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Quantum Convolutional Neural Network Performance for Efficient Image Analysis and Prediction

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Abstract
To study Quantum Convolutional Neural Network (QCNN) performance for Image classification and analysis.
Objective: The core objective is to harness the computational capabilities of quantum systems to expedite traditional machine learning tasks

Methods: Quantum computation is based on quantum mechanics. It uses special properties such as Superposition, Entanglement, and Unitary Transformation which are not there in classical binary systems.

Results: The QCNN model was tested using plant Leaf dataset. The model demonstrated prediction accuracy of 95.45% with precision and recall scores of 0.9555 and 0.9545 respectively

Conclusions: The Plant leaf image dataset had been used to quantitatively test the classification performance. The QCNN has presented 95.55% and CNN has given 80.9% of test accuracy with 10 epochs of training on a moderate size dataset, which is a considerable achievement on resource utilization efficiency. In this regard, QCNN outperformed the classical CNN by providing 97.7% of prediction accuracy, in contrast to 67% of prediction accuracy from Classical-CNN as inferred from the confusion matrices.
Keywords: CNN, Image classification, Machine learning, Neural network, QCNN

1. Introduction

Artificial intelligence and Machine learning has contributed remarkably in the field of image recognition. The Convolutional Neural Network (CNN) and its variants deliver tremendous and efficient results, when large amount of dataset are fed into the model. However, this leads to increased computing power and memory resources leading to limit the further development in this field. Thus, it is challenging to compute the real-world problems where processing of large amount of data is involved [1].
Traditional Convolutional Neural Networks (CNN) take longer time and utilize greater computational resources for processing huge data with higher-order polynomials [2]. With the advancement in the field of quantum computation, the advanced machine learning models can be efficiently built using quantum processing. A Quantum computer uses a different environment than that of a classical computing system, such as superposition and entanglement [3].
A novel computational technique is Quantum computing that processes both the conventional data as well as quantum bits [4-5]. The hard computing jobs can be performed by the Noisy Intermediate-Scale Quantum Computers (NISQ). The reduced circuit depth requirement and higher noise tolerance make the QCNN best choice to be implemented on a near-term quantum devices [6].
By amalgamating the power of quantum computing technology along with classical CNN, a hybrid model was proposed in this research. The authors proposed two methods to deal with the physics issues of the quantum: (i) Direct application of classical CNN structure to the quantum system. (ii) To improve results

by applying a quantum system to the prior solved problems [7-8].

In continuation to the existing work, the proposed technique utilizes the power of quantum computation and accelerates the classical machine learning tasks for the plant leaves disease prediction. The QCNN results are compared with the results of classical CNN models, which shows a better trained QCNN model that are able to predict more accurately.

The organization of the paper is as follows: Section-II deals with the Literature Review, Section-III explains the Proposed Methodology, Section-IV deals with the Results and Discussion, and the paper is concluded in Section-V.

2. Literature Review

The performance of machine learning applications can be improved by utilizing the quantum deep learning techniques. In general, this work was used in medical image classification, which was based on the training of classical neural networks using the quantum circuits and to train the quantum orthogonal neural networks for the images of retinal color fundus [9].

The Hybrid Quantum-Classical Convolutional Neural Network (HQCNN) was used for the CXR image along with the Random Quantum Circuits (RQC). Here 6952 CXR images were utilized out of which 5216 pneumonia images, 1575 normal images and 1161 COVID-19 images were there [3]. The quantum progressive training was attained with the utilization of the quantum circuits, here the classical depth wise blurred convolution was attained by the implementation of hybrid quantum-classical model produced [11].

Quantum parameterized circuit based quantum deep convolutional neural network (QDCNN) model was proposed and it was compared with the classical deep convolutional neural network (DCNN). The different types of datasets like GTSRB and MNIST were numerically simulated and the experimental results verified the validity and feasibility of the QDCNN model [12].

The authors employed quantum machine learning techniques, in which a quantum neural network makes inferences from images encoded in quantum states. But the input image size is very small and limited to only 4x4. In other upgraded framework it can distinguish 16x16 images from the MNIST dataset, which was implemented on a regular laptop [13].

The authors utilized the CNN in conjunction with the quantum circuits to process the large amount of data at once, whereas the entanglement and superposition were used by the quantum random access memory (QRAM) to store the large amount of data [14].

Both 2D and 3D medical image datasets were analyzed by different types of QCNN, and it had distinctive encoding and quantum circuit design [15]. The 2D medical images were classified and a deeper analysis for the different pooling mechanism for hybrid quantum classical convolutional neural network (H-QCCNN) was studied. Using the quantum circuit parameter optimization technique, the cross-entropy loss was minimized. The SoftMax activation function was utilized to process these quantum outputs [16].

The gradient-based learning method for the multilayer neural network utilizes the back-propagation algorithm. They are extensively used to evaluate various handwritten characters with little to no pre-processing thus used in digit handwriting recognition techniques. They perform better than any other methods for dealing with the variability of two-dimensional (2-D) shapes [4-5]. Field extraction, segmentation, recognition, and language modelling are some of the modules that make up actual document recognition systems. Graph Transformer Networks (GTN), minimizes the detection error and it is predominantly used in reading bank checks [19-20].

The arrival of large amounts of labelled data, and the addition of better algorithms contributed to the advancement of Convolutional Neural Networks (CNNs) and brought them to the forefront of the neural network renaissance for the task of image classification [21-23].

Learning control in the quantum computer technology is a potent strategy. Differential Evolution (DE) is utilized to create the best possible controls for a variety of quantum systems, Evolutionary Markov Strategy Differential Evolution (EMSDE) uses a mixed strategy used for quantum control [24].

The methodology for the parameterized quantum circuits allows the parameterization of the quantum circuits to enable the machine learning models. They can perform supervised learning and generative modelling [25].

Machine learning approaches have developed into effective tools for identifying patterns in the data. It is feasible to hypothesize that quantum computers may surpass classical computers on machine learning tasks, since quantum systems yield counter-intuitive patterns that are effective, when compared to the classical systems. Recent research has shown that there are still significant hardware and software problems, but it has also paved the way for some answers. The precise tuning of quantum gates necessary for the quantum error correction is a significant hurdle in the field of quantum computation and information science [26-28].

Quantum computing can carry operations tenfold quicker than to a classical computer. Building a high-fidelity processor that can execute quantum algorithms in an increasingly huge computational space is an issue [30]. To generate quantum states on 53 qubits using a computer with programmable superconducting qubits which corresponds to a 253-dimensional computational state-space. The resulting probability distribution is sampled by measurements from multiple experiments, which we confirm using conventional simulations. The benchmarks now show that the identical task for a state-of-the-art classical computing for the same task would take about several years [31-33].

Recent research on neural networks that are based on machine learning are effective for a wide range of challenging applications such as image identification to the precision required in the medical field. The quantum circuit-based method that is inspired by convolutional neural networks, a widely successful machine learning model. Similar to this, quantum convolutional neural network (QCNN) may be trained and used effectively on practical. At present, the quantum devices only requires O(log(N)) finite difference parameters as an input of N qubits sizes [34-35].

The HQCNN performs four different pooling strategies such as: (i) controlled gates for ancilla qubits, (ii) qubit selection with classical postprocessing, (iii) mid-circuit measurements and (iv) modular quantum pooling blocks [36].

To classify the images convolutional neural networks are used. May challenges are faced by the classical CNN models such as: computational efficiency, generalization, explainability and accuracy. When the data dimensions are large then the CNN model also grows large, and it becomes difficult to train these models effectively, which results in slowdown processing [37].

The framework for quantum machine learning is built on quantum convolutional neural networks, which are efficient to solve the multiclass classification problems. The softmax activation function processes the quantum outputs. Quantum circuit parameter optimization reduces the cross-entropy loss [38].

Deep learning has achieved success in many domains, the large memory requirements and time efficiency tolerance have long been insurmountable obstacles for its growth. Due to the properties of superposition and entanglement, quantum computing exhibits superiority in some computation problems and may offer a fresh approach to solving the problems. This study examined the quantum deep convolutional neural network (QDCNN)

3. Proposed Methodology

Quantum computation is based on quantum mechanics. It uses special properties such as Superposition, Entanglement, and Unitary Transformation which are not there in classical binary systems. This section introduces the basic concepts of the quantum computation.

3.1. Quantum Principles of Qubits and Mathematical Model

In the quantum computers, qubits play very crucial role of performing superposition states of $|0\rangle$ and $|1\rangle$. A single qubit state is represented as a complex two-dimensional vector as represented in equation 1 and 2.

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle \quad (1)$$

$$||\alpha||^2 + ||\beta||^2 = 1 \quad (2)$$

Where: $|\psi\rangle$: State vector of quantum system as a superposition of two basis states of $|0\rangle$ and $|1\rangle$. α, β: complex numbers representing the probability of amplitudes. $||\alpha||^2 + ||\beta||^2$: probability of observing $|0\rangle$ and $|1\rangle$ from the qubits.

Geometric representation using polar coordinates of θ and φ are shown in equation 3:

$$|\psi\rangle = cos \cos\left(\frac{\theta}{2}\right)|0\rangle + e^{j\emptyset} \sin sin\left(\frac{\theta}{2}\right)|1\rangle \quad (3)$$

Where: $|\psi\rangle$: state vector of a single-qubit quantum system as a superposition of two basis states of $|0\rangle$ and $|1\rangle$. θ: polar angle (0 to π) radians. φ: azimuthal angle (0 to 2π) radians $e^{j\varphi}$: phase of the quantum state, $0 \le \varphi \le \pi$.

3.2. Dataset Transformer

To make decisions regarding crop problems and disease management, it is crucial to have knowledge of the leaf disease. The best way to solve the issue is to locate the plant's disease so that preventive measures can be taken to safeguard it. In this regard, the dataset for this work has been collected from PlantVillage, which consists of 54303 healthy and unhealthy leaf images divided into 38 categories. The leaf images of potato and tomato plants, each plant labelled with two different class such as: Tomato early blight, Tomato Healthy, Potato early blight and Potato Healthy data sets are illustrated in Fig 1.

Figure 1: Plant leaf dataset: (a) Potato early blight disease, (b) potato healthy, (c) Tomato early blight disease, (d) Tomato healthy

The images in classical computer are represented as array of numbers, but quantum computation operates on array of tensors. To meet the requirement, the images undergo a transformation, resizing them to 150×150 pixels and incorporating horizontal flip on random images so as to deal with overfitting issue. The $ToTensor()$ function is utilized to facilitate the conversion of images into the tensor form, which ensures effective learning during the training phase. Rather than feeding all images to the model simultaneously, they are presented in smaller batches in each training cycle. The execution API is given in Fig 2.

```
transformer = transforms.Compose([
    transforms.Resize((150,150)),
    transforms.RandomHorizontalFlip(),
    transforms.ToTensor()
])
```

Figure 2: Data-Set Transformer Execution API

3.3. Proposed QCNN Model

To improve traditional CNN's classification for plant leaves, the proposed QCNN separates the plant leaves into categories that are either healthy or unhealthy with diseases. The QCNN model's main concept is to use quantum processing to increase the effectiveness of classical learning. The basic comparison methodology followed between CNN and QCNN is depicted in the flowchart in Fig. 3.

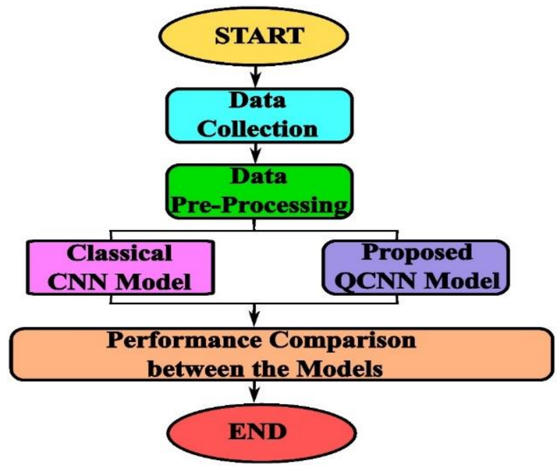

Figure 3: Flow Chart of Comparison Methodology

The Fig 4. illustrates the Quantum Convolutional Neural Network (QCNN) architecture for the image classification problem. In this model the input image is first processed by a classical computer, which produces equivalent qubits corresponding to input image by using Multi-scale Entanglement Renormalization Ansatz (MERA) technique. MERA is the form of the wave-function that belongs to the class of tensor networks, efficiently captures the high degree of entanglement, in quantum critical systems. It provides a compact and accurate representation of complex quantum states, which is then processed by Quantum computation and the final output is then predicted by classical computation.

The mathematical formulation of MERA involves the use of tensor networks to represent the quantum state of multi-variable system. The MERA wave function can be written as:

$$|\psi\rangle = \sum_{s}^{1} T_r\left(\prod_{i=1}^{N} T_i^{s_i}\right) |s_{1,} s_{2,} \ldots, s_{N,}\rangle \quad (4)$$

Where: $T_i^{s_i}$: MERA Tensors, s_i: Local degrees of freedom and N: Number of sites in the system.

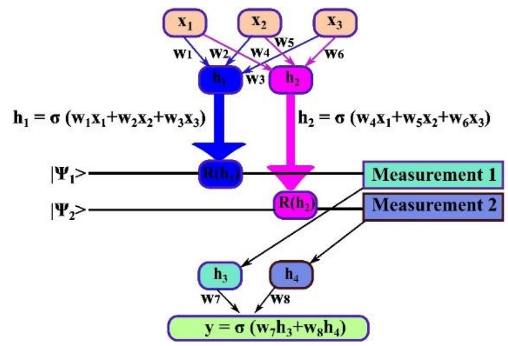

Figure 4: Quantum Convolutional Neural Network (QCNN) Architecture

In order to train a neural network, the main goal is to select the weights that will cause the network to function for Feed-Forward Neural Network (FFNN). Four distinct dataset image classes were used to train the model. The dimension of each image was 150 x 150. The QCNN model was evaluated using several epoch combinations and contrasted with a conventional CNN model. For training and testing the model, Cross Entropy Loss and Adam optimizer are used.

3.4. Quantum Circuits: Quantum Convolution Layer and Quantum Pooling Layer

Two-qubit unitary operations are applied to nearby qubits in the quantum convolutional layer and they only have local effects, indicating the local connectivity features. The qubits in a quantum pooling layer are measured and based on this decision, single-qubit gates are applied to the neighboring qubits.

The Bloch sphere is a 3D unit sphere, a geometric representation of a qubit's state space. The qubit states in the Bloch field are rotated via rotation operator gates Rx(θ), Ry(θ), Rz(θ) around the θ axis. The two qubits are entangled by the CX gate if one of the state is $|1\rangle$.

Confusion Matrix: A confusion matrix is a table that lists how many predictions a classifier made correctly and incorrectly. It can be used to determine performance metrics like accuracy, precision, recall, and F1-score to assess the effectiveness of a classification model.

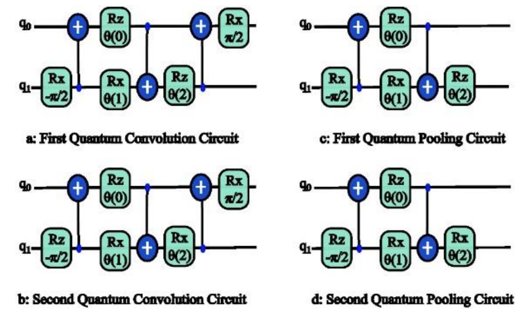

Figure 5: Circuit of Quantum Convolution and Pooling Layer

Fig 5. depicts quantum convolution layer and pooling layer. Unitary matrices for qubit parameters are generated for the pooling layer and the convolution layer. These gates can be constructed by gradually cascading two qubit parameterized unitary transformers to pairs of adjacent qubits. Rhetoric is an art of persuasion.

4. Results and Discussion

The outputs were generated based on the overall prediction and classification. The performance of the proposed method is evaluated using the following performance metrics for classification.

(i) Accuracy Score (ACC): It measures the proportion of accurate predictions to all available samples. It ranges from 0 to 1. Value near 1 indicates a more accurate prediction.

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

(ii) Precision (P): Prediction is calculated as the number of correct positive predictions divided by the total number of positive predictions. It ranges from 0 to 1. A value close to 1 indicates fewer false positive predictions.

$$P = \frac{TP}{TP+FP} \quad (6)$$

(iii) Recall: It is calculated by dividing the total number of valid positive predictions by the sum of all positive samples. A value that is close to 1 has fewer false negative predictions.

$$R = \frac{TP}{TP+FN} \quad (7)$$

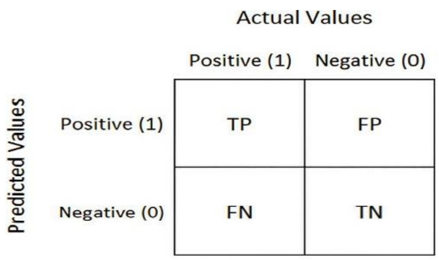

Figure 6: Confusion Matrix Representation

4.1. Training Results

The model is trained by four different classes of dataset images. Each image is of 150×150 size. The QCNN model is tested with different number of epochs and compared with a traditional CNN model. The loss and optimization function used for testing are CrossEntropyLoss( ) and Adam( ) respectively, same as training.

(i) CrossEntropyLoss( ): In classification problems, the deep learning and Quantum ML frequently use cross entropy loss for multi-class classification, which is defined as:

$$L_{CE} = -\sum_{i=1}^{n} t_i \log(p_i) \qquad (8)$$

(ii) Adam Optimizer: The optimizer executes the updates of the parameters through its step( ) method. In Adam optimizer, weight decay is performed only after controlling the parameter-wise step size. The weight decay or regularization term is exclusively proportional to the weight itself in outputs, which does not appear in moving averages. The Adam optimizer, produces better training loss; which implies, the model generalizes significantly better than stochastic gradient descent with momentum. Adam also automates the learning rate.

The epochs are chosen in incremental order from 3 to 24, each iteration incremented by 3 epochs, while training the QCNN model.

QCNN was also trained with negative log likelihood loss, minimized the negative log of the predicted probability for each of the four classes. Training convergence occurred with parameters optimized and loss being minimized, improving classification accuracy on quantum version of the image data. The Training loss of model is depicted in Fig. 7, almost the same irrespective of the epochs.

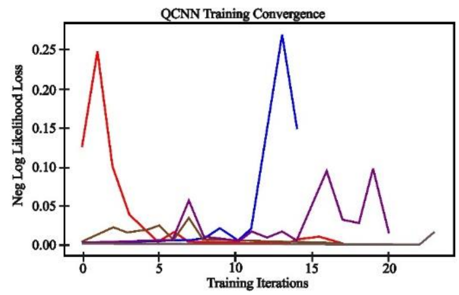

Figure 7: Training loss with different epochs

4.2. Testing Results

The trained model QCNN was tested by the same 4 different classes of image dataset, each image size was 150×150 and each class contained 22 images. The testing was evaluated for the accuracy, precision, recall and confusion matrix. Further, they were compared with the traditional CNN model, which was also trained and tested by the same dataset and trained for same number of epochs.

Iteration 1:	
Train Data	484
Test Data	226
Epoch	25
CNN Testing Accuracy	93.36
QCNN Testing Accuracy	97.34
Number of Classes	4

Iteration 2:	
Train Data	363
Test Data	204
Epoch	20
CNN Testing Accuracy	84.07
QCNN Testing Accuracy	94.11
Number of Classes	4

Iteration 3:	
Train Data	363
Test Data	88
Epoch	10
CNN Testing Accuracy	80.9
QCNN Testing Accuracy	95.45
Number of Classes	4

Iteration 4:	
Train Data	220
Test Data	88
Epoch	10
CNN Testing Accuracy	83.11
QCNN Testing Accuracy	94.31
Number of Classes	4

Iteration 5:	
Train Data	220
Test Data	88
Epoch	5
CNN Testing Accuracy	80.9
QCNN Testing Accuracy	95.55
Number of Classes	4

Figure 8: Comparison of QCNN and CNN with different combination of epochs and datasets

The QCNN model was tested using plant Leaf dataset. The model demonstrated prediction accuracy of 95.45% with precision and recall scores of 0.9555 and 0.9545 respectively as reported. The confusion matrix of both CNN and QCNN are displayed in the Fig. 9 and 10.

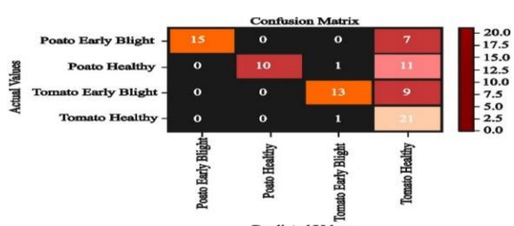

Figure 9: Confusion Matrix of CNN

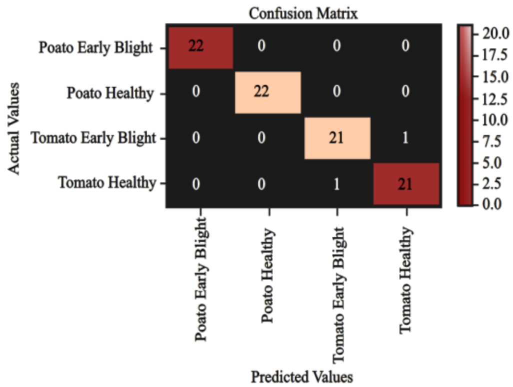

Figure 10: Confusion Matrix of QCNN

It can be clearly observed from the confusion matrix of QCNN that, images belong to all classes are majorly correctly classified excluding just two images of tomato leaves which were miss-classified, making 97.7% accurate prediction. However, confusion matrix of CNN model infers about the number of miss-classified images as: class Potato early blight has 7 images, Potato healthy has 12 images, Tomato early blight has 9 images and tamato healthy has 1 image out of 22 images from each class. This indicates CNN model has overall 67% accuracy for the same number of epoch, which is quite low compared to the performance of QCNN.

Training loss comparison between QCNN and CNN as shown in Fig. 11, it is concluded that QCNN training Loss had reduced and CNN training loss had been increased with increased iteration.

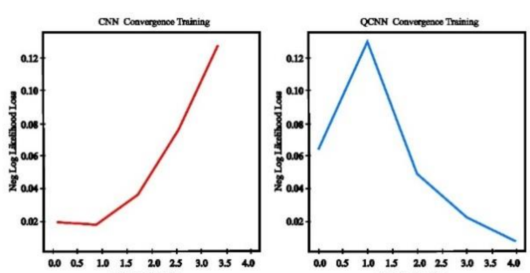

Figure 11: Comparison of training loss between CNN and QCNN models for 5 epochs

Training loss comparison between QCNN and CNN as shown in Fig. 11, it is concluded that QCNN training Loss had reduced and CNN training loss had been increased with increased iteration.

The Quantum Convolutional Neural Network (QCNN) model has achieved an impressive prediction accuracy of 95.45%, accompanied by a precision score of 0.95 and a recall score of 0.95, in comparison to the CNN model. The training loss for QCNN exhibits an initial increase followed by a decline to lower values. Conversely, the CNN's training loss gradually increases over iterations, as depicted in Fig 11.

When confusion matrices of both the models were compared, the QCNN produced a smaller number of miss-prediction. Whereas, the classical CNN produced a greater number of miss-predictions. From the Fig. 9 and 10, it is concluded that QCNN classifies the images almost accurately than CNN model for a smaller number of epochs and less size of datasets.

5. Conclusion

This work presents the performance of QCNN for image classification applications. It was based on parameterized quantum circuits and had a structure that was similar to the classical Convolutional Neural Network (CNN) in terms of its hierarchy. The low state preparation overhead and the Qubit efficiency were maintained by utilizing the amplitude encoding technique and rough quantum state preparation model.

The three different types of quantum layers structures were created, which were very similar to that of the traditional CNNs. The specially created quantum gates offer exceptional expressive capability. Additionally, the Plant leaf image dataset had been used to quantitatively test the classification performance. The QCNN has presented 95.55% and CNN has given 80.9% of test accuracy with 10 epochs of training on a moderate size dataset, which is a considerable achievement on resource utilization efficiency. In this regard, QCNN outperformed the classical CNN by providing 97.7% of prediction accuracy, in contrast to 67% of prediction accuracy from Classical-CNN as inferred from the confusion matrices. In addition to this, the training convergence was attained with minimized cross entropy and negative log likelihood loss.

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