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Comparing quantum convolutional and classical convolutional architectures

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Abstract. While machine learning technology evolves fast with the development of computing power and new algorithms, integrating theories of quantum mechanics gives novel opportunities to it. This paper focuses on the comparative analysis of Quantum Convolutional Neural Networks (QCNN) and traditional Convolutional Neural Networks (CNN), which are important techniques in the domain of machine learning, especially image processing. By doing a literature review and analysis, the comparison includes performance differences, application potential, and inherent challenges of QCNN. Although QCNN is comparably novel, it does exhibit superiority over CNN in specific cases theoretically like high dimensional and complex datasets. QCNN currently is facing problems due to hardware constraints and immaturity in quantum computing and doesn't show superior performance when running on actual quantum machines. With the development of quantum computing and hardware, QCNN has a strong potential for use in machine learning. The research compares the current performance of QCNN and CNN to make suggestions about applying them in real cases and guide the path for future research.

Keywords: Quantum convolutional neural network, classical convolutional neural network, quantum machine learning, deep learning.

1. Introduction

The creation of neural networks in the vast domain of artificial intelligence and machine learning has meant much too much research. A special type of neural network, Convolutional Neural Networks (CNN), have also played an important part in image processing and pattern recognition. CNN is one of many neural networks, but how its structure allows machines to process visual data efficiently and uniquely has seen widespread applications far beyond computer vision. It plays an important role in fields such as facial recognition and autonomous vehicles. Their efficient processing of complex visual information has made them important tools in machine learning. While the success is sweeping, as the complexity and volume of data continue growing by leaps and bounds exponentially, traditionally structured CNNs began to run into their limits in processing. While classical computation cannot handle large or high-dimensional data, traditional CNN is still operating within its bounds. Thus, this situation has created a demand for some kind of innovation that can mobilize the abilities further, to solve more complex problems. QCNN is a new design in which the method of quantum computation and traditional neural network architecture are combined. This combination has an excellent opportunity to dramatically increase processing power, at least as compared with previous methods of machine learning.

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It is a relatively new development: integrating quantum mechanics into neural networks presents both opportunities and challenges. In the exploration of theories and performance with QCNN there is certainly some progress, but still a gap remains in the research. This especially includes fully understanding where exactly its potentials lie, or just how mature are its capabilities compared with those of CNN.

This paper seeks to fill that gap via an in-depth comparative study between QCNN and CNN. The research looks at how QCNN performs in comparison to CNN on performance, scalability, and applicability. Its objective is to explore the kinds of scenarios under which QCNN outperforms CNN and identify current limitations as well as future possibilities for QCNN.

This comparative study is via comprehensive literature review and analysis. It delves into existing research of QCNN and CNN. By doing a literature review, this paper attempts to assess where we are now by exploring recent research results and experimental designs as well as theoretical explanations. The technique also serves to spotlight the progress being made in these fields, even as it points out problems that are yet to be resolved.

Beyond a purely comparative study, this research has laid the groundwork for future improvements in neural networks. The purpose of this paper is to provide an examination of both QCNN and CNN, to point the way forward for future research, and to predict where neural networks are headed.

2. Overview of CNN Background

Based on the biological neural network, a Neural Network usually has a three-part structure of an input layer, hidden layers, and output layer. The existence of the convolution layer and pooling layer is what makes a Convolutional Neural Network different from traditional Neural Networks. Traditional neural networks are limited by the computational complexity of processing images as input. We use a convolutional network for this reason. A 28 * 28 image alone requires that a single neuron to hold 784. The number increases greatly for more complex images. Thus, if one uses traditional neural networks to process images, one will encounter problems such as high intensity in computation power and a great possibility of overfitting [1]. Thus, with its attention to image inputs, CNN can resolve this problem. CNN applications mainly fall in the field of image processing, including image classification, object detection, and face recognition.

Besides necessary input and output layers, a typical CNN would have a convolution layer; pooling layer; and dense layer (illustrated in Figure 1). The convolution layer performs a convolutional operation on the input data. More precisely, the actual operation involves "sliding" a kernel over the input data and computing dot product at every position to produce an activation map that shows where key features of their input reside. Kernels play the role of a filter designed to selectively detect certain patterns such as edges or textures. Mathematically, the convolutional layer can be represented as:

$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I\big((i-m, j-n)K(m,n)\big) \tag{1}$$

With I as ithe nput image, K as kernel, and S as the activation map (feature map). In actual applications, there are multiple small convolution layers instead of a single large convolution layer to improve efficiency. The pooling layer always comes after the convolution layer to reduce and subsample the feature map. For this reason, it is usually done by using Max-pooling to select the maximum value from individual regions of the feature map. This reduces dimensions and computational complexity simultaneously. After the convolution and pooling layers comes a Dense (Fully Connected) Layer, which connects every neuron to every neighbor in the previous layer. It is very important in combining features for making final predictions.

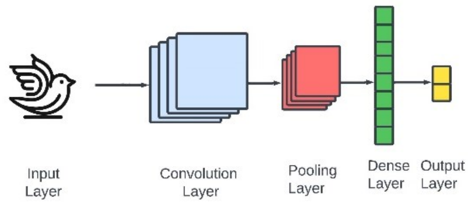

Figure 1. Structure of Convolutional Neural Network.

The technique of CNN looks intriguing. It is much better than classical neural networks; but there are still deficiencies, such as high computation demands and large memory demand. With several convolution layers, which are equivalent to many kernels, the required vectors for the calculation process are enormous. In addition, when processing high-resolution images, the memory requirement for CNN is quite large and thus input image size will be limited.

There are several ways to solve the problem, but they add a lot of steps and time during preprocessing (such as resizing images so that less complicated input images will be made) or using larger kernel sizes. In an ideal world, it would be much better if some different techniques could bring about tremendous efficiency in computation with no loss of features.

3. Theories of QCNN

The drawbacks of CNN necessitate the adaptation of its conventional deep learning architecture. QCNN is one such resultant product. The purpose is to enhance the data processing capability of CNN, especially for complex datasets. This part of the paper talks about the theories behind QCNNs and compares them with those of CNNs.

3.1. Quantum Data and Encoding

Using the quantum state as the foundation, QCNN relies on encoding classical data into a quantum space followed by corresponding learning and decoding to produce output patterns. This is in contrast to classical CNNs and conventional computers upon which data processing relies on the manipulation of binary information. But QCNNs process information by acting directly on quantum states, so-called qubits, allowing them access not only to two but superposed states (both 0 and 1 at once). The Multi-Scale Entanglement Renormalization Ansatz (MERA) is most likely the model used to simulate quantum systems. MERA is a tensor network that can give a representation of quantum states with many-body entanglement [2]. MERA's structure is several layers of unitary and/or isometry. It has a multi-layer nature like CNNs, applied to the input state. In particular, in each layer, quasilegal unitary gates are used to make the circuit able to deal with increasingly complex information. In terms of QCNNs, the MERA approach is flipped around to efficiently encode quantum data in a fashion suitable for convolution and pooling layers. It can be understood as the mathematical expression:

$$|\psi\rangle_{MERA} = U_{MERA}|\phi\rangle \tag{2}$$

Where U_{MERA} is the unitary operations and $|\phi\rangle$ is the initial quantum state.

3.2. Quantum Convolution and Pooling Theory

QCNNs are similar to CNNs in structure, with convolution and pooling layers. In QCNNs, convolution layers perform a series of unitary transformations through quantum gates that entangle qubits. One structure inspired by the CNN is parameterized quantum circuits (PQCs), which provide help in unitary transformations [3]. In contrast to the convolution of CNN that performs filtering on spatially structured images, quantum convolution can change high-dimensional quantum states by entangling operations. In particular, they aren't limited to merely getting operations tangled up. They play with the probability amplitudes of quantum states as well. Because quantum convolution works differently, it produces a quantum feature map that captures not just spatial symmetry, but also other kinds of connections in the underlying field such as complex patterns and correlations.

QCNNs' pooling layers function similarly to data dimensionality reduction but in the quantum field. Nevertheless, it works completely differently than CNNs which use down sampling with quantum measurements projecting the system into a lower-dimensional subspace. In QCNN, pooling operations are composed of measuring some qubits to condense the state or using quantum mechanics such as CNOT gates to gather information on different bits [4]. Another advantage of quantum pooling is that because a type of entanglement has already occurred, there will be no loss to each member's systems. However, in quantum theories, the act of measurement will lead to the collapse of quantum states. That means less information is available but at a higher level that quantity can be retained or even increased. In contrast, classical pooling operations can lose information in the process by taking only the maximum or average values of a region to represent it for example.

3.3. Distinct Features of QCNN Compared to CNN

The representation and processing of data is one major difference between QCNN and CNN. However, in classical CNNs, data must be processed at high dimensions that grow exponentially with the size of the systems. Having depth-scaled O(log (n)), QCNNs handle large-volume data easily with more compact parameters.

Unlike CNNs, which use convolution layers to apply kernels or filters encoded by the network itself onto input images in turn producing feature maps representing a hierarchical spatial representation of the data. QCNNs use quantum gates to construct states resulting from entanglement and superposition. It is therefore better poised than a classical neural network to deal with more complex, high-dimensional data sets. A second capability that makes the layers deal with complex data is its ability it use quantum computing environments and apply filters on input feature maps which help create new information representations. Therefore, one layer allows for greater depth and complexity than an ordinary convolution layer would ever be able to achieve in a classical computer environment.

QCNN also uniquely uses Quantum Error Correction (QEC). The quantum state is not lost even if it becomes slightly distorted. This reduces the error rate of computations.

But unlike CNNs that live and work exclusively in the classical information field, QCNN also has a channel to go from quantum data processing to classical concert halls.

In general, the theoretical differences between QCNNs and CNNs show considerable potential for the former over the latter. Taking advantage of the characteristics of quantum mechanics, QCNNs bring a new technique for information processing that can handle complex data.

4. Performance Comparison

To understand better the differences between QCNNs and CNNs, it is necessary to look at their actual performance in different cases. Without a doubt, QCNNs do have the potential to do better than CNNs in theoretical comparisons; but actual simulations will tell us whether this is true for all cases or not. This part of the paper reviews some simulation results from several papers on the performance comparison between QCNNs and CNNs and their common features.

4.1. QCNNs Outperform CNNs

The paper Kerenidis is full of helpful discussions on cases where QCNNs outperform CNNs [5]. By introducing a quantum algorithm for applying CNN architectures with speedup, they studied the efficiency of QCNNs. To perform some features regarded as difficult to implement in quantum circuits, they constructed a quantum circuit similar in functionality to the classical CNN. MNIST is a classic example of how convolutional neural networks are trained and their test results demonstrate that QCNN learns data with few parameters and high precision. Generally, QCNNs perform better than CNNs even when the sampling ratio is less than 0.5. Their training curves comparing CNNs and QCNNs show that, no matter how much noise exists in the corpus, both loss values are far lower for the latter to overcome completely.

Hur's team carried out simulations comparing different QCNN models with CNN in terms of classification on MNIST and Fashion-MNIST datasets [4]. This study showed that QCNNs are capable of adjusting the parameters and switching around among different quantum circuits to improve performance. Although the QCNNs also don't use a great number of free parameters which only range from 12 to 51 even so still perform high accuracy, with best cases reaching as close to 99 % for MNIST and 94% for Fashion MNIST. Furthermore, in their experiments under the same training conditions, QCNNs always outperform CNNs. The main reason why QCNNs are better is that they can capture quantum properties such as entanglement, which is more global than the local correlations CNNs focus on. In the training process, QCNNs are less sensitive to random initialization of parameters than those applied similarly in both QCNNs and CNNs. Their performance metric values have smaller standard deviations matching this idea.

Moreover, Hur's current contribution is that more convolutional filters can increase the accuracy of QCNN models. Take circuit 2 and auto encoding for an example, raising the number of convolutional filters from 1 to 3 results in accuracy moving up from an initial level of 85 % to as high as nearly every correct one (96 %). This shows that QCNNs can achieve a big improvement in performance by adjusting the convolutional filters.

These studies show that QCNN can achieve higher accuracy with lower parameter counts than CNNs. They thus retain high efficiency even in large-scale datasets and complex settings. Otherwise, QCNNs can adapt to various situations depending on different exit methods of quantum circuits and varying convolutional layers.

Although QCNNs proved superior in these simulations, it is important to emphasize that this was just a simulation and the actual performance of quantized CNN may vary when implemented on quantum hardware.

4.2. CNNs Outperform QCNNs

In many cases, QCNNs are strong and unique but in some other cases, CNN outperforms its quantum counterpart. This paper by Meedinti simulates an MNIST dataset on which CNNs are superior [6]. The quantum convolutional neural networks can only achieve an accuracy of 52.3%, while classical CNNs have already reached almost perfection at 99.9%. This training is a binary classification instead of a multi-classification. The experiment shows that CNN is better than QCNN for binary classification. The reason why QCNN performed so poorly appears to be the relatively small size of the dataset and its complex architecture lacking optimization, along with hardware limitations. Briefly speaking, in real quantum hardware and for straightforward tasks instead of complicated ones, QCNNs don't always have a leg up over CNNs.

Qian further exposed the inherent limitations of QCNNs against quantum hardware [7]. Even for the more complicated cases, QCNNs should theoretically do better with them, they show no obvious advantage in experiments. In processing datasets on today's quantum hardware, there are some current problems with QCNN. One is due to the small number of qubits available for computation and susceptibility to noise. For CNNs, because the technology and hardware are much more mature. Real hardware does have good performance and stability too.

In short, QCNNs don't have good performance mainly when running on actual hardware instead of pure simulations. Classical CNNs don't operate with the noise sensitivity and limited computation power that belong to QCNNs, which makes them stronger currently. As quantum computing matures, they have the potential to outperform CNNs, but for now, CNNs are more reliable tools to solve machine learning problems.

5. Current Challenges of QCNNs and Solutions

Even though the development of quantum computing is very rapid, there are still some problems that restrict their widespread application in QCNN. Qian and Kwak's papers offer some glimpses into those problems [8].

Kwak says that the problem with quantum neural networks is gradient vanishing. A similar phenomenon is found in classical neural networks, but the problem can be more difficult to solve for the quantum field. The nature of handling quantum transformations (which are non-linear) leads to a different gradient descent in quantum machine learning. Qian looked at the learning capacity of existing QCNNs and said that the current generation of QCNNs won't be able to learn highly complicated functions. Theoretically, QCNNs ought to be better at deep learning than traditional CNNs. However, in experimenting with label-assignment randomness for testing model capacity, the results of assigned data had only an accuracy that was slightly higher than that reached by blind guesswork. The model capacity problem demands that current quantum models be further improved. The problem is that quantum computing systems are very sensitive to noise, many errors through these stages. These errors reduce the performance of quantum models and are particularly bad on Noisy Intermediate-Scale Quantum (NISQ) devices. It can cause problems like reducing the model's capacity and generalization ability, which will lead to drops in accuracy.

As quantum computing and quantum hardware are still in the early exploration stage right now, most of these obstacles to applying a trendy concept like QNNs arise from defective equipment. Because the quantum hardware is still immature many of its capabilities are limited, error rate actualizes that it can not meet complex tasks that CNNs perform.

Hardware problems aside, a much more serious obstacle to quantum machine learning comes in the form of Barren Plateaus, meaning that the gradient of cost function becomes exponentially flat when initializing a quantum circuit. This flatness means that the gradients that guide optimizers through training in high-dimensional space shrink to zero, so become meaningless. High dimensional cases are supposed to be one of QCNN's strong suits, but the Barren Plateaus is precisely due to high dimensionality and uniform randomness in quantum state space. Because of the existence of Barren Plateaus, gradient descent fails to converge and makes matters even more complicated in its learning. Compared to other problems of quantum computing, Barren Plateaus are particularly difficult since this is the most basic feature distinguishing quantum systems and circuits from classical ones. This is because the circuits that make up quantum neural networks have a 2-design property. A 2-design is a collection of quantum operations that imitate statistical features of the Haar measure. The 2-design used in quantum neural network parameter initialization will shape the landscape into a flat landscape, devoid of any slope that is capable of driving optimization. New circuit design and parameter optimization strategies are needed if the performance of QCNNs is to be improved.

Currently, since QCNNs have many obstacles that hinder their performance, some researchers proposed hybrid models that combine the advantages of both CNNs and QCNNs to have practical applications.

Trochun has then designed an integration of quantum circuits with CNNs to create the Hybrid Quantum Convolutional Neural Network (HQCNN), and applied it to datasets such as CIFAR-10 or CIFAR-100, respectively [10]. Their result is better than that obtained from a simple use of only CNNs in small number class classification Their results suggest the hybrid models can do multi-class classification and even handle complex images with colors, but not limited to mere MNIST datasets. Despite these limitations--such as long running time and low accuracy in special cases--it can still handle complicated images.

In addition, Chalumuri has also made important contributions to the HQCNN model [11]. This approach is based on a quantum design that reduces the number of parameters. In scene classification, applying the combination of CNN layers and quantum computation can break through an existing tech barrier. Its accuracy rate reaches 85.28 % on the UC Merced land-use dataset. So it should be seen as a model showcasing the advantages of both QCNNs and CNNs.

Additionally, Li widened the playing field by introducing the Quantum Deep Convolutional Neural Network (QDCNN) [12]. Their model is based on a parameterized quantum circuit to accomplish image recognition. So they coded images as quantum states and used sequences of unitary transforms in an attempt to exploit the power of parallelism for deep feature extraction. The QDCNN model shows an acceleration over traditional computing methods with quantum computation. The QDCNN's better performance in image classification can be seen from the fact that a quantum circuit with two feature mappings capable of nonlinear transformations can handle this sort of operation. In addition, the quantum circuit's ability to handle datasets like MNIST and GTSRB indicates that quantum computing can enhance traditional CNNs.

These hybrid models all make use of connecting classical neural networks to quantum computing. Although quantum computing technology has yet to catch up, partially implementing it in artificial neural networks is beneficial and worthy of consideration. Practically speaking, this union of quantum states and neural computation represents a completely new level of parallelism combined with speed that allows formerly intractable problems to be tackled.

6. Future Outlook

Over the short term, as quantum hardware improves in stability and accuracy QCNNs should also progress. With NISQ (noisy intermediate-scale quantum) being the current state of Quantum devices, there are many limitations on the performance of QCNN. As these technologies develop further we expect a drastic fall in noise levels and an increase in the number of qubits which should be favorable for QCNN structures. QCNNs theoretically have the potential to handle large, high-dimensional datasets with fewer parameters than CNN models and so could beat the performance of regular CNNs on tasks beyond image recognition. This is provided the hardware can be upgraded further still. Looking even further ahead, the development of hybrid quantum-classical models provides a possible approach to solving QCNNs' problems with hardware and algorithms. The success of Hybrid Quantum Convolutional Neural Networks (HQCNN) by Trochun and Chalumuri shows that layering quantum neurons along with classical ones yields much better performance for multi-class classification problems than either alone can achieve. These are hybrid models taking advantage of both quantum parallelism and classical computation, combining QCNN's depth and complexity management with CNN's robustness and familiarity. Making the interfaces between quantum and classical layers efficient will continue to be one of the key challenges for hybrid models. It will need some very clever quantum algorithms able to easily convert classical information into this new kind of data and back again so that the layers involving qubits can be taught effectively by the bulk of a completely standard neural network.

Another area just waiting to be explored is the application of hybrid models beyond image processing. Being able to capture complex patterns and highly correlated information, quantum circuits have great potential for a wide range of applications such as natural language processes, generative modeling, or even drug discovery. If quantum states can depict probabilistic models and neural networks excel at pattern matching, then hybrid mixed models would be capable of solving an array of problems we cannot deal with today. Yet the path to a QCNN that fully exploits its potential is not free of obstacles. The problem of the barren plateaus in the quantum landscape poses a major obstacle to training quantum circuits. To avoid these flat regions, and that QCNNs can learn effectively, innovative approaches to circuit initialization and parameter optimization are needed. In addition, the future is expected to see advances in techniques for quantum error correction that will help compensate for the effects of noise and ensure the reliability of computations within these more advanced models. Eventually, the ideal is to make it possible for quantum-augmented neural networks to be trained and applied as effortlessly as their classical counterparts in a true unity of quantum computing and artificial intelligence. Besides advances in quantum hardware, this will also require the creation of software frameworks and tools for developing hybrid models. Quantum computers may one day help make deep learning faster. At this watershed period, as we enter a new era with integrated research and development it is up to the researchers themselves to meet these complex challenges. With the coming together of quantum physics and neural computation, machine learning is about to undergo a paradigm shift. No longer will data processing or intelligent decision-making be crammed into some tiny box; rather they'll come to envelop us in virtual space.

7. Conclusion

QCNN and CNN have been compared in this paper's potentials, as well as their challenges. QCNNs show potential in carefully selected applications, including handling high-dimensional data and complex tasks. They have theoretical computational advantages over other algorithms as well as improved accuracy on niche problems. Yet at present CNNs excel QCNNs in standard tasks thanks to more sophisticated optimization and riper technology. Therefore, if integrated with quantum computing the research on neural networks still has many problems to surmount. One is hardware limitations and another is training difficulties like barren plateaus. In this regard, combining the depth of QCNNs with CNN's reliability looks to offer a compromise solution. Though it is still quite new and unheard-of in the real world. Although these conclusions serve as a glimpse of the current situation in QCNN research, they are based on only those published within a few years. The field is rapidly developing and our view could be quite different from now to tomorrow. The future of quantum-enhanced machine learning relies upon empirical testing, the development, and perfection of hybrid models capable of incorporating both days present-day possibilities as well as those developing in the lab today via ongoing research.

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