Quantum Convolutional Neural Network for Image Classification

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Abstract

In the field of image processing, a well-known model is the Convolutional Neural Network, or CNN. The unique benefit that sets this model apart is its exceptional ability to use the correlation information included in the data. Even with their amazing accomplishment, conventional CNNs could have trouble improving further in terms of generalization, accuracy, and computing economy. However, it could be challenging to train CNN correctly and process information quickly if the model or data dimensions are too large. This is since it will cause the data processing to lag. The Quantum Convolutional Neural Network, or QCNN for short, is a novel proposed quantum solution that might either enhance the functionality of an existing learning model or solve a problem requiring the combination of quantum computing with CNN. To highlight the flexibility and versatility of quantum circuits in improving feature extraction capabilities, this paper compares deep quantum circuit architecture designed for image-based tasks with classical Convolutional Neural Networks (CNNs) and a novel quantum circuit architecture. The covidx-cxr4 dataset was used to train quantum-CNN models, and their results were compared against those of other models. The results show that when paired with innovative feature extraction methods, the suggested deep Quantum Convolutional Neural Network (QCNN) outperformed the conventional CNN in terms of processing speed and recognition accuracy. Even though it required more processing time, QCNN outperformed CNN in terms of recognition accuracy. When training on the covidx-cxr4 dataset, this dominance becomes much more apparent, demonstrating how deeper quantum computing has the potential to completely transform image classification problems.

Keywords: Quantum computing, Quantum circuit; Convolutional Neural Network; COVID-19; Quantum convolution; Quantum pooling; Quantum Convolutional Neural Network; Image classification.

1. Introduction

In recent months, COVID-19 has been quickly expanding in several nations due to the infection of human beings with a coronavirus that causes severe acute respiratory syndrome. The current COVID-19 pandemic is having a negative impact on human health, producing respiratory sickness as well as acute renal damage. At the end of 2019, China was the location of the disease's first confirmed breakout [1]. Fever, sore throat, vomiting, nasal congestion, persistent cough, dyspnea, diarrhea, muscular soreness, anosmia, exhaustion, shortness of breath, chest discomfort, and chills are the most prevalent clinical signs of the disease. Other symptoms include dyspnea, diarrhea, and anosmia. The pandemic status of COVID-19 was announced by the World Health Organization in March of 2020 [2][3][4].

The combination of conventional computing with machine learning (ML) opened the door to the possibility of resolving a few challenges faced by a wide range of businesses. However, when processing speeds, large amounts of data, and the ability to solve higher-order polynomials are taken into consideration, classical computations are very restricted and fail to meet the requirements [5][6][7][8]. The effectiveness of several traditional methods, such as data fitting and low-rank matrix decomposition, may be equivalent to that of the methodology of quantum phase estimation [9][10][11].

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Quantum mechanics refers to a comprehensive collection of principles that are formulated inside a mathematical framework or physical theory. Quantum computing is a novel computational framework that incorporates the principles of quantum mechanics [12]. It leverages the unique capabilities of quantum mechanics to manipulate both quantum and classical information [13], potentially leading to a significant disparity between quantum and conventional computers. With the advancement of quantum technology, there has been a notable emergence of noisy intermediate-scale quantum computers (NISQ) that are capable of handling rather difficult computational tasks. In certain domains, the computational capabilities of NISQ computers have even surpassed those of conventional computers [14][15]. In recent years, there has been a recent uptick in interest about the incorporation of quantum techniques into a variety of conventional machine learning methods, such as supervised learning, principal component analysis, and other dimension reduction procedures. This emerging field has garnered significant attention in the scientific community [9][16][17]. Quantum machine learning algorithms encompass a variety of approaches, and among them, the implementation of quantum (convolutional) neural networks is comparatively more feasible using near-term quantum devices. This is primarily due to the noise-tolerant nature of these networks and their reduced demand for circuit depth [18].

Numerous challenges prevalent in the real-world domain continue to pose significant difficulties in their resolution using conventional machine learning techniques. The challenge in quantum physics, as described inside the many-body Hilbert space, necessitates the conversion of this data into conventional computer data to effectively employ machine learning methodologies. As the scale of the system expands, the volume of data also grows rapidly, posing challenges for efficient resolution even when employing machine learning techniques [19]. Numerous research has been conducted to address challenges associated with the Quantum Convolutional Neural Network (QCNN) by leveraging the integration of quantum computing systems with the CNN paradigm. One viable method involves the use of CNN architecture directly on a quantum system, enabling the efficient resolution of quantum physics quandaries. Additionally, another method entails enhancing the performance of previously solved issues by incorporating a quantum system into the existing CNN framework [19] [10][20].

The primary goal of proposing QCNN, and deeper QCNN for image classification is to harness the power of quantum computing to significantly enhance the accuracy and efficiency of image recognition tasks. By harnessing principles such as quantum superposition and entanglement, QCNNs aim to process complex visual data more effectively than classical Convolutional Neural Networks (CNN). The overarching objective is to provide quantum solutions for image recognition tasks. QCNNs seek to explore the quantum advantage, offering faster, more efficient, and highly accurate methods for image classification in comparison to classical approaches. Ultimately, deeper QCNN seeks to explore more complex patterns to make quantum networks capable of learning complex features and relationships, leading to increased accuracy.

The contributions of this works are:

1. Representation in Quantum CNNs lie in their ability to redefine how image data is encoded and processed, leading to advancements in accuracy, efficiency, and interdisciplinary collaboration, while also expanding the understanding of quantum feature spaces in the context of deep learning.

2. A new quantum circuit for convolutional layer and pooling layer for parameter reduction and speed up computational operation is proposed, reducing the number of parameters directly reduces the computational load during convolutions and it reduces processing time.

The remaining sections of the paper is organized as follows: The related works is described in Section 2, which is followed by an explanation of the necessary context for comprehending the architectures of quantum convolutional neural networks in Section 3, Section 4 described the used dataset, while Section 5 discussed the methodology, which is followed by a demonstration of the performance of these algorithms on various medical imaging datasets in Section 6, finally the conclusions and recommendations for further research is presented in Section 7.

2. Related Works

The quantum deep learning network has been most popularly modeled through many applications like healthcare, handwriting classification, and other applications:

Detecting a disease early is crucial to medical diagnosis and clinical practice, as it lessens stress on the healthcare system and achieves high degrees of accuracy, although neural networks and classical computers have limitations. The work in [21] used quantum algorithms for linear algebra and quantum neural networks. Quantum deep learning techniques have been proposed to enhance the performance of machine learning applications. Using quantum circuits for training classical neural networks and developing and training quantum orthogonal neural networks for medical image classification, they developed two different quantum neural network techniques. Their

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techniques were tested on chest X-rays and retinal color fundus images. Although QNN provides similar accuracy to classical NN, quantum accuracy drops for more challenging tasks.

Houssein et al. [22] used a hybrid quantum-classical convolutional neural network (HQCNN) to detect COVID-19 patients with CXR images using random quantum circuits (RQCs). In the first dataset, this study used 6952 CXR images [22], including 1161 COVID-19 images, 1575 normal images, and 5216 pneumonia images. Compared to other available models, the proposed HQCNN model achieves higher performance and accuracy. The model is tested on a binary and multiclass dataset, with confirmed COVID-19 cases in the first dataset. But this model has a more complex architecture. Moreover, on the second dataset, the researchers obtained a higher degree of sensitivity and accuracy. Furthermore, it reached an accuracy and sensitivity of 88.6% and 88.7%, respectively, on the third multiclass dataset. There are 5445 images [2] in the second dataset, including 1350 COVID-19, 1350 normal, 1345 viral pneumonia images, and 1400 bacterial pneumonia images. But the method worked in [22] and [2], which were complex; the disease was diagnosed in these two cases only and was not tested to diagnose new cases of the disease.

The current hardware used to train neural networks' size, control, and utility are still greatly limited. The physical limitations of conventional computers are causing performance improvements to be slowed in the coming years, and therefore, these concerns have become increasingly pressing. In the research presented in [23], a quantum-classical hybrid neural network design was presented. In this architecture, each neuron is a variational quantum circuit. When determining how well the hybrid neural network performs, both a simulation of a quantum computer and a quantum computer that is at the cutting edge of its field are employed. When contrasted with a variational quantum circuit that was constructed in a vacuum, a hybrid neural network achieves around 10% greater classification accuracy and 20% better cost reduction. Each quantum hardware model can only perform well when the qubit and gate counts are small enough. However, VQC is cheaper and more robust, so adding more parameters does not guarantee better results. In tests on the iris, bars, and stripes datasets, HQNN and quantum hardware performed poorly.

Emmanuel Ovalle et al. [24] used a hybrid transfer-learning paradigm in which a quantum network drove and enhanced a classical network trained for stenosis detection. In an intermediate step between classical and quantum networks, the classical features are transformed into a hypersphere of a fixed radius using a hyperbolic tangent function. Following normalization of these features, these probabilities are computed in the quantum network using the SoftMax function. Further, rather than a single quantum circuit, multiple quantum circuits are used to divide the training data within the quantum network to improve training time without compromising stenosis detection performance. A small dataset of 250 images was used to evaluate the proposed method. Hybrid classical-quantum networks outperform classical networks significantly; this method has very complex operations.

To overcome the complexity in the above works, Viraj Kulkami [25] created a hybrid neural network to detect pneumonia from chest radiographs using a classical neural network. It combined a variational quantum circuit with a layer of a classical convolutional neural network. On a chest radiograph image dataset, they train both networks and benchmark their results. Multiple rounds of network training are used to minimize the effects of different sources of randomness. According to the study, hybrid networks outperform classical networks on various performance measures, and these improvements are statistically significant. As a result of their work, they show that quantum computing has the potential to improve the performance of neural networks in real-world applications relevant to society and industry. However, the work was expensive in terms of time and depended on a number of factors.

3. Dataset

An open-access dataset that is made available to the general public by the Kaggle platform (https://www.kaggle.com/datasets/andyczhao/covidx-cxr2), was used to perform our experiments. Released COVIDx CXR-4, The new dataset contains 84,818 images from 45,342 subjects, and includes separate validation and tests sets, Figure 1 shows COVIDX CXR-4 dataset.

The researcher's mission was to compile an exhaustive and precise dataset that could be used for study and analysis in the field. This was the overarching goal of their effort. Images of COVID-19 and normal people's chests taken from X-rays are included in the collection, respectively, as shown in figure 1. The X-ray images have a standard variable size ranging from 512x512 to 1024x1024 pixels, and they were captured from a variety of different angles and positions.

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Figure 1: COVIDX CXR-4 dataset.

4. Methodology

The proposed simple quantum CNNs model (QCNN) has the goals of enhancing CNNs classification for medical pictures and accurately predicting COVID-19 as well as healthy individuals in early stages. The fundamental concept behind the QCNN model is that classical learning can be improved by the use of quantum computing. The proposed model consists of four parts: first, preprocessing. Second, the classical CNN structure. Third, propose enhancement quantum circuit of CNN, as shown in Figure 2.

4.1 Preprocessing

To avoid oversaturating the model and to improve training, the images are normalized before being fed into the CNN model. Aside from that, the images are scaled down from 1024x1024 to 200x200 to save the computational expense. Additionally, the images are mixed to make the data more diverse, which finally results in generic training and broadens the scope of the model. To get a more balanced dataset and a higher resolution in the COVID X-ray pictures, many different augmentation approaches are used. These techniques are salt noise, which is a type of image noise where random pixels in the image are set to either the maximum or minimum intensity values (usually 255 for white and 0 for black in grayscale images), resembling salt and pepper sprinkled on the image. It helps in making machine learning models, especially those related to image processing, more robust by training them to recognize objects even when the images are corrupted by noise. Horizontal flipping involves flipping the image horizontally, as if looking at it in a mirror. Vertical flipping, on the other hand, flips the image upside down. It increases the diversity of the training dataset. It provides the model with different perspectives of the same object, helping it generalize better to unseen data. Rotation involves changing its orientation by a certain angle (40 degrees), rotation can be clockwise, rotating images helps the model become invariant to rotation, meaning it can recognize objects regardless of their orientation in the image. Brightness control involves changing the intensity values of all pixels in the image uniformly. Increasing brightness makes the image lighter, while decreasing it makes the image darker, controlling brightness helps the model become more robust to varying lighting conditions. It ensures that the model can recognize objects in images taken in different lighting environments. Because the system recognizes each picture as a unique entity, these augmentation approaches are helpful for avoiding underfitting and overfitting.

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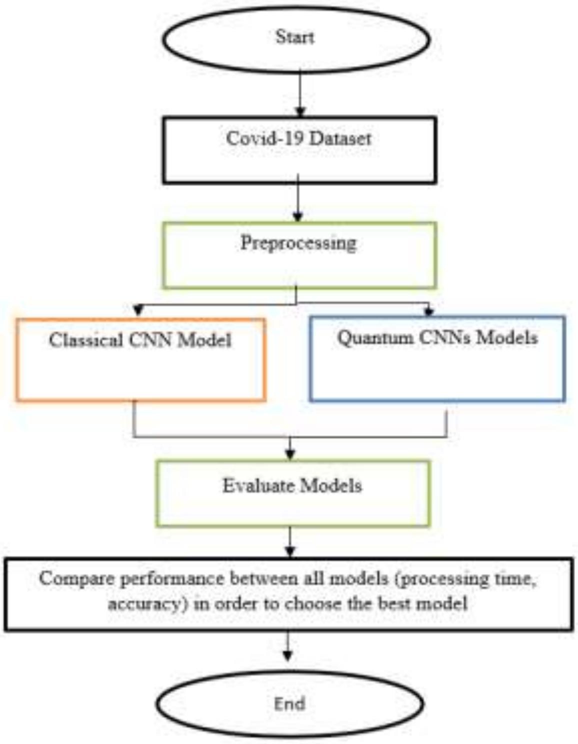

Figure 2: General diagram for proposed system.

4.2 Classical CNN

The suggested CNN network is composed of three layers, including three convolutional layers, and then a max-pooling layer is placed on top of each convolutional layer. The Sigmoid layer is used for classification after the dropout layer, which is followed by the flatten layer, which is followed by two dense layers, the first of which is followed by the dropout layer, which is then followed by the batch normalization layer, and finally by the Sigmoid layer. In addition, the Relu activation function is utilized in each convolution layer as well as the first dense layer, as demonstrated in Figure 3.

The three dropout layers are used with dropout to reduce the overfitting, the features extracted by convolutional network are flattened into 1-dimensional vector so that the fully connected network classify them using Sigmoid into two classes (COVID and Normal).

Our model's batch size was 128, a popular setting for deep learning models, which defines the amount of data analyzed before updating parameters. The learning rate, 0.001, determines the optimization step size to minimize the loss function by adjusting the model's weights. Adam optimizer is employed, which is popular for its adjustable learning rate and accelerates optimization convergence. A dropout rate of 0.5 was also utilized to avoid overfitting by randomly dropping out a percentage of neurons during training to enhance model generalization. The proposed deep learning model is trained and optimized for task performance using these hyperparameters.

4.3 Quantum CNN

To recognize quantum states, QCNN can be created. It is vital to research how local characteristics fit into the overall QCNN circuit construction as well as how to link them.

In contrast to past research and current developments, we will use QCNNs to examine if the physical state/phase classification mode can be translated into learning the classic image classification issue and to determine which type of image is most likely to learn. It's crucial to prepare quantum starting states. The separated weight function increases as the entangled state increases. When compared to an entangled state, it is more persuasive. QCNN would be more powerful than its conventional equivalent.

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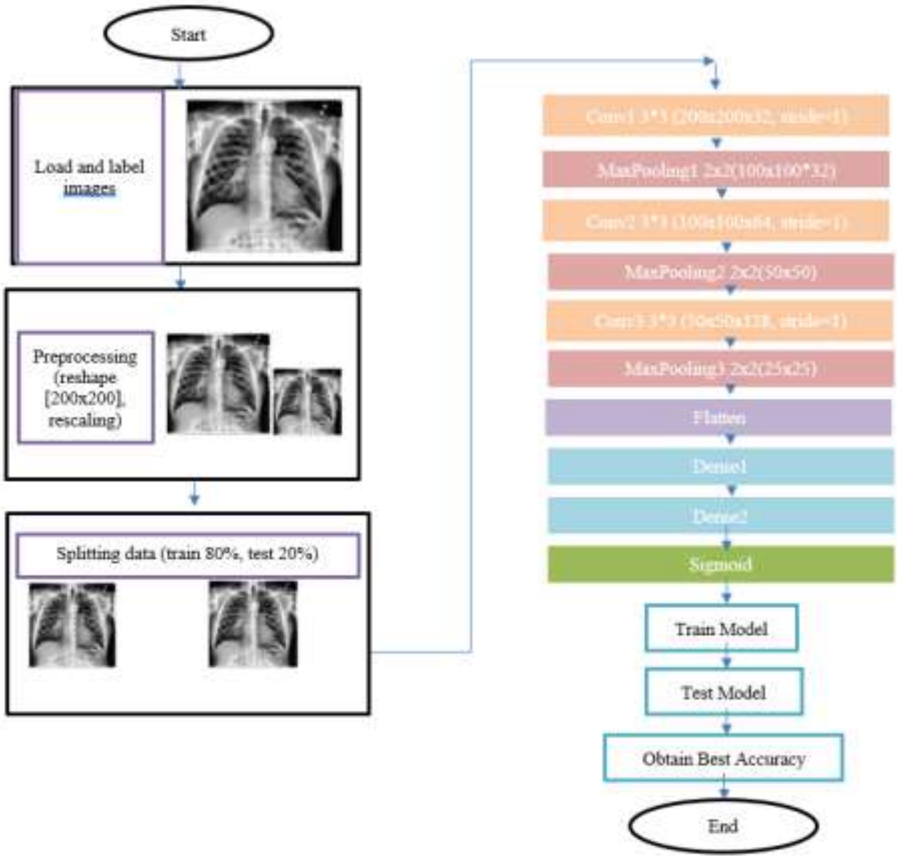

The steps below describe the process for assembling circuits:

1. Define the quantum circuits, set up a state appropriately, and then train the quantum classifier to see whether it works. "Entanglement" is used to speed up the procedure. By reading two qubits, we may get the classification result when the entanglement is decreased. Figure 7 illustrates the QCNN architecture's generality for this image classification problem. The first layer of the QCNN architecture is quantum cluster state prepare layer as shown in Figure 4. We create synthetic image data from images in the database under certain conditions to match the nature of the images and the number of qubits used in our work, it creates two arrays to represent horizontal and vertical line patterns, respectively. These arrays contain values of angles (in radians) that can be used to represent these patterns, where the goal might be to classify images of patterns into two classes (horizontal or vertical), with some level of noise added to the patterns to increase the complexity of the dataset. The class labels are represented as -1 and 1, and the patterns are represented as arrays of angles.

2. The input layer where the encoded features via the ZFeatureMap [26], it is a quantum circuit that prepares a quantum state in a way that can be used to encode classical data into a quantum state for processing on a quantum computer. Specifically, the ZFeatureMap is used to encode classical data as rotations around the Z-axis of qubits in a quantum circuit, see Figure 4a.

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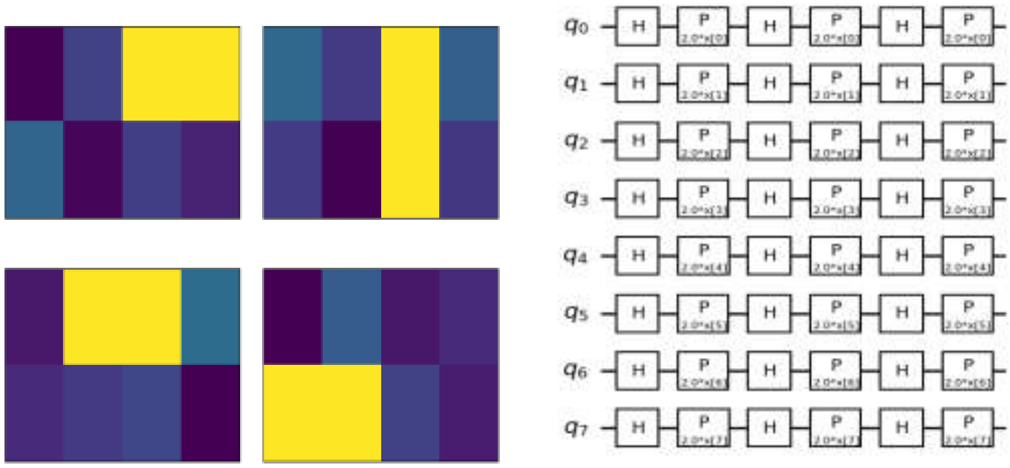

a: Prepare x-ray dataset image b: ZFeatureMap Architecture

Figure 4: a: Prepare x-ray image and b: ZFeatureMap Architecture.

3. The convolution and pooling layer incorporate two unitary matrices that are specified by qubits. The subsequent layer in the architecture is the quantum convolution layer. Equation 1 shows quantum circuit modification, and figure 5 illustrates the inclusion of H, RX, RZ, and CNOT gates inside a quantum convolution layer, which may be achieved by the sequential application of two-qubit parameterized unitarizes to pairs of adjacent qubits in a progressive manner. Let θ0, θ1, θ2 represent the parameters for the H, Rz, Ry, and Rz gates respectively. The quantum circuit can then be represented as:

$$U(\theta_0,\theta_1,\theta_2)=H\cdot Rz(-\pi/2)\cdot CX\cdot Rz(\theta_0)\cdot Ry(\theta_1)\cdot CX\cdot Ry(\theta_2)\cdot CX\cdot Rz(\pi/2) \quad (1)$$

This represents the unitary transformation performed by the quantum circuit. Each gate is applied sequentially to the initial state ∣00⟩.

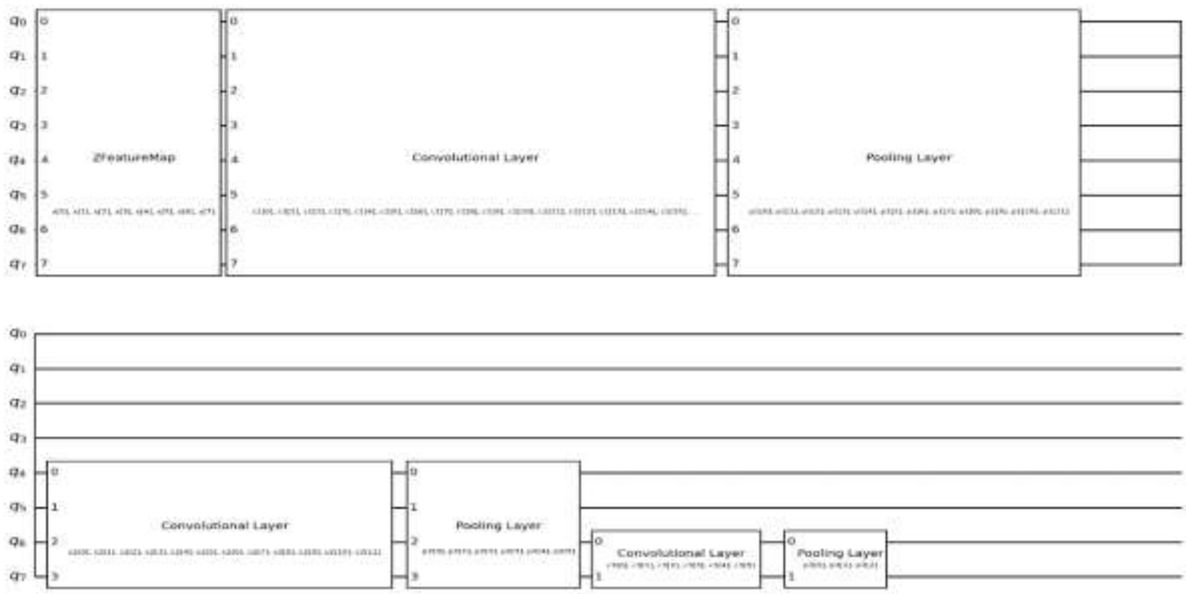

Figure 5: Quantum convolution layers

4. Quantum pooling layer. Figure 6 illustrates the presence of RX, RZ, and CNOT gates within the quantum pooling layer. CNOT gates are employed for the purpose of regulating the entanglement process. In the given

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circuit, a parameterized pooling operation is performed on two arbitrary qubits, resulting in the reduction of entanglement from a two-qubit state to a one-qubit one. The quantum pooling layer performs pooling operations on half of the qubits by utilizing the afore mentioned two-qubit pool. The pooling layer selects the relevant qubits, with the label 1 representing one state and the label -1 representing the opposite state. The present architectural framework utilizes classical data derived from a picture collection, specifically for the purpose of binary classification. The use of pixels as image features for classification in a quantum network is not deemed appropriate. To facilitate the downsizing of the picture and the preparation of features as input parameters, the QCNN architecture is depicted in Figure 7.

Let θ_0,$\theta 1$,$\theta 2$ represent the parameters for the Rz, Rx, and Rz gates respectively. The quantum circuit can then be represented as:

$$U(\theta_0,\theta_1,\theta_2)=Rz(-\pi/_2)\cdot CX\cdot Rz(\theta_0)\cdot Rx(\theta_1)\cdot CX\cdot Rz(\theta_2) \quad (2)$$

This represents the unitary transformation performed by the quantum circuit. Each gate is applied sequentially to the initial state $|00\rangle$.

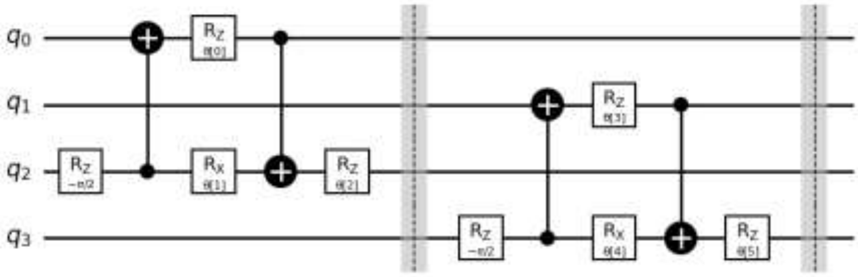

Figure 6: Quantum pooling layer

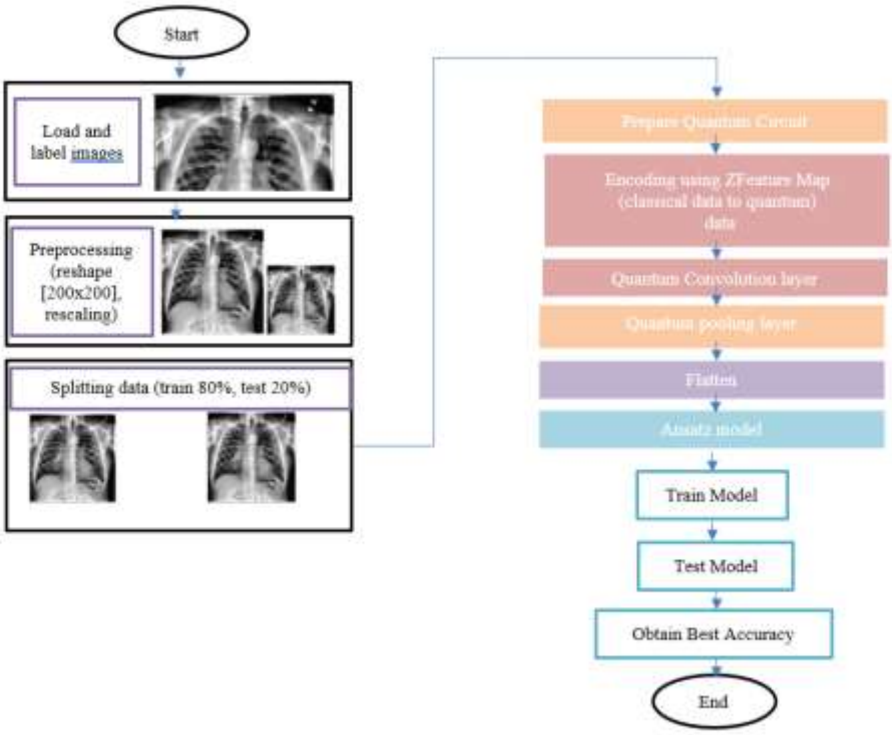

Figure 7: A QCNN architecture.

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5. Results and Discussion

The objective of this section is to show the effectiveness of the proposed QCNN classifier, which utilizes scale-inspired picture characteristics. To achieve this objective, we conducted two sets of experiments. The trials were conducted using the IBM Qiskit framework.

The initial experiment comprises a medical dataset consisting of COVID-19 images, within the initial cohort, 80% of the images were designated for the purpose of training, while the remaining 20% were allocated for testing.

In our experimental setup, the features underwent normalization to the range of [- π/2, π]. This normalization was applied to the parameters associated with rotation angles in H, RX, RZ gates, as well as CNOT gates. Subsequently, the normalized features were distributed over the eight qubits in the parameterized quantum circuits. The incorporation of encoded local correlation features with QCNN effectively emphasizes the multi-scale characteristics inherent in the distribution of data. The comparison of performance between QCNN model and the conventional CNN model indicates that notable advancements have been made through the incorporation of quantum characteristics.

The accuracy value for CNN and QCNN with multiple quantum layers for two dataset groups 2000, 10000 images were about 89.4% and 91.83% respectively, training time is 57.993 and 282.307 seconds for each epoch, respectively. The first proposed QCNN (has three convolutional and pooling layers) achieved accuracies of about 94.9 and 96.53% respectively, training time is 3.22 and 18.58 seconds for each epoch respectively, respectively as shown in Table 1.
The effectiveness of QCNNs with a specific number of convolution and pooling layers can vary depending on the complexity of the task, the nature of the dataset, and the quality of the quantum hardware being used.

Convergence of pure QCNN has a large fluctuation in a small range when compared with the other quantum models. Better convergence may still be expected for quantum-based models, particularly the pure QCNN one. the images. 80% of these images were also each class selected for training data and the remaining 20% for validation.

Table 1: Comparison between Classical CNN and quantum CNN

No sample	Classical CNN Accuracy	Classical CNN Times per epoch (sec)	QCNN (three conv & pool layers) Accuracy	QCNN (three conv & pool layers) Times per epoch (sec)
2000	89.4	57.993	94.94	3.22
10000	91.83	282.307	96.53	18.58

Much like how multiscale images are scrutinized and encoded, X-ray images exhibit comparable correlations crucial for understanding diverse measurements' properties. This similarity prompts significant advancements in quantum networks, marked by swift enhancements in accuracy coupled with rapid reductions in loss.

The images depicted in Figure 4a and the accuracy of data distribution within the category significantly impact the outcome. The varying positions of pixel values, ranging from disturbed to disagreeable states, prompt the utilization of image data noise. The proposed quantum CNN employing the prepared encoding method, outperformed classical CNN networks across all experiments, showcasing superior accuracy and processing speed. Notably, the performance exhibited a steady improvement throughout the experiments.

The value of the objective function is the cost associated with differences between target quantum states (which represent real labels) and forecast quantum states (which indicate the predictions of the model). This objective function is usually designed in quantum machine learning models, like QCNN, to reduce the differences between these quantum states. Depending on the job at hand and the quantum model architecture used for training, its exact structure may vary. As Figure 8 shows, the architecture of the quantum model and the nature of the job both influence the design of this objective function.

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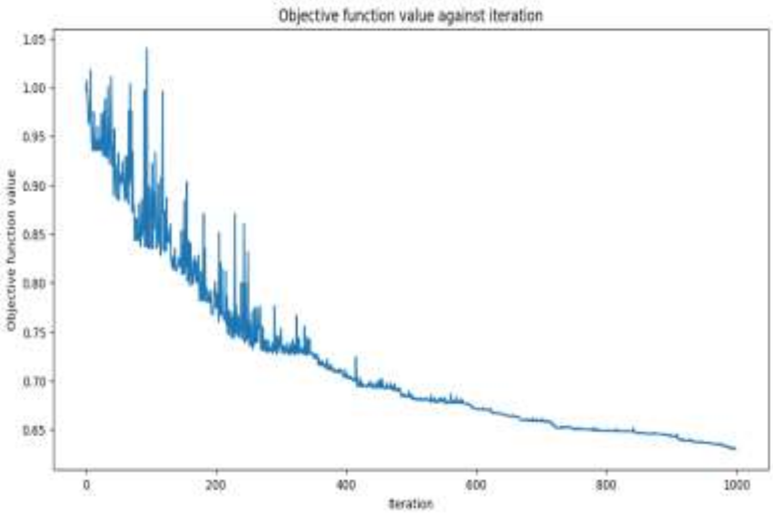

Figure 8: Objective function values.

The obtained results show that our proposed methods reduce the required time, and therefore, quantum CNN contains a smaller number of layers compared to classical CNN.

6. Conclusions and Future works

In this paper, we offer two scale-inspired local feature extraction algorithms for binary pattern Covid-19 image classification based on IBM's quantum framework for QCNN. When entanglement is minimized, a high or suitable entangled state corresponds to a high separated weight function, and we may get the classification outcome from the qubit. To assess the effectiveness of the quantum classifiers, we trained them using CNN and quantum CNN models. The simulation results on the Covid-19 image datasets demonstrate that, when compared to the traditional CNN, the QCNN achieve performance improvement in terms of recognition accuracy and classification accuracy. This finding encourages us to investigate the relationship between the chaotic character of an image and how QCNN classifiers might improve classification performance. QCNNs outperform classical CNN in processing time due to quantum parallelism and entanglement. Quantum states enable simultaneous exploration of vast solution spaces, a capability classical CNNs lack. QCNN utilizes quantum entanglement for efficient feature correlation, enhancing pattern recognition. As quantum computing matures, QCNN promises reduced processing times. The architectural complexity of Quantum CNNs arises from the probabilistic nature of quantum computations, the intricacies of quantum gates and qubit entanglement, and the challenges in integrating classical and quantum components. Successfully navigating these complexities is pivotal for harnessing the full potential of QCNN in solving complex real-world problems. In the future, as quantum circuits delve deeper into complexity, they are poised to unlock unprecedented potentials, bridging the gap between abstract quantum phenomena and the tangible world of visual data, paving the way for groundbreaking advancements in the field of image classification.

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