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RESEARCH ARTICLE

A New Quantum Circuits of Quantum Convolutional Neural Network for X-Ray Images Classification

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ABSTRACT A common model for classifying images is the convolutional neural network (CNN), which has the benefit of effectively using data correlation information. Despite their remarkable success, classical CNNs may face challenges in achieving further improvements in accuracy, computational efficiency, explainability, and generalization. However, if the specified data dimension or model grows too large, CNN becomes difficult to train effectively with a slowdown processing. In order to address a problem using CNN utilizing quantum computing, Quantum Convolutional Neural Network (QCNN) proposes a novel quantum solution or enhances the functionality of an existing learning model in terms of processing time during training. This paper presents a comparative analysis between classical Convolutional Neural Networks (CNNs) and a novel quantum circuit architecture tailored for image-based tasks, emphasizing the adaptability and versatility of quantum circuits in enhancing feature extraction capabilities and then final accuracy and processing time. A MNIST and covidx-cxr3 datasets was used to train quantum-CNN models, and the results of these comparisons were made with traditional CNN performance. The results demonstrate that the suggested QCNN beat the traditional CNN in terms of recognition accuracy and processing speed (process time) when combined with cutting-edge feature extraction techniques. This superiority is particularly evident when trained on the covidx-cxr3 dataset, highlighting the potential for quantum computing to revolutionize image classification tasks.

INDEX TERMS Quantum computing, quantum circuit, convolutional neural network, covid19, quantum convolution, quantum pooling, quantum convolutional neural network, image classification.

I. INTRODUCTION

In recent years, COVID-19 has been quickly expanding in a number of nations as a result of coronavirus infections in humans that produce severe acute respiratory syndrome. The continuing COVID-19 pandemic harms people's health by producing acute renal damage and respiratory illness. China saw the disease's first breakout around the end of 2019 [1]. The most common clinical symptoms include fever, sore throat, vomiting, nasal congestion, persistent cough, dyspnea, diarrhoea, muscle pain, anosmia, tiredness, shortness of breath, chest pain, and chills. In March of 2020, the World Health Organization declared COVID-19 a pandemic [2], [3], [4], [5].

Traditional computing combined with Machine Learning (ML) paved the way for tackling several issues in a variety of industries. However, when considering processing speeds, huge data, and the solution of higher-order polynomials, classical calculations are rather constrained and fall short [2], [6]. Many conventional approaches, including data fitting,

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sparse matrix inversion, and low-rank matrix decomposition, can perform as well as the quantum phase estimation algorithm [7].

A mathematical framework or physical theory is used to establish the laws of quantum mechanics. Quantum computing [8] is a novel computational paradigm that applies the principles of quantum physics to the processing of both quantum and conventional data [9], It could result in a fundamental difference between quantum and conventional computers. Noisy intermediate-scale quantum computers (NISQ) have started to tackle some reasonably hard computing jobs as quantum technology progresses, and in some cases, their computational capability has surpassed that of conventional computers [10], [11], [12]. Many classic ML methods, including supervised learning, principal component analysis, and other dimension reduction algorithms, have found new inspiration from quantum approaches, which have become a hot area in study in recent years [7], [13]. Due to their noise tolerance and reduced circuit depth requirements, quantum (convolutional) neural networks among these quantum ML algorithms may be implemented with near-term quantum devices significantly more easily [14].

With traditional ML techniques, many real-world issues are still challenging to resolve. These data must be transformed into classical computer data in order to be used with machine learning approaches to solve the quantum physics issue specified in the many-body Hilbert space. Even using the ML approach, the problem is challenging to tackle successfully since the scale of the system and the number of the data both grow exponentially [15]. Combining the CNN modelling technique with quantum computing technology has resulted in the creation of the Quantum Convolutional Neural Network, also known as the QCNN. This network has been utilized in a number of studies to address various problems. There are two ways to effectively tackle quantum physics issues: one is to apply the CNN structure to the quantum system directly, and the other is to add a quantum system to previously solved problems to get better results [10], [15].

The primary goal of the proposed Quantum Convolutional Neural Networks (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, potentially revolutionizing fields such as medical imaging, remote sensing, and object detection. Ultimately, QCNNs seek to explore the quantum advantage, offering faster, more efficient, and highly accurate methods for image classification in comparison to classical approaches.

The contributions of this works are listed below:

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 pool 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 integration of quantum computing and deep learning poses several technical challenges that need to be addressed for successful implementation. One major challenge is the high error rates inherent in quantum bits (qubits), which can lead to inaccuracies in computations.

Another challenge is the complexity of quantum circuit design, especially when designing circuits for specific deep learning tasks. Quantum circuits need to be tailored to effectively encode and process data in a quantum mechanical manner, which requires expertise in both quantum physics and deep learning algorithms.

Developing quantum hardware is challenge, such as the development of more stable qubits and scalable quantum processors, are crucial for overcoming technical limitations and enabling the seamless integration of quantum computing with deep learning.

The following outline constitutes the framework of this study. Following the discussion of related works in Section II, which is followed by an explanation of the necessary context for comprehending the architectures of quantum convolutional neural networks in Section III, Section IV described the used dataset, while Section V discussed the methodology, which is followed by a demonstration of the performance of these algorithms on various medical imaging datasets in Section VI, finally the conclusions reached and recommendations for further research is presented in Section VII.

II. 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 [16] used quantum algorithms for linear algebra and quantum neural networks. Quantum deep learning techniques have been proposed as a way 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 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. [3] 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 [3], 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 [3] in the second dataset, including 1350 COVID-19, 1350 normal, 1345 viral pneumonia images, and 1400 bacterial pneumonia images. But the method worked in [3], which were complex; the disease was diagnosed in these two cases only and was not tested to diagnose new cases of the disease.

The mutated SARS-CoV-2 RNA sequences have led to the emergence of new epidemic strains of COVID-19, like Delta and Omicron, that cause high mortality while spreading rapidly. Jin et al. [17] proposed a hybrid quantum-classical model that achieved blurred convolution like classical depth-wise convolution while also successfully implementing quantum progressive training with quantum circuits. These features simultaneously guarantee that their model is the quantum counterpart to the well-known style-based quantum generative adversarial networks (GAN). According to the results, the percentages of the randomly generated spike protein variation structure are always over 96% for Delta and 94% for Omicron. In the HQNN model, by using the quantum algorithm, they have contributed to predicting mutant strains effectively, and the training loss curve is more stable and converges better than conventional methods. The generated images generated by ProGAN cannot be controlled, and the random parameter inputs have slight changes.

The work in [18] introduces a quantum deep convolutional neural network (QDCNN) model based on the quantum parameterized circuit. A comparison of the proposed model with the classical deep convolutional neural network (DCNN) indicates an exponential speedup compared with its classical counterpart based on variational quantum algorithms. Furthermore, the MNIST and GTSRB datasets are simulated numerically, and the quantitative experimental results are used to verify the validity and feasibility of the model. However, there is a lack of information about network complexity.

Mohsen et al. [19] used quantum machine learning techniques where images are encoded in quantum states and inferences are made by a quantum neural network. Quantum machine learning techniques are particularly useful for classical image classification. Unfortunately, input images have been limited to extremely small sizes, no more than 4*4. Using larger input images has proven problematic due to the need for more qubits than are physically feasible in the existing encoding schemes. Their proposal is to use quantum systems to classify larger, more realistic images. Rather than requiring more qubits than prior work, their approach involves embedding images in quantum states. The framework is able to distinguish images up to 16*16 for the MNIST dataset on a laptop computer and is accurate enough to compete with classical neural networks with the same number of learnable parameters, and we also proposed a technique for reducing the number of qubits needed to represent images, which may lead to less computing power but better performance in the end, but the challenges remain in high-dimensional data.

The researchers in [20] used the concept of quantum together with CNN (QCNN). As a technique for processing large amounts of data at once, quantum random access memory (QRAM) uses superposition and entanglement to store large amounts of data. The model is more efficient on the resource side, the computational capacity side, and the depth side. The QRAM method is used to extract features and is more efficient on the resource side. But it is time-consuming and difficult to apply. QRAM directly stores classical data in the quantum state of the computer and enables direct random access to individual data components, Qiskit encodes data into quantum states and processes it using quantum circuits. QRAM uses quantum circuits to process the data. QRAM is still a theoretical notion, and practical implementations are still in the process of being developed. Despite the fact that it has the ability to store and retrieve data in an efficient manner, The technique used by Qiskit, on the other hand, offers a versatile framework that can be utilized for encoding and processing classical data on simulators and hardware that are already in existence.

In [21], Several hybrid quantum-classical convolutional neural networks (QCCNNs) were suggested by the researchers. Each of these QCCNNs had a unique quantum circuit design and encoding methodology. Both two-dimensional and three-dimensional medical imaging datasets have been analyzed using these unique methodologies. For example, the datasets that highlight discrete, possibly malignant lesions that are seen in computed tomography scans have been used. An encouraging finding is that the performance metrics demonstrated by these QCCNN models are comparable to those of their classical counterparts. This finding opens up a tempting route for future research that aims to incorporate these algorithms into a variety of medical imaging applications.

An in-depth investigation of the pooling approaches used by hybrid quantum-classical convolutional neural networks (QCCNNs) for the purpose of categorizing two-dimensional medical pictures is carried out by Maureen Monnet and other researchers [22]. The performance of four distinct quantum and hybrid pooling strategies is investigated. These techniques include mid-circuit measurements, ancilla qubits with controlled gates, modular quantum pooling blocks, and qubit selection with classical postprocessing. The findings indicate that the performance of QCCNNs without pooling is comparable to or even superior to that of an analogous classical model. As a result, it is promising to investigate the architectural options in QCCNNs in more detail for various future applications.

A framework for quantum machine learning was presented by the researcher in [23]. This system was built on quantum convolutional neural networks and was designed to solve issues associated with multiclass classification. Quantum outputs are processed by a SoftMax activation function, and then cross-entropy loss is minimized through quantum circuit parameter optimization with the use of this technique, which applies a hybrid quantum-classical approach. More precisely, a variational model is utilized. The introduction of a unique quantum perceptron model and the optimization of the construction of a quantum circuit are two noteworthy advancements. This technique is used in order to handle a 4-class classification job utilizing the MNIST dataset. The data is encoded using eight qubits and include four ancilla qubits, which is a break from prior work that concentrated on 3-class classification issues. It seems that the findings imply that the accuracy of these networks is equivalent to that of traditional convolutional neural networks that feature comparable trainable parameter counts.

III. BACKGROUND

Information processing in quantum computing is based on the tenets and properties of quantum physics, including quantum bits, interference, superposition, and entanglement. We are now able to tackle complicated problems more quickly and effectively than ever before, thanks to quantum computing.

Qubits are the important computational units in quantum computers, which perform a superposition state between $|0\rangle$ and $|1\rangle$ [15], [24], It is possible to represent a single qubit state as a complex two-dimensional vector, i.e., as shown in eq. 1 [25], [26], [27].

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle, ||\alpha||^2 + ||\beta||^2 = 1 \tag{1}$$

Here, $|\psi\rangle$ is the state vector representing a quantum system. This system is in a superposition of two basis states, represented by $|0\rangle$ and $|1\rangle$. The coefficients α and β are complex numbers that determine the probability amplitudes of the system being in each of the two basis states, and $||\alpha||^2$ and $||\beta||^2$ are the probabilities of observing $|0\rangle$ and $|1\rangle$ from the qubit, respectively. It can also be represented geometrically using the polar coordinates θ and φ, as shown in eq. 2 [25], [27].

$$|\psi\rangle = cos\, cos\left(\frac{\theta}{2}\right)|0\rangle + e^{i\emptyset} sin\, sin\left(\frac{\theta}{2}\right)|1\rangle \tag{2}$$

Here, $|\psi\rangle$ is the state vector representing a single-qubit quantum system. This system is in a superposition of two basis states, represented by $|0\rangle$ and $|1\rangle$. The coefficients are determined by the angles θ and ϕ. θ is the polar angle, which ranges from 0 to π, and ϕ is the azimuthal angle, ranging from 0 to 2π. Both angles are expressed in radians. The term $e^{i\phi}$ is a complex exponential representing the phase of the quantum state, where $0 \le \theta \le \pi$ and $0 \le \varphi \le \pi$. A single qubit state is represented by the surface of a three-dimensional unit sphere, referred to as the Bloch sphere. A multiqubit system can be performed as the product of n single qubits, which is equivalent to a superposition of n basis states from $|00\ldots00\rangle$ to $|11\ldots11\rangle$. In this system, quantum entanglement connects different qubits. In quantum circuits, these systems perform quantum computations by means of quantum gates [28].

It is well known that a quantum gate transforms a qubit system into another, and as a matter of classical computing, it can be combined with several classical operators, such as rotation operator gates and CX gates [29]. Rotation operator gates Rx(θ), Ry(θ), Rz(θ) rotates a qubit state in the Bloch field around the corresponding axis by θ and CX gate entangles two qubits by overturning a qubit state if the other is $|1\rangle$. Those quantum gates use quantum overlap and entanglement to add utility to classical computing, and it is familiar that quantum algorithms can add a rapid computational gain to the current algorithms in specific functions such as major factorization [30], [31].

Quantum neural networks have been developed recently as a subfield of quantum computing that explores how quantum computers are used for neural network missions. That is, quantum deep learning is an integrative field that consolidates quantum physics and deep learning; it uses the power of quantum computing to create quantum categories of deep learning algorithms that are used in the associated fields.

IV. DATASETS

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-3, a version of the dataset contains 29,986 images (13992 negative cases, 15994 positive cases) from 16,648 patients, see figure 1 show COVIDX CXR-3 dataset.

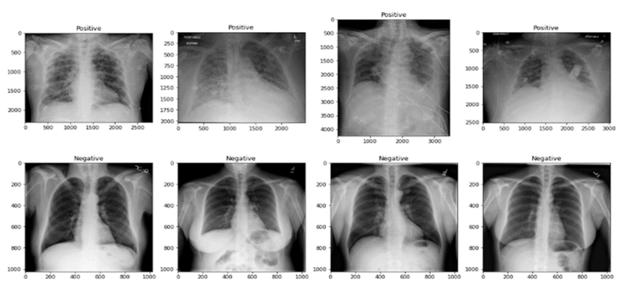


FIGURE 1. COVIDX CXR-3 dataset.

The aim of researcher's endeavor was to provide a comprehensive and accurate dataset that can be utilized for research and analysis in the field. The dataset includes chest X-ray images of COVID-19, and Normal subjects. At the time that the research was conducted, the categories that were discussed before comprised a total of 15994 and 13992 samples, respectively, as shown in figure 1. The

X-ray images have a standard variable size ranging from 512×512 to 1024×1024 pixels, and they were captured from a variety of different angles and positions. In this study, we downsized the photos to 200 by 200 pixels since we found that this resolution gave findings that were comparable to those obtained with bigger image sizes. As a result, it was able to speed up the training process as well as the testing procedure.

V. METHODOLOGY

The proposed QCNN divides patients into COVID-19 infected or healthy groups in order to enhance CNN's categorization for medical pictures. The primary idea behind the QCNN model is to improve the efficiency of classical learning by using quantum computation. The suggested model is divided into three sections: first, preprocessing. Second, the classical CNN structure. Third, propose two quantum circuit of CNN, As shown in Figure 2.

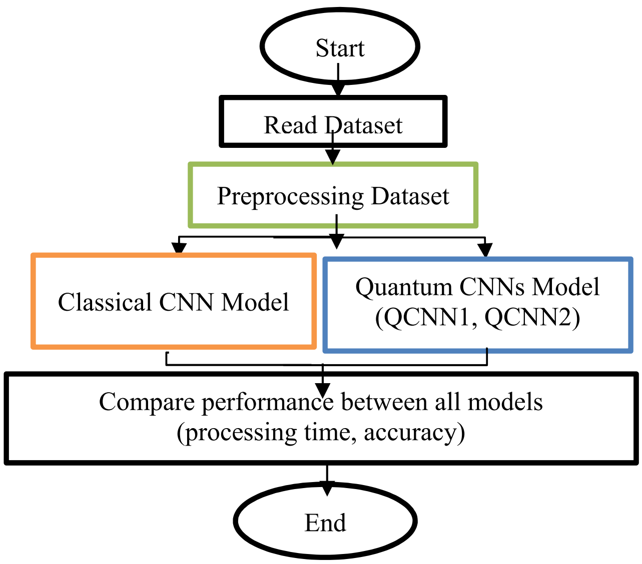


FIGURE 2. General diagram for proposed system.

A. 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 1024×1024 to 200×200 to save the computational expense. Additionally, the images are mixed together to make the data more diverse, which finally results in generic training and broadens the scope of the model. Several augmentation techniques are used to increase the COVID Xray images and to make the dataset balanced. 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. and 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, these augmentation techniques are useful to avoid underfitting because the system is recognizing each image as a new entity.

B. 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 employed with a dropout of 0.5 in order to reduce the overfitting. The features that are retrieved by the convolutional network are flattened into a one-dimensional vector in order for the fully connected network to categorize them using Sigmoid into two classes (COVID and Normal).

C. 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. The QCNN would be more powerful than its conventional equivalent.

The following steps are about the procedure on how to assemble circuits:

1.Define the quantum circuits, appropriately set up a state, train the quantum classifier, and then check to see whether it

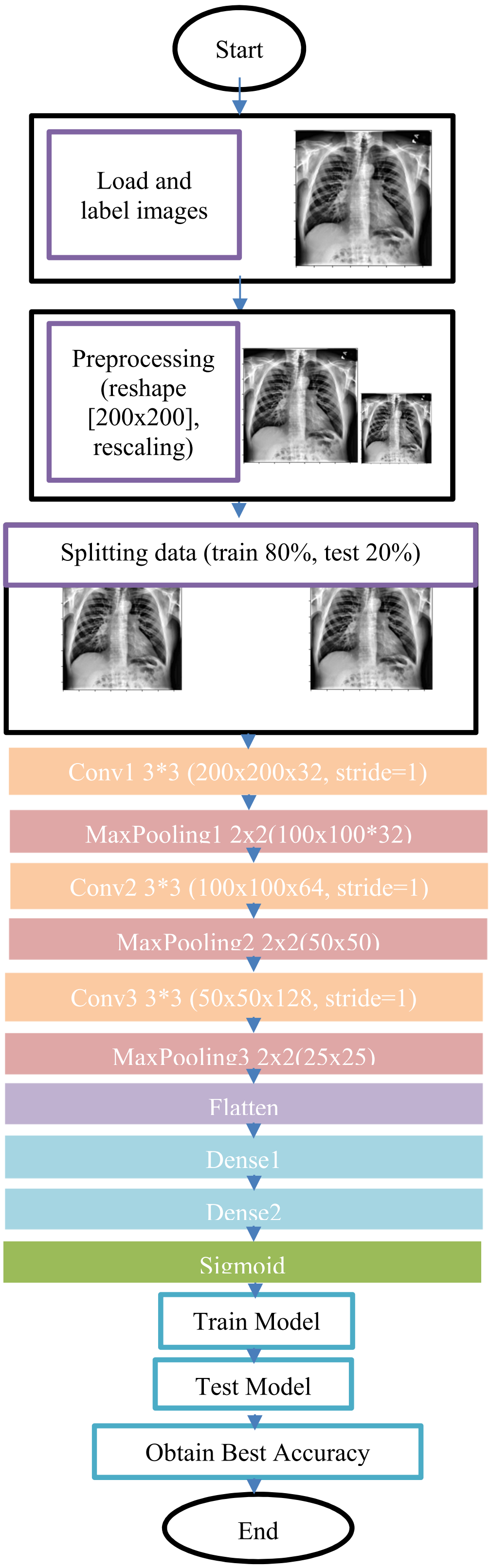
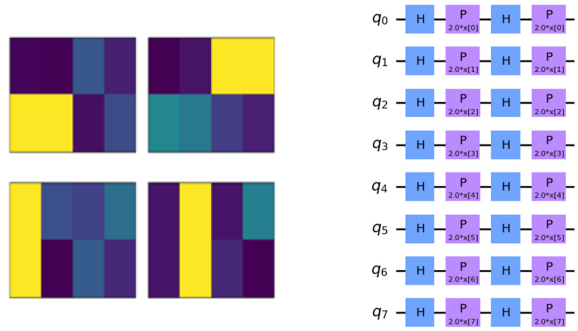


FIGURE 3. The proposed CNN networks.

works. To speed up the processing, there is "entanglement". We can read a two qubit to get the classification outcome when entanglement is decreased.



a: X-ray dataset image preparation b: ZFeatureMap Architecture

FIGURE 4. X-ray image preparation and ZFeatureMap architecture.

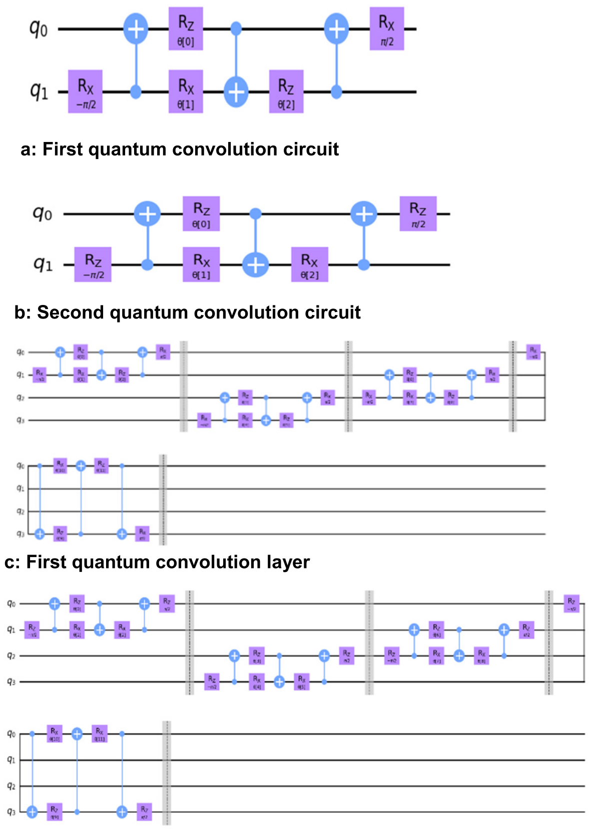
Figure 7 provides an illustration of the QCNN architecture's generalizability for this image classification problem. Figure 4 illustrates the quantum cluster state preparation layer, the initial layer of the QCNN architecture. We create synthetic image data from images in the database under certain conditions, 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 [32], 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.

3. Included in the convolution and pooling layer are two unitary matrices with qubit parameters. Quantum convolution is the third layer. RX, RZ, and CNOT gates in a quantum convolution layer are shown in Figure 5, which may be built by a cascade of two-qubit parameterized unitary to pairs of neighboring qubits progressively.

Specifically, ZFeatureMap is used to encode classical data as rotations around the Z-axis of qubits in a quantum circuit, see figure 4a.

In order to map classical data onto a quantum state, the ZFeature Map performs a number of procedures. The term "ZFeature" comes from the fact that these operations often entail rotating qubits around the Z-axis of the Bloch sphere. The information that is derived from the classical data is encoded into the amplitudes of the quantum state vector, while the mapping operation is being carried out. The manner in which this encoding is carried out is determined by the particular rotations that are done by the ZFeature Map. After the encoding process is finished, the classical data is then represented as a quantum state. The amplitudes of the state



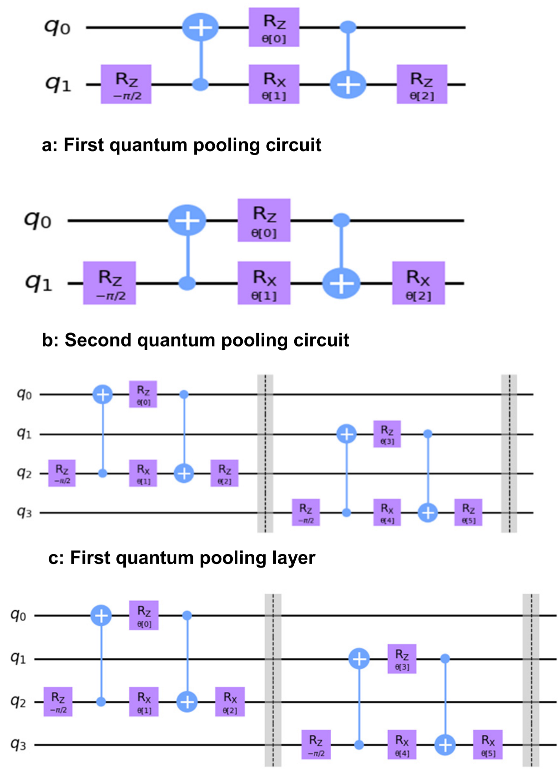
a: First quantum convolution circuit

b: Second quantum convolution circuit

c: First quantum convolution layer

d: Second quantum convolution layer

FIGURE 5. Quantum convolution layers.



a: First quantum pooling circuit

b: Second quantum pooling circuit

c: First quantum pooling layer

d: Second quantum pooling layer

FIGURE 6. Quantum pooling layer.

vector include information about the classical data that was first encoded.

4. The quantum pooling layers are shown in Figure 6 as RX, RZ, and CNOT gates. The entanglement is managed via CNOT gates. Entanglement is lowered down from a two-qubit circuit to a one-qubit unitary circuit using two arbitrary unitary qubits to create a parameterized pooling. A two-qubit pool is used by the quantum pooling layer to combine half of the qubits. The relevant qubits that have the label 1 affixed to one state and the label 1 affixed to the other state are output by the pooling layer. An image data collection for binary classification serves as the traditional data source in this design. When downscaling an image and preparing the features as the input parameters for a quantum network, the pixel is not an acceptable image feature for classification, figure 7 illustrates the QCNN architecture.

The distinction between the 1st and 2nd quantum circuit:

1. Sequence of gates: The first circuit begins with a rotation around the X-axis, while other circuit begins with a rotation around the Z-axis.

2. The order of the application and qubits targeting the gateway varies.

3. Both circuits include controllable gates, such as CNOT, which provide entanglement between the qubits, and their locations differ between the two circuits, leading to different entanglement patterns and the resulting quantum states. These differences can affect the quantum transformations achieved by each circuit, highlighting the importance of understanding the subtle differences between quantum circuits in quantum computing applications).

In figure 7, This encoding process involves converting pixel values into quantum amplitudes or using specific encoding schemes (ZFeatureMap). Quantum Convolution Layer and Quantum Pooling layer there are two-qubit quantum circuits known as QCNN1 and QCNN2, and they were created specifically for certain quantum tasks. The initial rotation gates that are applied to the qubits in QCNN1 and QCNN2 are different, despite the fact that their structures are comparable. There is a possibility that the selection of initial rotation gates (Rz vs Rx) in QCNN1 and QCNN2 will have an effect on the development of the quantum state and the entanglement patterns in the circuits. It is possible that one circuit design will perform better than the other in terms of accuracy, gate count, or depth but this will depend on the particular quantum algorithm or job being performed. The ansatz model uses a parameterized quantum circuit. It usually has a predetermined layout of quantum gates, such as entangling gates (CX) and rotation gates (Rx, Rz). It all starts with some arbitrary settings for the ansatz circuit's parameters. In order to minimize a cost function,

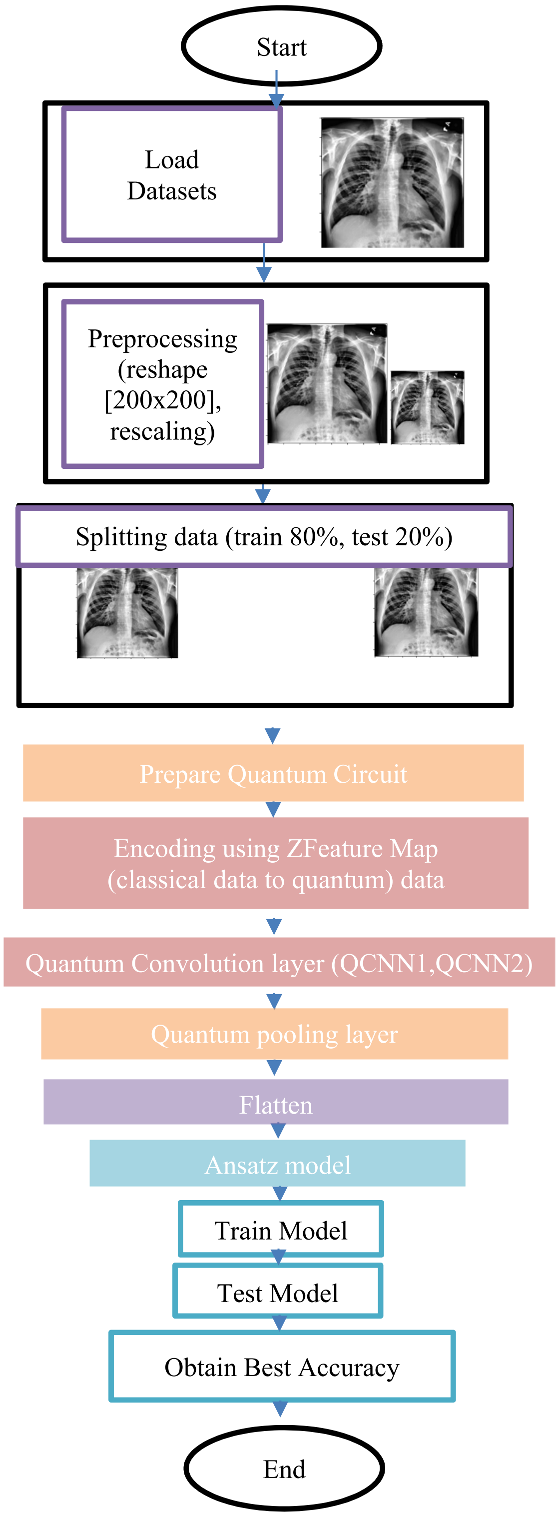


FIGURE 7. A QCNN architecture.

the parameters of the ansatz circuit are repeatedly modified during the training phase.

SparsePauliOp is used a quantum computing framework. It can represent measurements along different axes by composing tensor products of Pauli matrices (I, X, Y, Z) acting on different qubits. This class offers a more efficient way to represent and manipulate large quantum operators that are mostly composed of zeros. It stores only the non-zero elements of the operator, making it much more memory-efficient for sparse operators compared to a dense representation.

Decoding in ansatz models inside a quantum neural network (QNN) requires the interpretation of the measurement results of the output qubits in order to ascertain the class label of the data that is being input. Immediately after the execution of the ansatz circuit, measurements are carried out on the qubits that are output. As a result of these measurements, bitstrings are produced as outcomes, with each bitstring representing a different potential state of the output qubits.

Usually, traditional optimization algorithms like gradient descent are used for this optimization process, which involves computing the gradient of the cost function with respect to the ansatz parameters using methods like quantum gradients.

VI. RESULTS AND DISCUSSION

The purpose of this section is to show how effective the suggested QCNN classifier based on scale-inspired image characteristics is. We conduct two sets of experiments to achieve this. The tests were conducted in an IBM Qiskit environment.

A medical dataset of Covid-19 images from the first trial comprises 13992 photographs of healthy people without illness and 15994 images of benign Covid positive people. In the first group, 80% of the photos were chosen for training, while the other 20% were chosen for testing.

In our experiments, features were distributed out into the eight qubit parameterized quantum circuits after being normalized to $[-\pi/2, \pi]$ as rotation angle parameters in RX, RZ, and CNOT gates. The multi-scale structure of the data distribution is further highlighted by this fusion of encoded local correlation features and QCNN. The incorporation of quantum features appears to have improved performance when compared between the QCNN model and the traditional CNN model.

The value accuracy in CNN and QCNN with multiple quantum layers for two groups dataset 2000, 10000 images have achieved CNN accuracies of about 89.4, 91.83, and 80.14% respectively, training time is 57.993, 282.307, and 818.3026 sec per each epoch, respectively and the difference is negligible. A first proposed QCNN has achieved accuracies of about 91.57, 92.36, and 83.72% respectively, training time is 2.84, 12.06, and 37.8684 sec per each epoch. A second proposed QCNN has achieved accuracies of about 94.21, 95.07, and 86.614% respectively, training time is 3.104, 15.743, and 47.4634 sec per each epoch, respectively as shown in table 1.

When compared to the other two quantum models, pure QCNN convergence exhibits a considerable fluctuation across a relatively limited range. The pure QCNN model,

TABLE 1. Comparison between classical CNN and two proposed quantum CNN.

	Classical CNN		Proposed QCNN1		Proposed QCNN2	
No sample	Accuracy	Times per epoch (sec)	Accuracy	Times per epoch (sec)	Accuracy	Times per epoch (sec)
2000	89.4	57.99	91.57	2.84	94.21	3.104
10000	91.83	282.3	92.36	12.06	95.07	15.743
26000	80.14	818.3	83.72	37.86	86.61	47.463

out of the two quantum-based models, may still show better convergence. The images consist of 15994 photographs that are covid positive and 13992 images that are normal without illness. Additionally, each class chose 80% of these images for training data and the remaining 20% for validation.

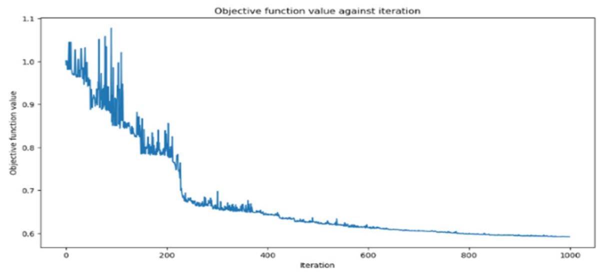
One reason for the accuracy decreases is when using 26000 from a dataset with QCNNs could be related to the complexity of quantum computations, the decrease in accuracy when using larger datasets, such as a sample size of 26,000, with QCNNs can be attributed to the complexity of quantum computations. Quantum algorithms, including those used in QCNNs, often involve complex mathematical operations and circuit implementations, which may have difficulty handling large data sets efficiently. This complexity lead to increased computational load and potential accuracy degradation, as observed in the results, Current quantum hardware platforms are very limited and the scope of quantum systems is restricted and does not scale to accommodate big data [33]. Quantum computing is highly specialized and rapidly evolving field. Current quantum computers have limitations, such as high error rates, short coherence times, and inadequate design choices can result in decreased accuracy when processing larger datasets. These limitations can lead to inaccuracies in computations, especially when dealing with large datasets.

Similar to the way multiscale images are analyzed and encoding, X-ray images have similar correlations that are important for studying the properties of different measurements. Which leads to a rapid improvement in the performance of quantum networks, like a rapid increase in accuracy accompanied by a rapid decrease in loss.

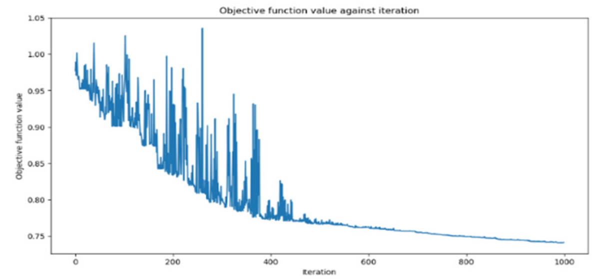
Creating images in Figure 4a and the accuracy of the data distribution in the category affects the result by distributing the different position of the pixel values, where there are images from the disturbed state to the disagreeable state and this motivates us to use the noise of the image data.

The proposed quantum CNN networks with the prepare encoding method used outperformed the classical CNN network in terms of accuracy and processing time in all experiments, and the performance gradually improved.

The objective function value represents the cost associated with the difference between the predicted quantum states (representing the model's predictions) and the target quantum states (representing the actual labels). The objective function in quantum machine learning models, including QCNN, is generally defined to minimize the difference between these quantum states. The specific form of the objective function can vary based on the task and the quantum model architecture being used in training process to optimize the quantum model for accurate predictions. The specific form of the objective function depends on the task and the quantum model's architecture, see figure 8.



a: Objective function value of QCNN1



b: Objective function value of QCNN2

FIGURE 8. Objective function value against epochs.

Analysis of the experimental results shows that two our proposed methods reduce the time required, and therefore, quantum CNN contains a smaller number of layers compared to classical CNN.

Complex tasks may require a higher number of qubits to capture subtle patterns and relationships within the data. The number of qubits in a Quantum CNN significantly impacts its performance, influencing the model's complexity, capacity, and the parallelism it can exploit. However, it's crucial to balance these advantages with the required computational resources, the sensitivity to noise, and the overall scalability of the quantum system to ensure practical and efficient quantum machine learning implementations, while a small number of qubits currently limit the accuracy of quantum models in image classification compared to classical methods, ongoing advancements in quantum computing technologies and algorithm development hold the promise of overcoming these limitations in the future.

When doing a comparison examination of the performance of several models on subsets of the MNIST dataset, the major statistic that was taken into consideration was accuracy. Specifically, the MNIST (3,4,5,6) and MNIST (0,1,2,3) subsets were examined and appraised. Quant1 and quant2 in [23] across both subgroups, showing an improvement in accuracy. This was the case among the quantum models, which are designated by the reference numbers [23]. QCNN models, QCNN1 and QCNN2, on the other hand, demonstrated greater performance in comparison to their quantum counterparts, as shown in table 2.

TABLE 2. **Comparation proposed our quantum models with related works.**

dataset	Quant1 [24]	Quant2 [24]	QCNN1	QCNN2
MNIST (3,4,5,6)	71.44%	85.14%	91.05%	93.36%
MNIST (0,1,2,3)	77.67%	90.03%	94.78%	96.3%

The QCNN1 algorithm attained an accuracy of 91.05% for the MNIST (3,4,5,6) subset, while the QCNN2 algorithm demonstrated an even greater accuracy of 93.36%, beating both quant1 and quant2 algorithms in [23]. Similar to the previous example, the QCNN1 algorithm obtained an accuracy of 94.78% on the MNIST (0,1,2,3) subset, while the QCNN2 algorithm displayed the maximum accuracy of 96.3%. These findings demonstrate that quantum convolutional neural networks are capable of doing quite well when it comes to image classification tasks, especially when applied to subsets of the MNIST dataset.

In general, the comparative study highlights the significant performance gain that QCNN models give in comparison to previous quantum techniques. QCNN1 and QCNN2 have consistently outperformed other neural networks, which demonstrates their potential to improve accuracy and efficiency in image classification tasks. This suggests that there is a viable route for exploiting quantum computing methods in machine learning applications.

When it comes to our work, arranging the gates and rotating the circuit is more ideal for capturing the vital aspects, and this results in improved performance. This is in addition to the fact that the suggested circuits have the capability of adapting to a new data set as a result of their design and the parameters that they have been set to. This provides a larger capacity to train and further increases its efficacy.

Quantum in [23] makes use of a variety of quantum circuit designs, including as 4-qubit, 3-qubit, and 2-qubit filters, which results in an architecture that is both sophisticated and versatile. It places a significant amount of reliance on entanglement processes that span several qubits in order to get intricate correlations and characteristics within the input data. In order to achieve entanglement, it makes use of parameterized rotations, which in turn increases the flexibility of the learning method. demonstrates high performance and accuracy in multiclass image classification tasks, producing results that are equivalent to those achieved by traditional CNNs with a comparable number of trainable parameters. It is able to effectively capture significant aspects from the input data thanks to its flexible design and entanglement techniques, which contribute as well to its efficacy.

A particular two-qubit unitary circuit architecture that is specifically designed for image classification tasks is the focus of this article. In comparison to other architectures, it has a more straightforward overall structure since it makes use of a condensed circuit topology that is accompanied by a predetermined sequence of gates. The controlled-NOT (CX) gates that are used between two qubits are the primary means by which entanglement is implemented. Although it is possible to capture entangled states, the process that causes entanglement is more confined and less diverse in comparison to previous work that is linked to this topic. It is possible that the established circuit design may result in simplified optimization techniques and shorter training durations; nonetheless, the performance of the circuit will ultimately be determined by the particular properties of the dataset and the job that is being performed.

Compared to our approach, [21] and [22] used RZZ gates increase complexity and cause quantum clustering instability during training. This instability yields worse outcomes than without sophisticated gates. Instead of using complicated gates, our strategy simplifies training for stability and good outcomes. The differences in results between the two techniques show that quantum machine learning must balance complexity and stability. Complex gates like RZZ can capture detailed data patterns and be expressive, but training stability and convergence may be difficult. Simpler gate topologies, like those used in our study, may lose expressiveness but frequently result in more stable training dynamics and dependable performance. By simplifying our technique, we reduce the danger of quantum clustering instability and guarantee our model can be taught and deployed in real-world applications. Our successful technique shows that advanced gate topologies are not necessarily needed to compete in quantum machine learning problems. Instead, balancing simplicity and efficacy may provide solid solutions.

VII. CONCLUSION AND FUTURE WORK

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. In order to assess the effectiveness of the quantum classifiers, we trained them using CNN and two different quantum CNN models. The simulation results on the Covid-19 image datasets demonstrate that, when compared to the traditional CNN, the proposed QCNN with the suggested feature extraction methods may 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. QCNN outperform classical CNNs in processing time due to quantum parallelism and entanglement. Quantum states enable simultaneous exploration of vast solution spaces, a capability that 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, more methods for features extraction needs to be carried out to explore the interpretability and performance improvement of QCNN models, Finally, the QCNN architecture can be enhanced to overcome limitations of the proposed model.

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