Multiclass Image Classification Based on Quantum-Inspired Convolutional Neural Network

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Abstract

Multiclass image classification is considered a challenging task in computer vision that requires correctly classifying an image into one of the multiple distinct groups. In recent years, quantum machine learning has emerged as a topic of significant interest among researchers. Using quantum concepts such as superposition and entanglement, quantum machine learning algorithms provide a more efficient method of processing and classifying high-dimensional image data. This paper proposes a new image classification model using quantum-inspired convolutional neural network architecture or, shortly, QCNN. The proposed model consists of two main phases; pre-processing and classification based on the QCNN phase. Seven benchmark datasets with different characteristics are adopted to evaluate the performance of the proposed model. The experimental results revealed that the proposed QCNN outperformed its classical version. Additionally, the results demonstrated the effectiveness of the proposed model compared with the state-of-the-art models.

Keywords [1]

Quantum Computing, Convolutional Neural Networks, Image Classification, Quantum Machine Learning

1. Introduction

Convolutional neural networks (CNNs) have experienced rapid expansion in the image classification and multiclass image classification fields. Which computer vision task requires categorizing an image into one of many categories? As the number of classes increases, the task's difficulty increases, and it requires identifying fine-grained details that differentiate between distinct objects or classes. In recent years, convolutional neural networks (CNNs) have become a popular solution to this issue. The CNN architecture is designed to mimic the structure of the visual cortex in humans and animals. It consists of multiple layers of interconnected nodes trained to extract and identify various image features. The input image is fed to the CNN's first layer, and each successive layer extracts increasingly complex features. The class with the highest probability is selected as the predicted class based on the probabilities generated by CNN's output layer.

Although CNNs have been demonstrated to be an effective tool for image classification and other computer vision tasks, they may not always perform at their best with small datasets [12]. Quantum computing comes into play at this point. Using quantum concepts such as superposition and entanglement, quantum computing can potentially improve traditional machine-learning techniques [13]. Notably, it has been demonstrated that quantum machine learning algorithms provide superior feature selection capabilities than classical methods, enabling more efficient processing and classification of high-dimensional data [14]. Consequently, a growing interest has been in developing machine-learning models inspired by quantum mechanics, such as quantum-inspired CNNs [15].

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These models aim to combine the power of convolutional neural networks (CNNs) with the benefits of quantum computing to improve performance on complex image classification tasks [16]. This paper proposes a new image classification model based on quantum computing principles, including entanglement and superposition, in conjunction with the CNN layer. The proposed model comprises two principal phases: pre-processing and the classification-based quantum convolutional neural network phase. The original image undergoes image resizing and data normalization during the pre-processing phase. The processed images are then used as input for the proposed QCNN architecture. This paper's primary contribution is summarized in the following points:

1. A new QCNN architecture is proposed.
2. The proposed QCNN is applied to the multiclass image classification problem.
3. Seven benchmark datasets are used to evaluate the proposed model.
4. A comparative analysis between the proposed model and state-of-the-art models is considered.

The remainder of the paper's format is as follows: Section 2 presents the related work; Section 3 introduces the overall proposed image classification model based on QCNN in detail; and Section 4 presents and discusses the results of experiments conducted on various datasets using the proposed QCNN architecture. Section 5 concludes with a summary of the paper's key findings, a discussion of the limitations of the proposed model, and suggestions for future research directions.

2. Literature review

CNNs have demonstrated efficacy in multi-class image classification by extracting higher-level image information and outperforming conventional image processing [1]. CNNs' ability to capture complex image characteristics has led to significant advances in computer vision tasks such as object recognition [4], semantic segmentation [6], and target detection [8]. Recent studies have proposed altering CNN's architecture to enhance its performance in multi-class image classification tasks [2]. These alterations are intended to improve the network's precision, reduce computational complexity, and accelerate the training procedure. These modifications include the addition of skip connections [3], the use of various activation functions [4], and the incorporation of attention mechanisms [5]. In numerous studies involving computer vision, CNNs have produced outstanding results. For instance, some papers [5, 6] focused on target detection. The authors of [5] created a CNN-based infrared dim small target detection algorithm that proved effective and precise for detecting small targets in infrared images with low SCR and complex scenes. They incorporated spatially finer, target-oriented shallow features and semantically more robust deep features.

In contrast, the authors of [6] presented a depth recognition algorithm for robot vision systems used for apple picking. Using deep learning techniques, the algorithm achieved greater recognition accuracy and robustness than conventional methods, demonstrating the potential of deep learning in agricultural robot applications. Other studies [7, 8] have investigated semantic segmentation. The authors of [7] proposed a multi-receptive-field convolutional neural network (MRFNet) to extract rich and useful context information from complex and dynamic medical images. On three public medical image datasets, including SISS, 3DIRCADb, and SPES, the MRFNet demonstrated exceptional performance. In the study [8], the authors introduced a novel network architecture for thermal image semantic segmentation called edge-conditioned convolutional neural network (EC-CNN). The end-to-end-trained EC-CNN generated high-quality segmentation results by incorporating prior edge knowledge. In addition, they presented a new benchmark dataset, Segmenting Objects in Day and Night (SODA), to facilitate exhaustive evaluations in thermal image semantic segmentation. In addition, CNN architectures have demonstrated their effectiveness in image classification, as demonstrated in [9, 10–11]. Regarding image classification, the authors of [9] proposed the dilated CNN and the HDC models, demonstrating improved training efficiency and accuracy on the MNIST dataset and a wide-band remote sensing image dataset. The research in [10] centered on classifying biological images using inverted residual blocks to replace some CNN modules to address the increased computational time. The method demonstrated promising performance online on five benchmark datasets, including two biological IM performances. Lastly, [11] sought to identify an appropriate architecture for transfer learning and identified Inception-v3 as such. The retrained

Inception-v3 model performed significantly better than previous state-of-the-art works on the CIFAR-10 dataset. This study's findings demonstrated the utility of transfer learning and paved the way for future developments in deep neural networks.

Researchers are investigating the potential benefits of combining CNNs with quantum computing techniques in light of the development of quantum computing. The training and application of quantum CNNs (QCNNs) have the potential to accelerate significantly. Quantum mechanics enables QCNNs to perform specific calculations significantly faster than their classical counterparts. As full-fledged quantum computation is still a distant prospect, the research in [13] discusses the potential of quantum-inspired (QI) algorithms implemented on classical computers to improve existing machine-learning techniques. Based on the theory of Quantum State Discrimination (QSD), they developed a QI algorithm for direct multi-class classification that provides a systematic method for locating sub-optimal solutions. This strategy enabled them to extend the capabilities of previous QI classifiers, which were restricted to binary classification, and address general multi-class datasets. In [14], the authors proposed a novel algorithm for feature selection based on a generalized embedding of Quadratic Unconstrained Binary Optimization (QUBO), which is executable on both classical and quantum hardware. They used mutual information as the basis for measures of importance and redundancy, with an interpolation factor serving as a counterbalance. Experiments comparing standard feature selection methods and their performance on various machine learning models demonstrated the effectiveness of the researchers' framework. In addition, they successfully executed one of their experiments on actual quantum hardware, demonstrating the algorithm's viability and compatibility with NISQ. Although their experiments were conducted on low-dimensional problems due to hardware constraints, the authors anticipate that the algorithm will scale with future quantum computing advancements.

3. The Proposed image classification based on QCNN model

The two primary phases of the proposed image classification model are the pre-processing phase and the classification based on the QCNN phase. The overall design of the proposed image classification model is depicted in Figure 1. From this figure, it can be seen that the original images are first normalized, after which the normalized images are fed into the quantum convolutional layer, after which a series of classical convolutional layers are applied, followed by a fully connected layer to obtain the final class. The following sections will go over each part's full description.

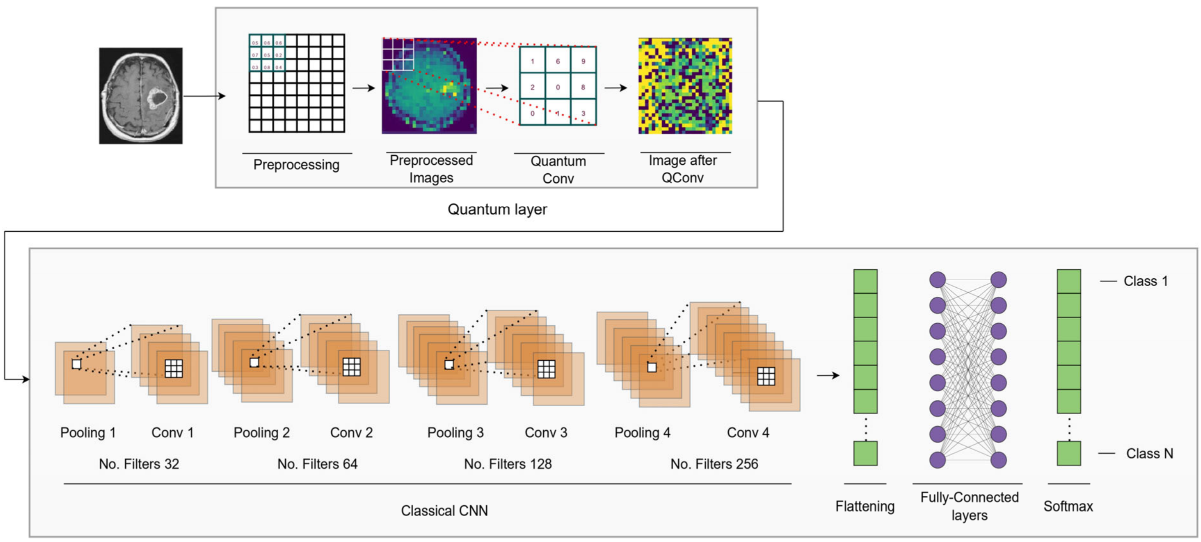

Figure 1: The architecture of the proposed image classification model

3.1. Pre-processing phase

Preparing and transforming the raw dataset into a more acceptable format for subsequent analysis and modeling is the primary goal of the pre-processing phase. The original images in this study are downsized to 28x28, and after that, data normalization is applied to all of the images in the dataset. Data normalization is crucial to improve the effectiveness and interpretability of machine learning algorithms. Normalization is a method that rescales the input features to a uniform range, usually between 0 and 1. This standardized range aids in reducing the influence of data distribution and scale differences, which could otherwise result in biased and less-than-ideal model performance. Each pixel in the image is normalized in this study by multiplying it by the highest number, 255. Each data point in the image is effectively scaled down to a value between 0 and 1 when this procedure is done to the entire dataset's image. The model is made to be less sensitive to the input characteristics' absolute values and more focused on the underlying patterns and relationships in the data by doing this normalization.

3.2. Classification based on QCNN phase

This phase feeds the processed image into the quantum convolutional neural network (QCNN). The quantum and classical components of the proposed QCNN make up its two main components. The proposed creates a powerful and effective classification system by combining the advantages of both quantum and conventional methodologies. Next, a detailed description of each part is presented.

3.2.1. Quantum part

The quantum part transforms the input data using the capabilities of quantum computing as a pre-processing layer. Quantum encoding, convolution, and measurement comprise its three main components. The block diagram for the quantum part of the proposed QCNN architecture is shown in Figure 2.

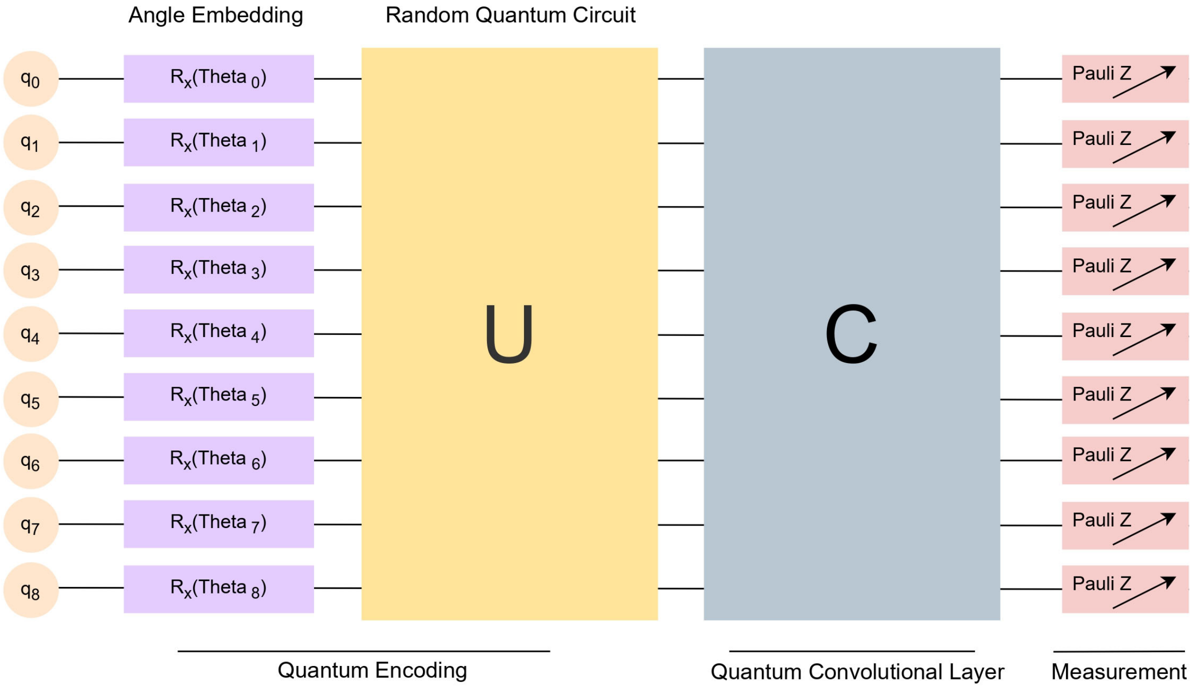

Figure 2: The block diagram of the quantum part of the proposed QCNN

The input data is first embedded into a quantum state during the quantum encoding stage. Nine qubits total are used in this study. The following equation is commonly used to represent a quantum state.

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle = \alpha\begin{pmatrix}1\\0\end{pmatrix} + \beta\begin{pmatrix}0\\1\end{pmatrix} \tag{1}$$

where $|\psi\rangle$ is the quantum state, α and β are complex coefficients or amplitudes, and $|0\rangle$ and $|1\rangle$ represent the basis states. In quantum computation, the amplitude contains the probability information of finding qubits in a specific state, and the normalized $|\alpha|^2 + |\beta|^2 = 1$ expresses this probability.

The input data can be embedded using various methods, depending on the embedding method. These embeddings each have unique traits and use cases. For instance, one method prepares a quantum state using binary data, another utilizes that data to encode data into the amplitudes of a quantum state, and yet another encodes data into the rotation angles of quantum gates. An essential step in quantum encoding is to embed the input data into a quantum state, enabling the model to use quantum computing. The type of data being used and the problem being solved determine the embedding approach to be used; each method has unique properties and applications.

The embedding approach used in this paper is called AngleEmbedding. AngleEmbedding modifies the behavior of quantum gates based on the input data values by encoding classical information into the rotation angles of the gates. In our case, the rotation gate employed is the gate denoted by the equation below.

$$R_X(\theta) = \begin{pmatrix} \cos\frac{\theta}{2} & -i\sin\frac{\theta}{2} \\ -i\sin\frac{\theta}{2} & \cos\frac{\theta}{2} \end{pmatrix} \tag{2}$$

This method is especially effective for continuous or real-valued data since it enables a concise representation of the input data within the quantum system. AngleEmbedding allows the model to benefit from the unique features of quantum computing, which may improve speed and make it possible to identify intricate patterns in the data that conventional methods could miss. The application of a random quantum circuit comes after the input data has been integrated into a quantum state. Many single-qubit gates, including the RX and controlled-NOT gates with the same angle, were randomly selected to make up this circuit. The random circuit operates as a non-linear transformation of the input data, which might aid in revealing intricate patterns in the data that traditional methods might find challenging to identify.

The image is then processed by a quantum convolutional step, which works similarly to a conventional convolutional layer but uses quantum circuits. This step entails processing the image through many quantum filters, each of which is a quantum circuit that only processes a small portion of the image. The output tensor, which depends on the quantum kernel size and the type of padding employed, will take a particular shape depending on the stride and padding used. After that, a selected activation function, such as ReLU, sigmoid, or tanh, is applied to the output tensor to create nonlinearity. The Pauli-Z operator is then used for each qubit to measure it on a computational basis. The expectation values are employed as features and fed into the traditional CNN layers in the classical part.

3.2.2. Classical part

Convolutional and fully connected blocks are combined to create a deep learning architecture in the classical part. The primary classifier for the processed dataset is represented by this architecture, which uses the predictive capabilities of traditional deep learning architectures. Max-pooling layers are put first, then convolutional layers, to create convolutional blocks. To lessen overfitting, they also have dropout layers. These blocks are in charge of identifying regional patterns and features in the input data, assisting the model in recognizing crucial data details for the classification task.

On the other hand, fully connected blocks act as the model's final steps, merging the information that the convolutional blocks have learned and deciding how to interpret the data. The final dense layer, which has a SoftMax activation function, comes after the fully connected layers and generates the class probabilities for each potential class. Classical architecture may learn intricate patterns in the data and produce precise predictions based on the cleaned dataset by combining these building blocks with information derived from the quantum layer.

4. Experimental results and discussion

Four main experiments are conducted to evaluate the general effectiveness of the proposed image classification model based on QCNN. Seven benchmark datasets are used to assess how well the proposed model based on QCNN performs. These datasets include BreastMNIST, OrganMNIST, ChestMNIST, PneumoniaMNIST, FashionMNIST, CIFAR-10, and Brain MRI Images. The adopted datasets are described in Table 1 according to the number of samples and classes. The adopted benchmark datasets have a varying number of classes, as can be shown.

It should be noted that the proposed model was evaluated on 200 training samples and 50 testing samples due to the existing constraints of quantum hardware. These samples were chosen at random. The first experiment aims to identify the best kernel size by experimenting with different kernel sizes. The model's performance in the second experiment is contrasted before and after adding the Quantum convolutional layer. The third experiment evaluates the proposed model using several benchmark datasets. The fourth experiment examines the proposed model with state-of-the-art models. These experiments used accuracy, sensitivity, precision, and f1-score as evaluation criteria. The CoLab notebook platform and the Pennylane Quantum Library were used for all experiments.

Table 1
Datasets description

	Number of Samples	Number of Classes
Brain MRI	253	2
PneumoniaMNIST	5,856	2
BreastMNIST	780	2
OrganMNIST	23,660	11
FashionMNIST	70,000	10
CIFAR-10	60,000	10
ChestMNIST	112,120	2

Finding the ideal kernel size for the proposed model is the goal of the first experiment in Figure 3. It should be noted that the Brain MRI Images dataset, one of the adopted datasets, is used to test the ideal kernel size. As can be seen, the accuracy for the kernel with a size of 1x1 is 73.75%; for the kernel with a size of 5x5 it is 77.50%; for the kernel with a size of 10x10 it is 97.95%; and finally, for the kernel with a size of 20x20, it is 98.65%. From this chart figure, it can be demonstrated that a 20x20 kernel size is the most efficient kernel size. The following experiments will continue to use this kernel size in the upcoming experiments. Also, 700 epochs will be used as well.

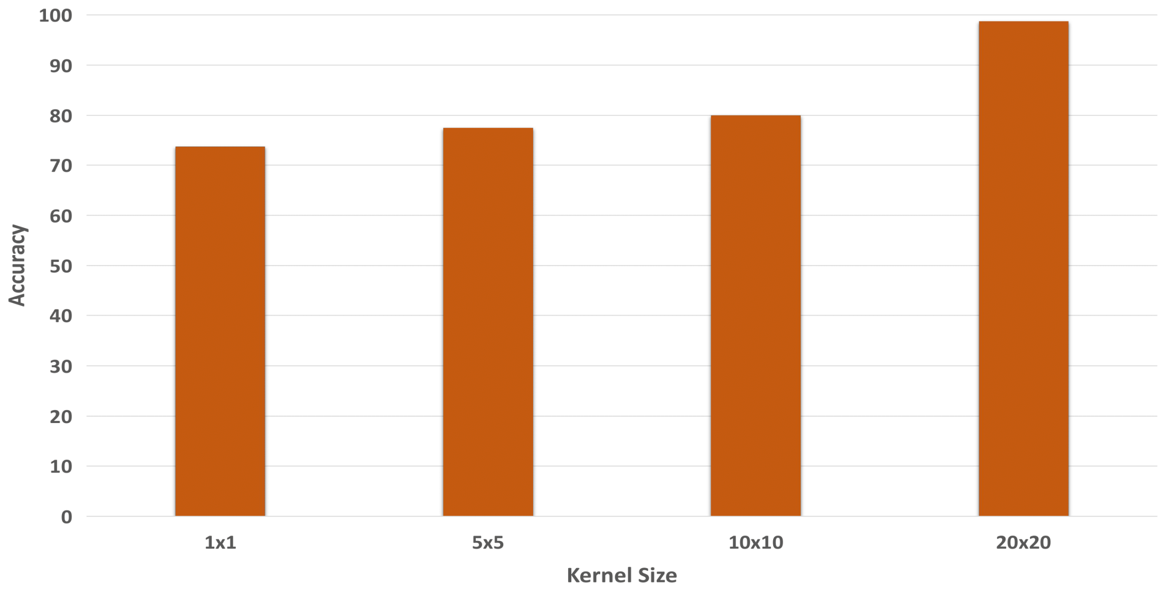

Figure 3: Comparison of using different kernel sizes in terms of accuracy

Results are obtained before and after applying the quantum convolutional layer to the dataset of Brain MRI images to demonstrate the significance of using the layer in the proposed QCNN. The experiment makes use of some evaluation metrics. Accuracy, precision, recall, and f1-score are the measures used for evaluation. Using the quantum convolutional layer increased the proposed model's accuracy to 98.65%, while doing without it reduced it to 92.68%, as shown in Table 2. Thus, it can be seen that applying the fundamentals of quantum computing to one of the convolutional layers can considerably boost the functionality of CNN architecture.

Table 2
The results before and after applying the quantum convolutional layer

	Accuracy (%)	**Precision (%)**	**Recall (%)**	**F-score (%)**
Before	0.92	0.80	0.76	0.76
After	0.98	0.98	0.98	0.98

The proposed model was subsequently assessed and tested on seven benchmark datasets in the third experiment in Table 3, including the Brain MRI dataset and six other benchmark datasets: PneumoniaMNIST, BreastMNIST, OrganMNIST, FashionMNIST, CIFAR-10, and ChestMNIST. Table 3 compares the proposed model's performance on several datasets, presenting the findings regarding accuracy, precision, recall, and f-score. As demonstrated, the proposed model exhibits superior learning and picture classification abilities across all datasets. Furthermore, the proposed model performs well in multi-class and binary classification issues, demonstrating its adaptability and versatility in handling different classification tasks. This emphasizes the proposed model's adaptability and robustness in various image classification cases. The training and validation accuracies are presented for 700 epochs in Figure 4 to assess the proposed model's performance further. The proposed model is up-and-coming, as this graph shows. Both the validation and training datasets showed high classification accuracy. These outcomes match those of the experiments shown in Table 3.

Table 3
The performance of the proposed model using seven benchmark datasets in terms of accuracy, precision, recall, and an f-score.

	Accuracy (%)	Precision (%)	Recall (%)	F-score (%)
Brain MRI	0.98	0.98	0.98	0.98
PneumoniaMNIST	0.99	0.99	0.98	0.98
BreastMNIST	0.96	0.96	0.96	0.95
OrganMNIST	0.98	0.98	0.97	0.97
FashionMNIST	0.98	0.98	0.98	0.98
CIFAR-10	0.90	0.90	0.89	0.87
ChestMNIST	0.99	0.99	0.91	0.95

The performance of the proposed model in comparison to the state-of-the-art models, namely hybrid quantum-classical convolutional neural network (HQC-CNN) [17], attentive octave convolutional capsule network (AOC-Caps) [18], Feature Pyramid Vision Transformer (FPViT) [19], cross-stitch Affine Network (CANet) [20], and convolution neural networks with 3x3 filter size (ConvNet) [21] is shown in Table 4 for further assessment of the robustness of the model. This table demonstrates how competitive the proposed model is. On most of the adopted datasets, it achieves the highest accuracy.

Table 4
The performance of the proposed model vs. the state-of-the-art models in terms of accuracy

	The Proposed Model	HQC-CNN [17]	AOC-Caps [18]	FPViT [19]	CANet [20]	ConvNet [21]
Brain MRI	98.69	97.8	-	-	-	-
PneumoniaMNIST	99.56	-	93.1	-	-	-
BreastMNIST	96.00	-	-	88.46	-	-
OrganMNIST	98.22	-	93.1	-	-	-
ChestMNIST	99.59	-	-	-	98.8	-
FashionMNIST	98.00	-	-	-	-	93.68
CIFAR-10	90.00	-	-	-	-	73.04

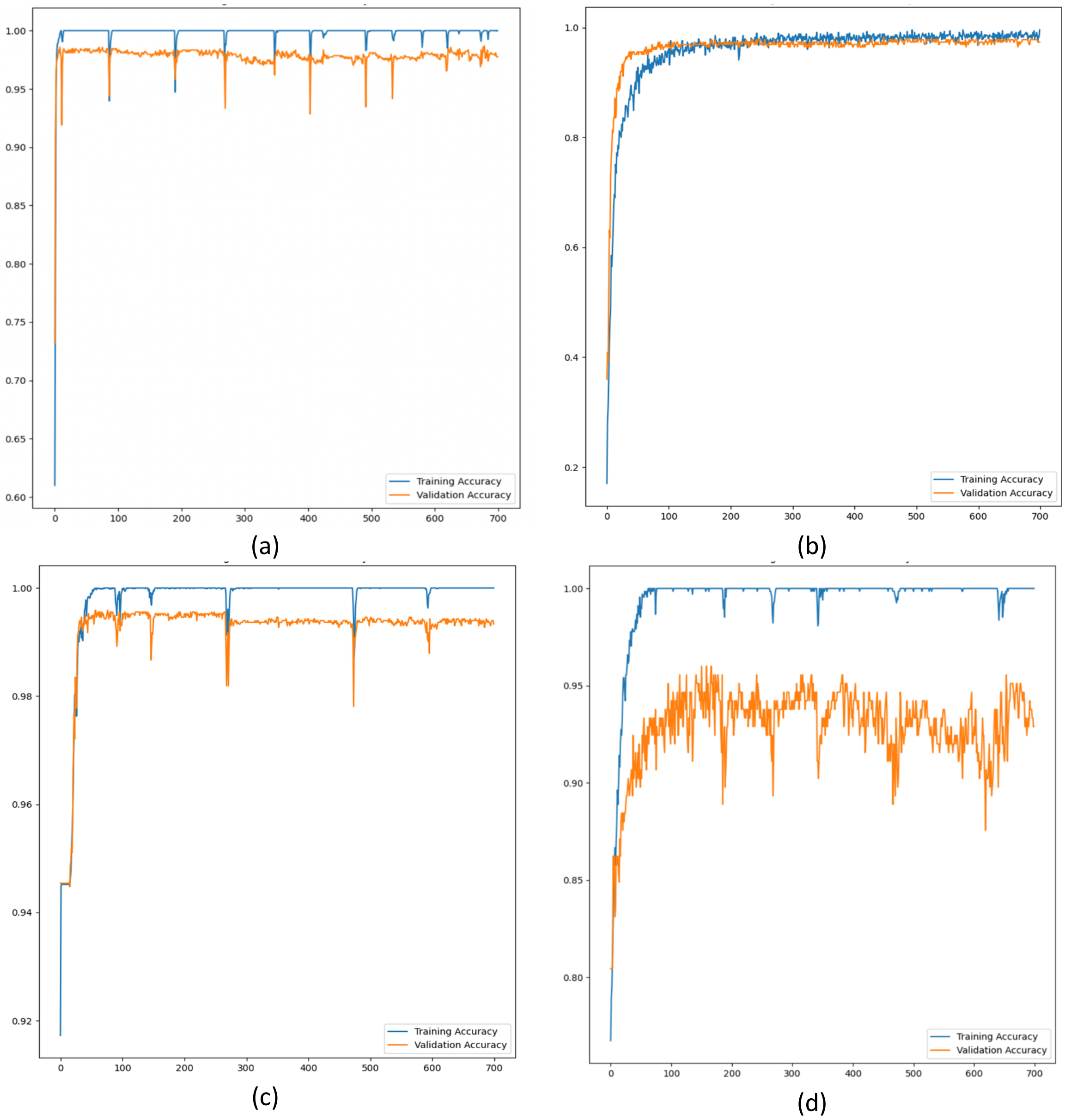

Figure 4: Training and validation accuracy through 700 epochs, (a) Brain MRI Images, (b) OrganMNIST, (c) ChestMNIST, and (d) BreastMNIST

5. Conclusion

This study proposed a new quantum convolutional neural network architecture. The proposed QCNN is applied to the image classification task. PneumoniaMNIST, FashionMNIST, CIFAR-10, BreastMNIST, OrganMNIST, ChestMNIST, and Brain MRI Images benchmark datasets are adopted. The experimental results revealed that exploiting quantum principles such as superposition and entanglement in the classical CNN can positively boost its performance. The results showed that increasing the kernel size of the quantum layer can significantly boost the performance of the proposed QCNN. Moreover, the results revealed that the proposed QCNN obtained the best results compared to several well-known landmark models. The overall proposed image classification model achieves an accuracy of 98% for Brain MRI Images, 99% for ChestMNIST, 98% for OrganMNIST, 96% for BreastMNIST, 90% for CIFAR-10, 98% for FashionMNIST, and 99% for PneumoniaMNIST. The main challenge in implementing the proposed QCNNs to large-scale image classification tasks is the restricted capacity of quantum hardware, which limits the size of input images and the number of layers employed in the network. As a result, in the future, the proposed QCNN may be implemented using simple quantum circuits.

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7. References

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