Using Quantum Circuits with Convolutional Neural Network for Pneumonia Detection*

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Abstract. Image classification has emerged as one of the most important areas of machine learning approaches. Face recognition, object detection, driverless vehicles or robotics, and disease recognition are all areas where it is already making an impact. The introduction of convolutional neural network (CNN) layers to image classification and object detection has also resulted in substantial improvements. Using lower dimensional sliding kernels, CNN is capable of extracting characteristics from images without difficulties. When quantum circuits, which is the fundamental element of quantum computing, are added to this kernel, it becomes highly complex, classically intractable kernel. This hybrid combination of a quantum circuit and a CNN can be used to detect pneumonia early, which is an important step for curing the disease before it damages the infected person's lungs. In this paper, we propose a hybrid-CNN model with CNN based model architecture implemented with quantum circuit on chest x-ray images to diagnose pneumonia disease. We used data from a public repository with more than 5K images, applied classical and quantum algorithms within classification context. Our results show significant performance with better accuracy values after using quantum circuit with classical CNN. The model's performance in detecting pneumonia demonstrates that the proposed quantum convolutional neural network-based model can efficiently categorize regular and irregular X-ray images in practice.

Keywords: Quantum circuit · CNN · image classification.

1 Introduction

Convolutional neural network layers have aided significant advancements in image classification and object detection [13,23]. In image analysis, convolutional filters are applied to multiple layers of images. Within each layer, the abstracted representation of images is created by systematically convolving numerous filters

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across the image, resulting in a feature map that is utilized as input to the next layer. This design allows images in the form of pixels to be processed as input and the required categorization to be output. With increasing number of layers, the number of parameters in a neural network rapidly rises. This can make a model's training computationally costly.

According to Havlek *et al.*, using high-dimensional Hilbert space in quantum computing allows us to create sophisticated kernel functions that can fit complex nonlinear datasets [8]. The possibilities of CNNs are enhanced by these sophisticated kernel functions. The use of a random quantum circuit as the kernel in conjunction with a CNN results in improved accuracy and loss [10].

One of the essential tools for screening and diagnosing many lung disorders is a chest X-ray examination, although it is not always simple to identify with the naked eye. For example, one of the most popular ways medical professionals use to diagnose pneumonia is a chest X-ray. Therefore, the construction of a precise and reliable automatic detection model of pneumonia using a large number of chest X-ray pictures has significant medical value. Also, pneumonia is one of the world's leading causes of death in children and the elderly which a bacterial or viral infection can bring on. Radiographic evidence is a crucial component of pneumonia diagnosis since chest X-rays are routinely taken as part of standard therapy and can help differentiate between different types of pneumonia. Our primary goal is to detect pneumonia using chest X-ray images. The combination of quantum circuit with CNNs will allow us to detect this from chest X-ray images. The purpose of this research is to increase the accuracy of CNN by employing a quantum layer to diagnose pneumonia correctly.

2 Related Work

Several methods, including some machine learning algorithms, have been proposed to analyze pneumonia identification utilizing chest X-ray images in recent years. Wang *et al.* compared the performance of AlexNet [13], VGGNet [19], GoogLeNet [21], and ResNet [9] in predicting the existence of various diseases. In 2021, Zhang *et al.* created a CNN model based on VGG architecture to extract features from chest X-ray images and employ those features to determine if a patient has pneumonia [24]. In the study of Wu *et al.*, pneumonia prediction was made by utilizing convolutional deep neural learning networks on chest x-ray images [22]. The authors used publicly available chest x-ray image dataset, which contains 5863 images of 1574 unique patients. For classifying chest X-rays images of tuberculosis, Livieris *et al.* used an ensemble semi-supervised learning algorithm that employs a voting approach to determine how to get the most out of unlabeled inputs [14]. Guan *et al.* followed a unique category-wise residual attention learning (CRAL) approach for multi-label chest X-ray image classification that learns discriminative features for multi-label classification, using both category-specific and residual attention learning [7].

In 2019, Henderson *et al.* replaced convolution layer with quantum circuit and implemented a hybrid combination of quantum circuit and CNN. The authors

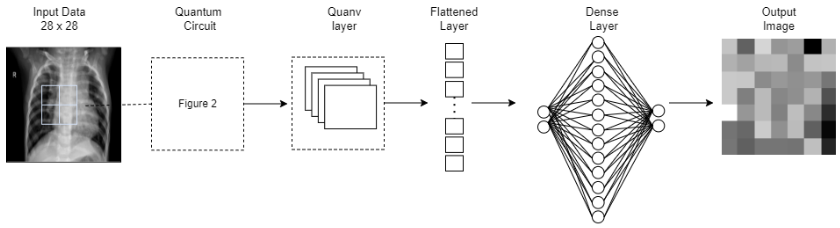

Fig. 1. Architecture of Quanvolutional Neural Network. The Quantum Circuit is displayed in Figure 2.

called this layer quanvolutional layer and named this approach as quanvolutional neural network (QNN) [10]. The authors ran this model on three publicly available datasets: MNIST, CIFAR, and SVHN [6,12,15] and obtained better accuracy than classical CNN. In another study, Cong *et al.* proposed quantum convolutional neural network that is entirely made of quantum circuits [5] to analyze problems in quantum physics.

3 Methodology

This section presents a brief overview of classical CNN, quantum circuits, and the combination of these two into quantum CNN. This section also discusses the data and the model architecture for this paper.

3.1 Convolutional Neural Network (CNN)

Convolutional neural networks (CNNs) are an essential tool for analyzing visual images. Over the last decade, CNNs have achieved cutting-edge results in the domain of image and video recognition, pattern recognition, image analysis, and natural language processing.

CNN reduces the number of parameters of the Artificial Neural Network with multiple layers, which aids in the creation of larger models in order to solve more complex problems. The architecture of a CNN is inspired by the organization of the cortex in the human brain and is akin to the connectivity pattern of neurons. The ability of neural networks to extract features from data in a hierarchical manner accounts for a large part of the advantage that they provide. These features are extracted using various layers, the most notable of which is the convolutional layer, which gives the network its name.

3.2 Quantum circuit implementation

A quantum circuit is a paradigm for quantum computation, where a computation is mainly a sequence of quantum gates. The creation of a quantum gates requires the most basic quantum system of all, which is a single qubit. Quantum

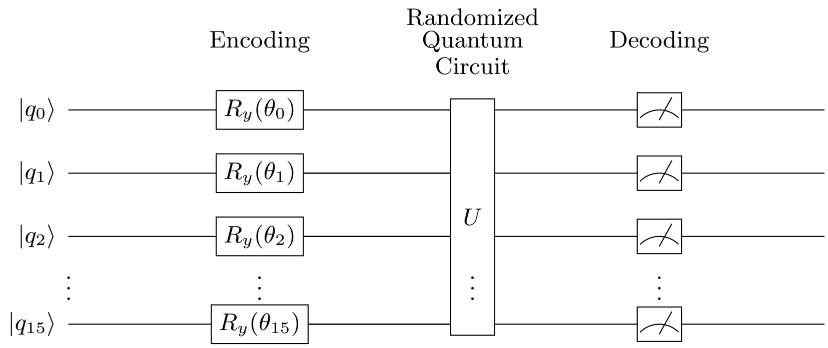

Fig. 2. Quantum circuit operates on input data, applies a rotation, transforms with a randomized quantum circuit, measures (decodes); finally we obtain the output.

circuits have the advantage of being reversible between initializing the qubits and measuring them. As well as matrices, quantum gates, which are reversible, can be described as rotations around bloch sphere. To perform rotations by θ parameter around the x, y and z-axis of the Bloch sphere, X, Y and Z Pauli gates are used. Those rotation are given by $R_{\hat{n}}(\theta) = \exp(-i\theta\hat{n} \cdot \vec{\sigma}/2)$. Where $\hat{n}$ is a real unit vector in three dimensions, and $\vec{\sigma}$ is a generalized vector of Pauli matrices [16]. In addition to previous words, Penrose *et al.* proposed the tensor diagram notation [18] and it has explored in the quantum computing context as diagrammatic notation [4,3]. Figure 2 shows the quantum layer implemented in Figure 1.

For the implementation, we used PennyLane [2]. Figure 2 shows the implementation of quantum convolution neural network. This concept is discussed in the section 3.3.

3.3 Quanvolutional Neural Networks (QNN)

With the growing amount of data, classical machine learning algorithms have started to face the challenge of computational complexity in tools. Quantum machine learning (QML) provides faster solutions than classical methods for a limited set of issues. This area is a combination of Quantum computing with machine learning techniques, and it has shown overwhelming success in the last decade. The implementation of Quantum neural networks have outperformed classical machine learning algorithms on pattern recognition, image reconstruction, image and video analysis.

Although the hardware and software constraints remain significant, quantum technology has viable components for implementing in machine learning programs. The Quantum convolution layer is an extension of CNN to the context of quantum circuits. By utilizing certain potentially mighty elements of quantum processing, QNNs enhance the potential of CNNs. In theory, quantum circuits can yield enormously complex kernels whose computing is classically unachievable in principle. Quantum convolution layers transform the input data using a few quantum variational circuits with small error correction. Unlike classical CNNs, quanvolutional layers are built up of N quantum filters that produce features maps by locally modifying input data (Figure 2). The main difference with the classical convolutional layer is that quanvolutional filters extract characteristics from input data by employing random quantum circuits to modify spatially-local subsections of data. Compared to classical CNNs, quantum CNNs have shown higher accuracy and faster training time.

A quantum layer can be implemented in a variety of ways, and in addition, a quantum algorithm has several potential applications in different areas. CNNs, for example, can be used with a quantum fully connected layer or in hybrid models. To mention one example, the authors of [1] investigate how to implement a classical neural network with quantum algorithms to create a hybrid quantum-classical neural network. Conversely, CNNs can be used with both a quantum convolution layer and classical fully-connected layers [10]. J. Orduz *et al.* describes the Quanvolutional autoencoder, which focuses on employing randomized quantum circuits as quantum convolutions to learn new image representations in a convolutional network[17]. Furthermore, instead of employing any traditional CNN layer, Cong *et al.* replaced every CNN layer with quantum circuits [5]. Using QNN (quanvolutional neural network) instead of CNNs has also shown higher performance. Korn *et al.* compared QNNs to CNNs in terms of accuracy, loss values, and adversarial robustness and showed their robustness in the presence of adversarial examples produced by their classic versions [20].

3.4 Data

The data used in this project was collected from Kaggle [11]. The original dataset contains a total of $5,863$ X-Ray images with two categories of pneumonia and normal. These two labels don't contain the same amount of images. Pneumonia has 75% of data, whereas normal label has 25%. We reduced the dataset to 2000 images for training and 100 images for testing while selecting the same number of images for both pneumonia and normal label. Due to limited resources, we lowered the dimension of data to 28×28. Figure 3 demonstrates a data sample.

3.5 Model Architecture

The work in this paper is largely built off of the work completed in Quanvolutional Neural Networks: Powering Image Recognition with Quantum Circuits [10], where CNN is implemented with quantum convolution layer. The approach taken in our study differs from the author's in that we did not post-process the expectation values and instead used the raw expectation values. Our proposed method's model architecture is demonstrated in Figures 1 and 2.

In order to generate each quantum filter, we needed to know how many qubits are necessary for the circuit, as well as the input size. A basic implementation of 4×4 quanvolutional filters was chosen so that each simulated circuit had exactly 16 qubits. At first, a small region of the input image is embedded into a quantum circuit by applying parametrized rotations ($R_y(\theta_i)$) to the qubits

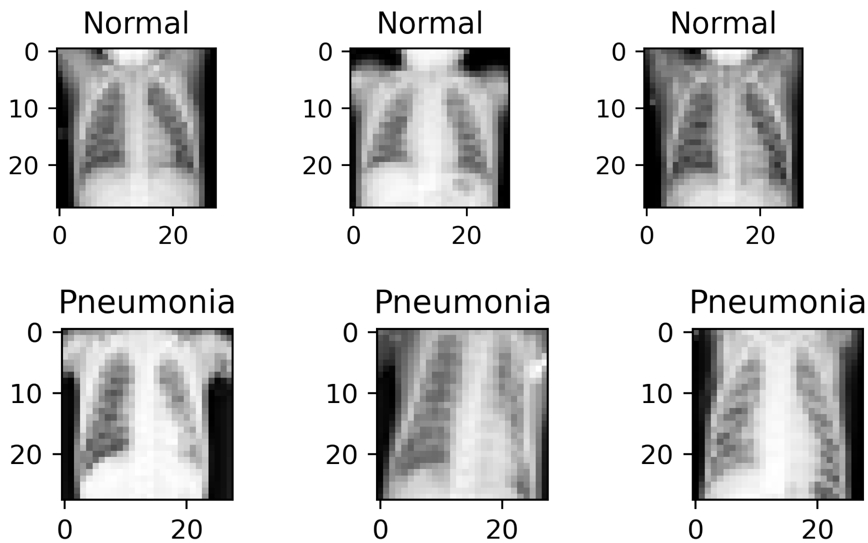

Fig. 3. Sample images from dataset. The image of a normal chest X-ray shows clear lungs with no regions of aberrant opacities, whereas pneumonia images exhibits more gray and vague areas.

started in the ground state. Then, a random unitary operator is performed on the system (U). A quantum measurement obtains classical expectation values from the quantum circuit (decoder). Each expectation value is translated to a separate channel of a single output pixel, similar to a traditional convolution layer. By repeating the method over different parts, the whole input picture can be scanned, resulting in an output object that is organized as a multi-channel image. A classical layer then follows the quantum layer. This classical layer includes a dense layer which uses `softmax` activation function. We used `adam` optimizer, `sparse_categorical_crossentropy` as loss function, and `accuracy` metrics function while compiling the model.

4 Results and Analysis

Figure 4 displays the sample output of quanvolutional layers in gray scale. The resolution downsampling and some local distortion induced by the quantum kernel are plainly visible. On the other hand, as one would anticipate from a convolution layer, the image's overall shape remains kept. After training the model and plotting the result of training vs validation accuracy and loss on graph (Figure 6), the result suggests that the accuracy was getting closer to 1.0, to be specific 0.96, while the loss was 0.1574. Although there is a zig-zag pattern in the validation loss and accuracy, this might be a consequence of reducing the pictures to a lesser quality. From Figure 7, we can see that adding quanvolutional layers achieves a validation loss of 0.43 in the 40th epochs, whereas classical CNN reaches the same loss in the 100th epoch. This shows that QNN gets to better accuracy than CNN in the same number of epochs. We also tried to change the model architecture by adding some more layers to it. We added a batch normalization layer, dropout layer and keras layer, but the result didn't show any improvement.

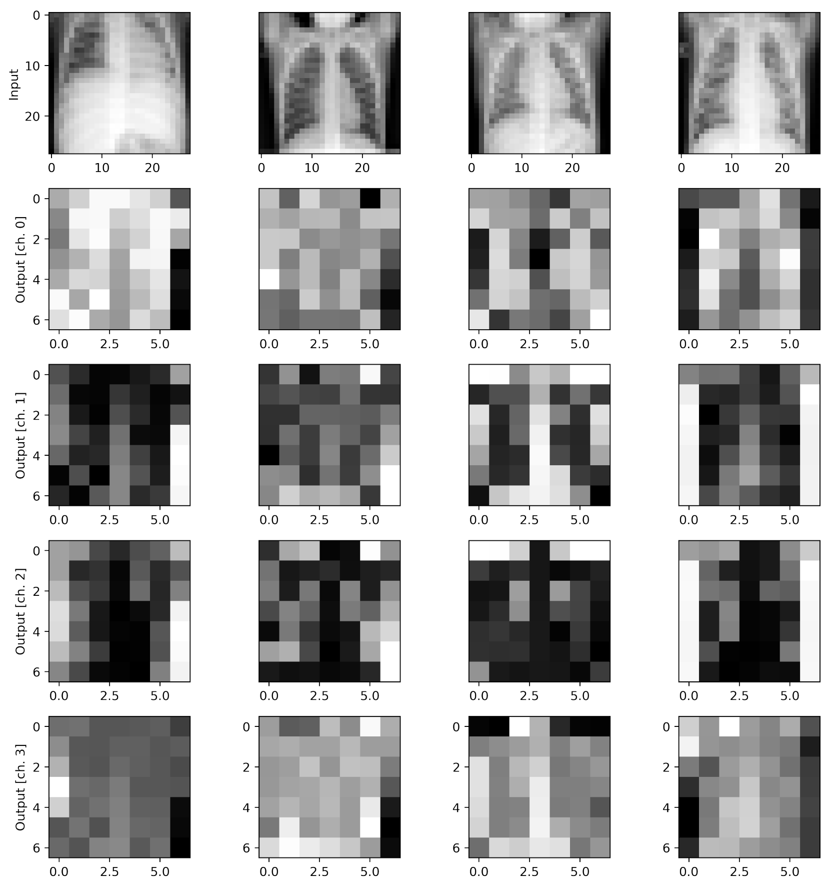

Fig. 4. Sample output from quanvolutional circuit layer.

A comparison is done with a classical CNN where only the convolution layer is different from QNN. The result of this comparison is shown on Figure 6. According to the findings, QNN outperforms CNN in terms of accuracy and loss. The result of 96% training accuracy and 84% validation accuracy shows that our proposed model performs well in comparison to CNN architecture.

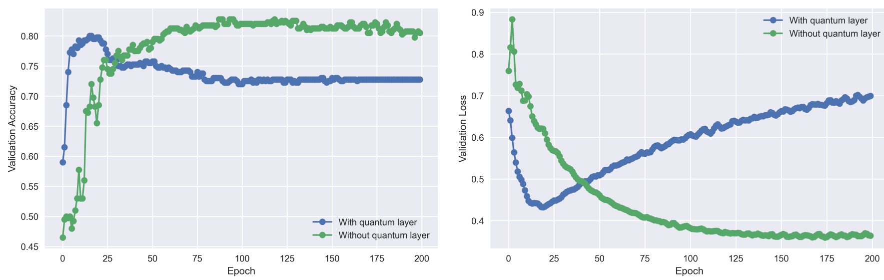

Fig. 5. Left: Comparison between CNN and QNN in terms of validation accuracy. Right: Comparison between CNN and QNN in terms of validation loss.

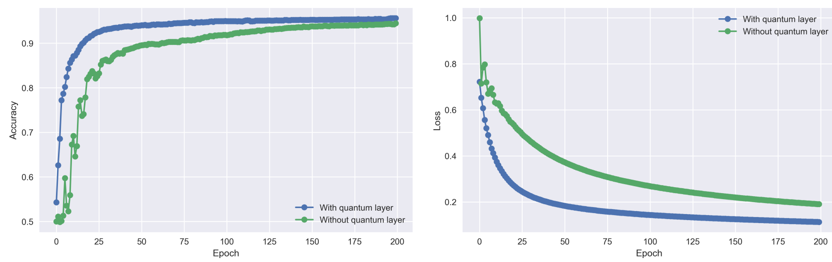

Fig. 6. Left: Comparison between CNN and QNN in terms of training accuracy. Right: Comparison between CNN and QNN in terms of training loss.

We have introduced a second model to see if our result persists in the new model. We have introduced a batch normalization layer, a dropout layer and a dense layer. The model was trained for 10 epochs. The average validation accuracy and loss for the first model is showed in Figure 8 and Figure 7. And average validation accuracy and loss for the second model is showed in Figure 10 and Figure 9. The implementation of our two models and our experiments are available on an open repository.[1]

From the figures, we can observe that the quantum model converges faster then the classic model before overfitting, although the classic model converges to a smaller loss after many more iterations. Another important fact is that the model exhibits a smaller variance in earlier stages of training in comparison to the classic approach; this suggests that the quantum-based approach is much more stable.

5 Conclusion and Future work

This paper proposes a quanvolutional neural network model that classifies pneumonia based on chest x-ray images. We designed a simple QNN based archi-

[1] `https://anonymous.4open.science/r/Quantum-Circuits-and-CNN-for-Pneumonia-Detection-CBF5/quanvolution_pneumonia_1st_model.ipynb`

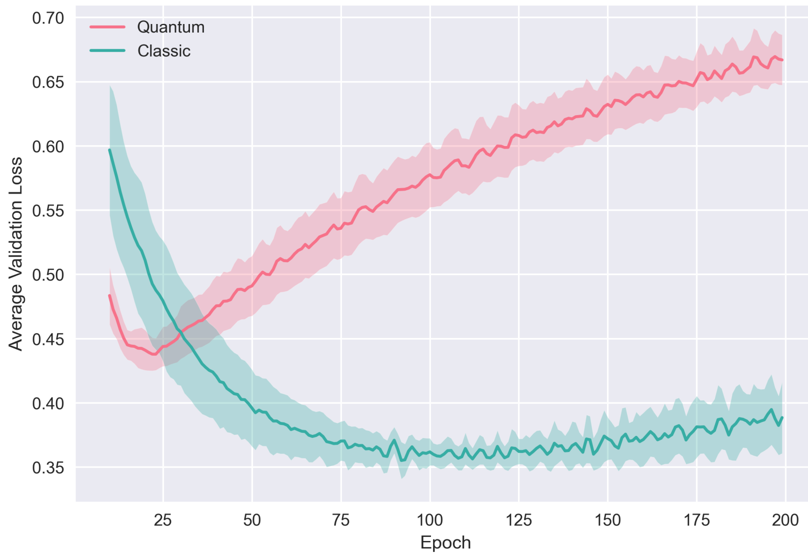

Fig. 7. Average validation loss for 10 runs in the **first model**

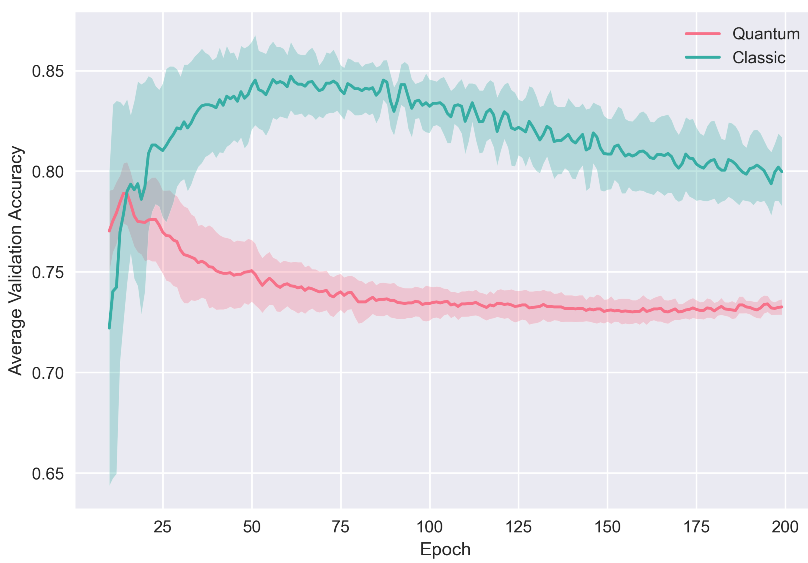

Fig. 8. Average validation accuracy for 10 runs in the **first model**

Fig. 9. Average validation loss for 10 runs in the **second model**

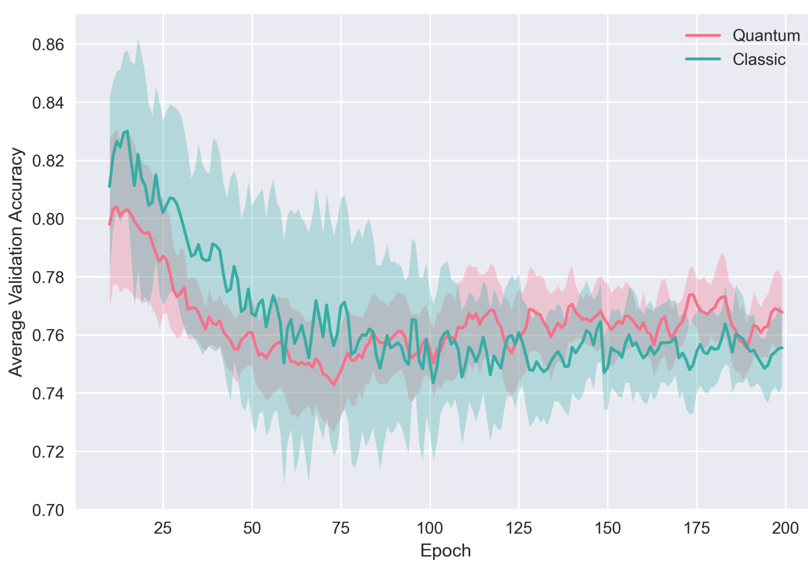

Fig. 10. Average validation accuracy for 10 runs in the **second model**

tecture where quantum circuit generates highly complex kernels. We performed classification on the chest x-ray image dataset by encoding them in a quantum state. We investigate the performance of our model by comparing with classical CNN layer. Since the experiment suggests that combining a quanvolutional layer with a classical CNN can produce better results, we will continue to improve the validation result by adding more CNN layers. The images were also downsampled to a lower resolution (28×28) due to a lack of computational resources, which might compromise the accuracy. Finding suitable downsampling that does not damage the x-ray image properties might be a worthwhile investigation. In addition, we conducted the entire experiment using a quantum simulator. The training would be faster if an actual quantum computer were used. Our future work will focus on expanding our experiments and applying the suggested approach to a variety of biomedical datasets for image classification. In the future, a more precise classification framework can be made for diagnosing two forms of pneumonia, virus and bacteria.

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