INTO QUANTUM CONVOLUTIONAL NEURAL NETWORKS (QCNNS) WITH DEEP LEARNING FOR COMPUTER VISION TASKS AND APPLICATIONS

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ABSTRACT

The CNNs have been paramount in the development of Computer Vision tasks by leveraging their prowess in data representation. However, despite these strengths, CNNs suffer from scalability issues whenever they are applied to high-dimensional data or complex model architecture. Alternatively, to solve the weaknesses of these classical CNN methods, Quantum Convolutional Neural Networks have recently been one of the ways through which these challenges, faced by their classic versions, can be solved by proffering solutions to them through an integration with the principles of Quantum Computing. A relevant work [3] presents a QCNN model to apply CNN structures within Quantum Computing, mainly targeting the classification tasks in Quantum Physics and Chemistry. This model leverages Multi-scale Entanglement Renormalization Ansatz (MERA) to achieve computational efficiency with a logarithmic depth of O(log(n)). Another recent trend is the addition of existing CNN models to realize quantum advantages by introducing quantum layers into an otherwise classical neural network architecture; hence, this approach can even be handled on small Quantum Computers. This hybrid approach enables adding or replacing any classical CNN architecture with Quantum Convolutional layers. Another work [4] focuses on the broader influence of Quantum Computing on Deep Learning, its limitations in the moment to available quantum hardware, suitable training algorithms, and the inherent non-linearity of neural networks. This work serves as an overview of the frameworks and architectures that are necessary to be done to develop the QCNN model and shows the potential to achieve better performance, not only in faster computation but also in tasks concerning Image Recognition and Object Detection. Further discussion is carried out with the possibilities that QCNNs can be applied to Computer Vision, Pharmaceuticals, and Cryptography. It underlines the potential that Cuantum Computing technologies are going to have in the future to tackle the classical challenges of neural networks by offering new avenues toward efficiency and performance increases in dealing with complicated problems.

Introduction and Motivation

Quantum Computers offer a different paradigm than their classical analogs, giving the user capabilities such as Superposition and Entanglement that have no counterpart in any traditional computing. The result of all this is unprecedented computational improvements, facilitated through parallelism on qubits. Hence, Quantum Computing is viewed as a promising approach for the resolution of algorithmic challenges beyond the possibilities of classical computers, especially in fields like Physics, Chemistry, and Optimization problems; such Quantum Computing models for addressing complex physical, difficult chemical problems and NP-hard algorithmic challenges have been proposed. There are further studies investigating the implementation of gradient descent optimization on quantum devices for efficient learning of Quantum Machine Learning models based on hyperparameters. While Quantum Computing in Machine Learning is still largely theoretical and under development for practical applications, it has great potential in many fields.

The CNNs have nowadays become an essential part of most recent classification models, especially in Computer Vision. This is because they can preserve the spatial correlations in data, such as those in images. Most traditional Deep Learning models using fully-connected layers have achieved high performance but without preserving the spatial relationship between neighboring pixels. CNNs get over this limitation by using convolutional layers, which extract hidden features through linear combinations of a neighborhood of pixels, and pooling layers that down-sample feature map sizes for the purposes of anti-overfitting and saving resources. This structured approach allows the CNNs to work well in image recognition tasks.

These classical Machine Learning methods involve some significant problems when dealing with the real world, especially large and complex data structures. Take, for example, the many-body problem evoked in the Hilbert space of Quantum Physics, in which a translation of quantum data is obliged into a format that a classical computer may process. They do so correspondingly grow exponentially with the increase in system size, mostly impossibly hard for the handling capability of classical Machine Learning models at large. Interest in studying Quantum Convolutional Neural Networks—a concept that takes the principles of CNNs into the paradigm of Quantum Computing—has been driven by this challenge.

The QCNN makes use of qubits, much like binary bits in a classical system, to construct neural architectures while preserving the basic structure of a CNN. In contrast to the classic fully-connected layers that cannot preserve the pixel correlations in images, the CNNs, and hence the QCNNs, do preserve these correlations, hence offering better performance in complex problem-solving. The QCNNs fill a dual role: In one sense, the CNN-like architectures on Quantum Systems allow effective solutions to crucial quantum problems; on the other hand, they enhance classical CNN models by the use of quantum elements for greater efficiency and performance that is normally strained by classical computations.

Quantum Convolutional Neural Networks

Artificial Intelligence, along with its subsectors, including ML and DL, has found applications starting from small-scale industries to high-end medication services in several areas. Neural networks that consist of several neurons interconnected among each other and fully connected layers that comprise the decision-making process in AI and ML sort out issues in real time in hardware computations. This also overcomes the limitations that one sees in using algorithms related to classical computation. However, considering today's date, some of the problems related to the optimization of architectures faced by classical neural networks are the time-consuming training processes and high memory storage.

In turn, Quantum Computation makes use of Quantum Mechanics: the wave function includes superposition-coherence, measurement-decoherence, Entanglement, and Unitary transformations that overcome the problem faced by the classical due to exponential memory capacity and ease of training. Still, it has a limitation concerning hardware implementation. The architecture of the Double-slit experiment gives the foundation for Quantum Artificial Neural Networks. However, the integration of both Quantum Computations and neural networks gives rise to Quantum Neural Networks (QNNs), which conquer all the existing limitations. At the same time, their analogies are utilized by researchers in establishing the connections between Quantum Computations and neural networks. QNNs take a similar structure compared to that used by classical neural networks, but the former replace convolutional filters with entangling gates and pooling layers with controlled rotations followed by qubits.

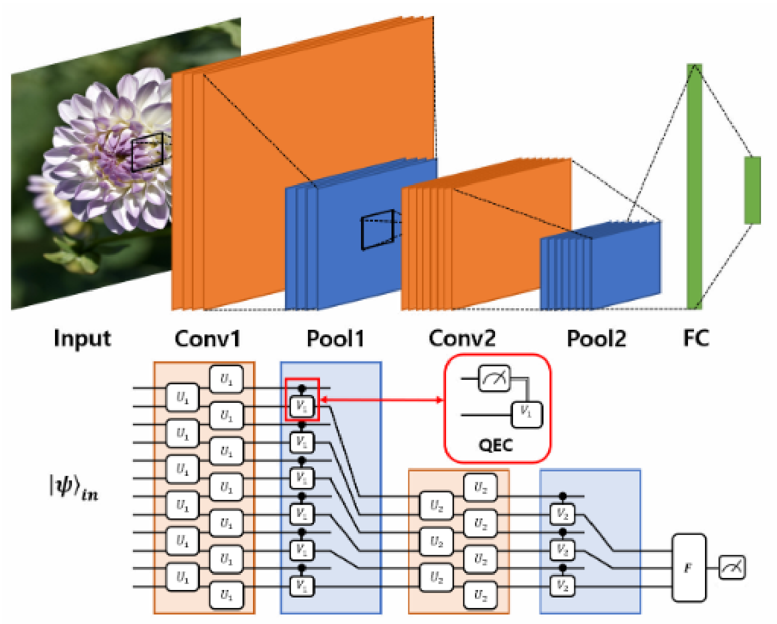

Figure 1: QCNN, like CNN, consists of a convolution layer for finding new states and a pooling layer to reduce system size. QEC can be enhanced by employing measurement instead of controlled-gate in the pooling process. [3]

QCNNs mainly extend the main features and structure of the existing CNN to quantum systems, as proposed by Cong [1]. When a Quantum Physics problem defined in many-body Hilbert space is brought into a classical computing environment, the size of the data increases exponentially according to the system size. Hence, it is not suitable for an efficient solution. Data can be expressed with the qubit in a quantum environment. One can, therefore, avoid the problem by performing the implementation of the CNN structure on a quantum computer. This section briefly introduces the structural design of this QCNN.

The model of QCNN maps the convolution layer and the pooling layer, characteristic features of CNN, into quantum systems. It goes as follows:

- The convolution circuit determines the hidden state by connecting the nearby qubits using many qubit gates.
- The pooling circuit minimizes the size of the quantum system either by watching the fraction of qubits or using a 2-qubit gate such as a CNOT gate.
- Repeat the convolution circuit and pooling circuit defined in steps 1-2.
- When the system size is suitably modest, it uses the completely linked circuit to generate the classification predictions.

Above would be the structure that satisfies Multi-scale Entanglement Renormalization Ansatz (MERA)[5]. MERA maps the quantum systems in an effective way to simulate many-body states. It, for now, exponentially increases the size of the Quantum System for every depth by adding qubits of $|0\rangle$. QCNN uses this MERA in the reverse direction. It reduces the exponential Quantum System size from the given data and is suitable for the model of QCNN.

Cong suggests that the performance of QEC in the QCNN model is able to reinforce further this MERA model. Each label has its representative state $|\phi\rangle$. Since QCNN uses the opposite direction of MERA, if an input data is fed with its $|\phi\rangle$, the corresponding label is able to be obtained as a definite solution. On the other hand, if QCNN accepts input data

$|\phi'\rangle$ that cannot be generated in MERA, it cannot get a definite solution. Use QEC to correct such a problem and solve it owing to additional degrees of freedom. If QCNN accepts $|\phi\rangle$ as input data, it must give the same measured result with the newly given state, namely, $|0\rangle$, in the MERA of the pooling layer. On the contrary, in case the MERA itself is unable to generate the input data accepted by QCNN as $|\phi'\rangle$, it is then possible that the measurement outcome could yield $|1\rangle$. By the use of them, since all the measurement outcomes can be $|1\rangle$, another gate is applied on the neighboring qubits with the aim of correcting that result. It can give even better performance with the aid of extra-deterministic measurement outcomes.

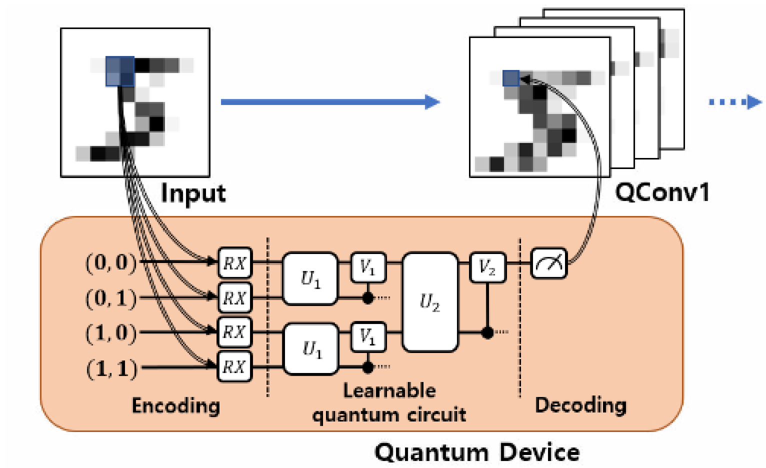

Figure 2: Example of QCNN for image classification [3]

Tasks and Applications

Image classification is one of the most applied fields in neural networks such as CNN. Quantum Computers have potent advantages with Superposition and Parallel Computation. Quantum Convolutional Neural Network proposed by Henderson [2] applies quantum environments in CNN to improve the performance of it. This section briefly introduces the research which suggested how to apply a Quantum Computing system to CNN. The quantum convolution layer defines a layer that would act similar to a convolution layer in its quantum version. It will apply a filter to the input feature map for feature maps composed of new data. However, the quantum convolution layer differs from a convolution layer in that it operates its filter operations in a Quantum Computing environment. Quantum Computers have the advantages of Superposition and Parallel Computation that do not exist in classical computing. That can reduce the learning time and evaluation time. However, up until now, the existing Quantum Computers are still limited to small Quantum Systems. A quantum convolution layer does not apply the whole image map to a Quantum System at one go but processes it as much as the filter size at one time. Therefore, small Quantum Computers can construct a quantum convolution layer.

It works according to the following procedures (see Fig. 2):

- The process of encoding stores the pixel data equivalent to the filter size in qubits.
- Learnable quantum circuits apply filters that may find the hidden state from the input state.
- Measurement provides new classical data in the decoding process.
- By repeating steps 1) to 3), the new feature map is completed. The encoding process in step 1) is essential to convert classical information into quantum information. One of the easiest methods is to apply a rotation gate corresponding to a pixel's data to qubits. Of course, various encoding methods are possible, and the chosen encoding method can influence the number of qubits needed as well as the learning efficiency. In step 3), the decoding process is determined based on measuring one or more quantum states. Measuring quantum states yields classical data.

In the case of 1), encoding will be a process which is necessary to change the classical information into quantum information. The simplest way is to apply the rotation gate corresponding to the pixel data to qubits. Of course, various encodings are possible, and the selected encoding method can change the number of qubits required and the learning efficiency. The decoding process of 3) is determined according to measuring one or more quantum states. By measuring quantum states, classical data are determined.

From step 2) the random quantum circuit can be constructed by using a series of gates. Additionally, this circuit can perform optimization through the gradient descent method by incorporating variable gates. There are numerous ways to design this type of circuit, and the design approach will significantly impact the learning performance. When using MERA intrinsically, the classical environment generally requires O(n^2) operations within an n^2-sized filter. However, in a Quantum System, parallelism at qubits can design filters with O(log(n)) depths.

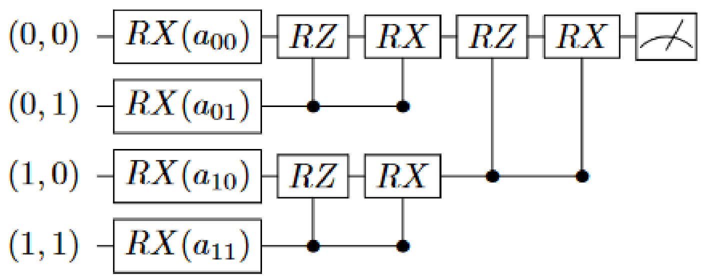

Figure 3: Example of a quantum convolutional layer (used for learning on a MNIST dataset) [3]

Conducting these simulations—performed for the verification that the actual quantum convolutional neural network works properly in Image Classification using the MNIST dataset—is shown here [3]. For Quantum Computing simulation, QCNN used the TensorFlow Quantum platform. However, due to the fact that a Quantum Computing simulation environment uses many resources, it has the following limitations:

- The 28×28 size MNIST dataset was downscaled to the 10×10 size.
- The filter size of the quantum convolution layer is constrained to 2×2.
- For every epoch, 2500 random images out of 60,000 are chosen for learning.

In an attempt to investigate the performance of QCNN models, fully-connected, CNN, and QCNN models are defined as follows:

- QCNN model: The quantum convolution layer consists of a quantum circuit defined by Fig.2. The quantum convolution layer returns a feature map with 8 channels. Then, the returned feature map predicts the classification result by connecting the feature map with a fully-connected layer with 64 and 10 hidden units.
- Fully-connected model: Construct the model using only the fully-connected layer in order to check whether the quantum convolution layer affects learning.
- CNN model: The quantum convolution layer is replaced with a regular convolution layer that returns a feature map of the same channel length to compare performance differences.

Fig.4 depicts the result of this simulation. First, the QCNN model always shows better learning results compared to the fully-connected layer, confirming that the quantum convolution layer improves learning performance. It also shows that the QCNN model and the CNN model have similar learning results, indicating that QCNN can achieve the same learning performance as CNN.

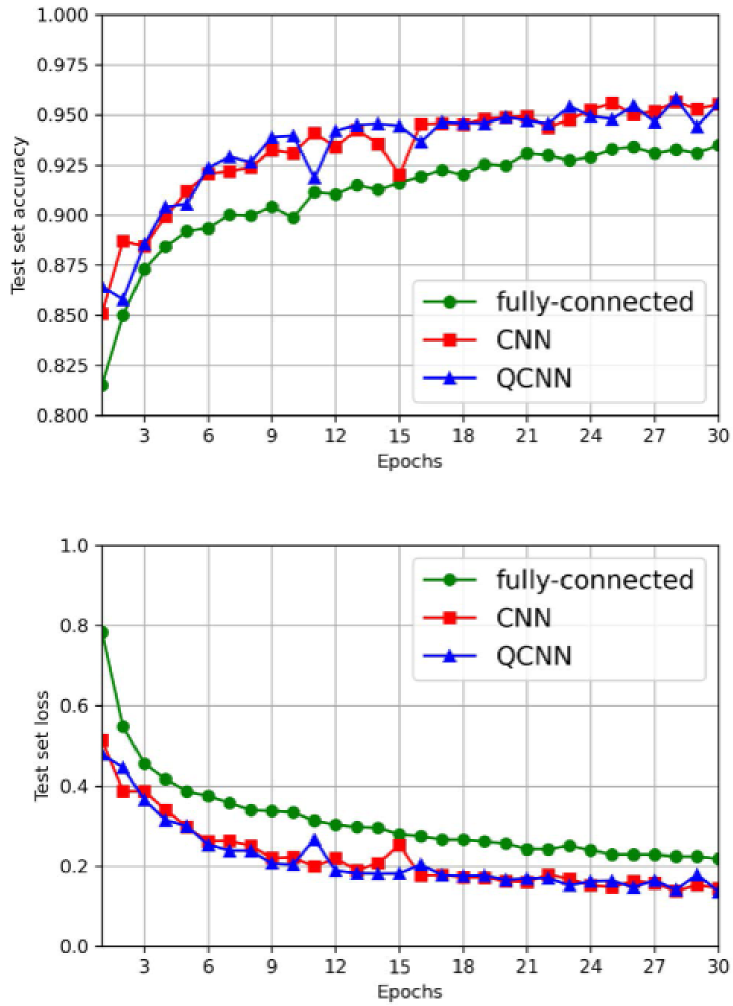

Figure 4: The Performance of QCNN compared to fully-connected layers only model and CNN [3]

Future Directions and Challenges

Quantum Computing, while still under development, has been facing a variety of problems—including the growth limitation of qubits. The Quantum Computer model must be structurally built with new parameters and should avoid transferring parameters. Transfer learning from the existing model can target the model's training data. Proper measures need to be taken to prevent poor outcomes from corrupted trained models or noise interference in communication channels. Schemes using nodes as intermediaries for data transfer and reception must be handled cautiously, ensuring they are protected from malicious attacks.

However, some quantum CNN models have shown performance improvements, and there is great potential for learning abilities while researching in this field—though challenges persist. There is also a vast opportunity to continue reviewing hybrid quantum algorithms that could support future machines and have significant applications in Machine Learning and Artificial Intelligence.

Currently, Quantum Computing is mostly theoretical, and its implementation is challenging due to the lack of Quantum Computers. However, this powerful and robust technique for developing Deep Learning models will become available in the near future. There is immense potential for research and technological learning in implementing QCNNs. Companies like IBM, D-Wave, and 1QBit are leading the way globally by providing real-time Quantum Computing environments. Many startups in India and other nations are also working on Quantum Computing, some offering end-to-end solutions, hardware requirements, and research labs.

Future work will focus on building Deep Learning models to develop the QCNN framework for various Computer Vision applications, such as Object Detection and Image Recognition, with better performance metrics than classical computations.

QCNN combines CNN models with Quantum Computing environments, enabling various approaches. The QCNN model could offer solutions for physical and chemical classifications that are difficult to solve, providing a more effective and efficient learning method than the traditional CNN model. Furthermore, in the NISQ era of Quantum Computing, the QCNN model can expect higher efficiency and better results in complex, large-scale learning tasks. While the results of the current experiment were at a microscopic scale, we plan to apply the QCNN model to more complex data in future work.

The QCNN offers more detailed implementation and approach options. By carefully designing the internal Quantum Circuit, the learning model's performance can be improved. Additionally, in imaging processing, encoding methods could enable more information to be stored in a single qubit, leading to more efficient learning. In future research, more efficient QCNN models with superior learning performance through simulations using various approaches will be studied.

Personal Thoughts

Nowadays, in Quantum Computing, devices such as QPUs are gaining significant attention as the number of qubits they can host continues to grow. This is great news for running Deep Neural Networks, as it allows for greater flexibility in terms of dimensions. Unfortunately, this also comes with the downside of increased energy consumption, demanding a massive amount of computational resources.

As quantum models continue to spread and deepen, they will become increasingly difficult to interpret and explain, posing a significant challenge for Explainable AI. There's also considerable uncertainty around hybrid deep models—those combining classical and quantum components—since the techniques, optimizations, and algorithms used in AI were designed for pure classical models. In many ways, current research in this area is pushing these classical tools to their limits to train and optimize Variational Quantum Circuits, for example (those have the so-called qurons, parameterised quantum gates).

At the same time, new pure classical models are emerging, which means there is still much work to be done in testing a wide range of architectures and block combinations to assess their viability against classical counterparts. Despite the challenges, this field remains active and continues to evolve daily.

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