta). \tag{2}$$

This value is fed back to the classical layer of our neural network to optimize the value of $\theta$ as shown in Fig. 2.

## III. Experiment

For our binary classification experiment, we load the MNIST dataset for images of labels "0" and "1". The HQCNN is created using the Pytorch and Qiskit frameworks. To evaluate both types of quantum circuits, we define the shots $= 100$, $\delta = \frac{\pi}{2}$, learning rate $= 0.001$. The metric used to evaluate the models performance is the negative log likelihood loss $(L)$ defined as

$$L = -\sum_k y_k.\log(p_k), \tag{3}$$

where $y_k$ is the correct label and $p_k$ is the predicted probability for the true class of the $k_{th}$ training sample of the data. We record loss during training of both the models with the number of epochs and plot the result.

## IV. Results

The Type-2 quantum layer causes the loss to decrease at a higher rate as compared to the Type-1 quantum layer. However, the losses of both types of quantum layers start to converge at around epochs $= 20$. After testing, the loss when using Type-1 is $L_1 = -0.9912$ and the loss using Type-2 layer is $L_2 = -0.9938$. We show the training convergence of Type-1 and Type-2 quantum layers in Fig. 3

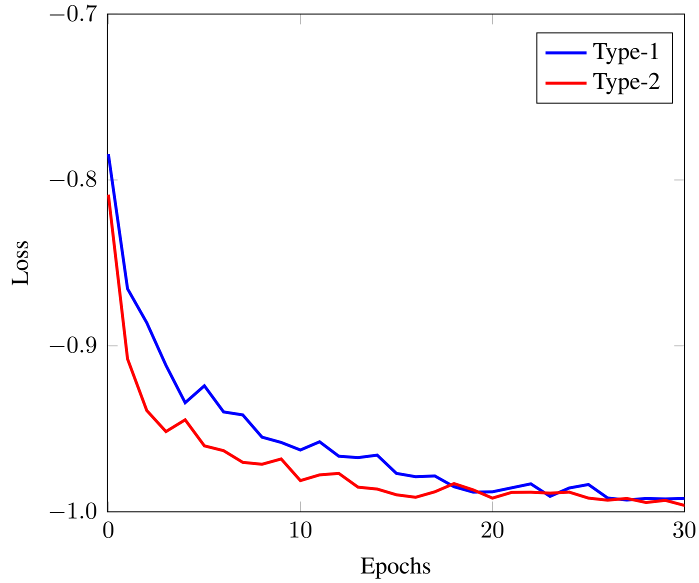


Fig. 3. A comparison between the training convergence of Type-1 and Type-2 quantum circuits with the loss($L$) plotted against the number of epochs. The loss of Type-2 circuit decreases at a higher rate as compared to Type-1 circuit.

## V. Conclusion

We have analyzed the performance of two possible quantum layers for binary classification tasks. The results of our experiment show that the Type-2 models will learn slightly faster as compared to the Type-1 layer models. However, the overall utility of both models would remain similar considering a significant number of training iterations are used. In such scenarios, a Type-1 layer model would be better for classification tasks as it provides a resource efficient alternative to the Type-2 layer models. To further improve the performance of such hybrid-models, we have to employ more sophisticated quantum layers, preferentially those that can use quantum effects such as generating quantum entanglement.

## Acknowledgment

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. 2019R1A2C2007037 and 2022R1A4A3033401) and by the MSIT (Ministry of Science and ICT), Korea, under the ITRC (Information Technology Research Center) support program (IITP-2021-0-02046) supervised by the IITP (Institute for Information & Communications Technology Planning & Evaluation).

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