

Quantum Secret Sharing and Error Correction

Mini Project - *CS-2-14(PO)*

By

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Introduction

Quantum computing is a new computing paradigm based on quantum mechanics that utilizes qubits instead of classical bits to store and process information. Quantum nature like superposition and entanglement aren't just theoretical figments, now with the capacity to actually engineer these quantum systems, this nature can be meaningfully utilized and harnessed to speed up NP Algorithms like “*Brute-Force Knapsack*”¹ and the “*Travelling Salesman Problem*” (TSP) and improve our modern AI models.

While the majority of our journey includes learning about theory of quantum circuits, learning and developing our own quantum algorithms for solving TSP etc. Our final aim of this paper will be the upcoming, *Quantum Convolutional Neural Networks (QCNNs)*². We will demonstrate not only of how we can use the ‘Quantum’ to develop better convolutional neural networks but also show an implementation of a quantum circuit-based algorithm, *quantum residual neural networks*³.

Finally, we will explain what we have learnt so far from this vast theory and then display the different results produced by a Classical CNN and a Quantum CNN. The results will on a fixed dataset for both the networks, and display the differences in the important parameters like accuracy, cost function trends and our current engineering limitations on implemetations of QCNNs.

Motivation

In this new quantum era, as the no. of qubits increase and our engineering catches up to our theory, the security of our existing cryptographic methods is starting to diminish. The main motivation for this project was ‘**Post-Quantum Cryptography**’. Later, we transposed from “How to make a problem which cannot be efficiently cracked by a quantum computer...” to “All such problems which can be efficiently cracked by a quantum computer...” where we encountered many NP hard problems but first

¹(insert reference [Knapsack])

²insert reference QCNNs

³insert referenc (paper)

we focused on a known solved problem of ‘Knapsack’ after which we started to develop our own algorithm with all that we have learnt for TSP.

Q. How does a Quantum Computer solve such “*Brute-force*” problems ‘*faster*’?

→ We will not elaborate on the theory as to keep this report concise. While we have to classically iterate over all solutions to check, in quantum we use the **Hadamard**⁴ Gate to check all such superpositions simultaneously.

This is used extensively in quantum algorithms. Our main focus was on how to make the brute-force solution $O(2^n)$ more optimal, which we did using **Grovers’ Algorithm**⁵ which reduced the complexity to $O(2^{n/2})$. In general, we can say that in such brute-force approaches, Grovers provides a well-known \sqrt{N} “quadratic-speedup”.

Q. Why did we choose *QCNNs*/*QRNNs*?

→ We think that making a hands-on quantum circuit in a domain which has practical implications in the future of machine learning and AI will not only show how we can turn our theoretical knowledge into practice, which is the best way to display what we have learnt, but also simultaneously work on the edge of scientific innovation happening in the field of quantum computing as we speak. This is why we will be implementing a very recent paper published in 2024 as our contribution to this field of research.

Q. What do we actually use, software or anything to implement and run these quantum algorithms and get results?

→ While we do not have a quantum computer, *IBM’s* quantum cloud computing provides us few qubits to work with. For this we are further using **Qiskit** to simulate qubits, even if due to the nature of qubits it gets difficult to simulate more than 14-15 qubits at a time on a classical computer, we can simulate for our use case.

Methodology & Implementation Idea

For our methodology, first we’ll make a Quantum CNN on a particular dataset, after which we will make a equivalent Classical CNN and compare the results to see which one performs better and their cost function trends. After this, we will implement the ‘Residual-block’ into our QCNN to see the difference it produces.

- **Dataset** consists of all tic-tac-toe games which have not ended in a draw. This dataset is actually very complex compared to all the dataset which a QCNN is typically trained on, i.e. detecting horizontal/vertical stripes on a 2x2 or a 4x2 grid, but we decided to push the limits of current standards. This is because we wanted to make a QCNN model never made before.

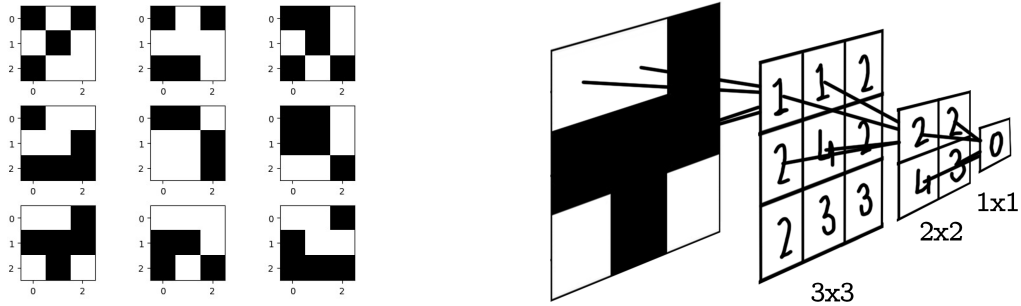


Figure 1: Our generated dataset and the overarching convolution model for both variations.

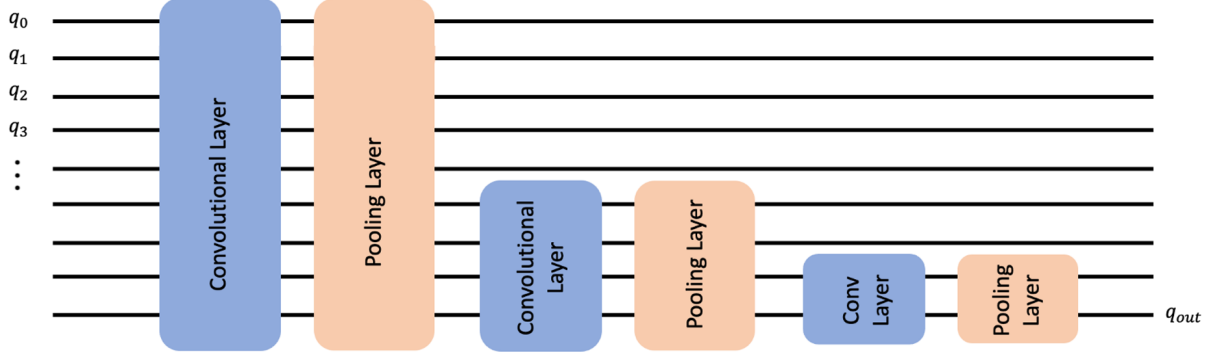
⁴insert reference (Quantum Circuits wiki)

⁵(insert reference [Grovers])

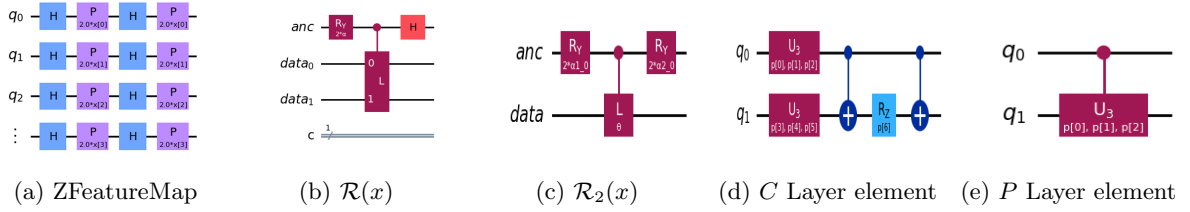
- **Layers** of pure convolutional networks are used. First is a convolution of a 3×3 to another 3×3 matrix, we'll call it $C_{3 \times 3}$. Next is a pooling layer from 3×3 to 2×2 , we'll call it $P_{3 \times 3, 2 \times 2}$. Similarly $C_{2 \times 2}$, $P_{2 \times 2, 1 \times 1}$. The only difference is that the QCNN model uses an additional $P_{2 \times 2, 2 \times 1}$ and $C_{2 \times 1}$ before pooling back via $P_{2 \times 1, 1 \times 1}$.

$$CCNN: \text{Input} \rightarrow C_{3 \times 3} \rightarrow P_{3 \times 3, 2 \times 2} \rightarrow C_{2 \times 2} \rightarrow P_{2 \times 2, 1 \times 1} \rightarrow \text{Output}$$

$$QCNN: \text{Input} \rightarrow C_{3 \times 3} \rightarrow P_{3 \times 3, 2 \times 2} \rightarrow C_{2 \times 2} \rightarrow P_{2 \times 2, 2 \times 1} \rightarrow C_{2 \times 1} \rightarrow P_{2 \times 1, 1 \times 1} \rightarrow \text{Output}$$



- **Training** of CCNN was done with Adam optimizer [PyTorch], Cost-function: Cross Entropy. QCNN was with COBYLA optimizer [Qiskit]⁶, Cost-function: Squared Error (Default).



- **Additional** blocks were added like ZFeatureMap⁷ before sending them to the layers to encode the data into qubits. And then we built and added our 'Residual-Blocks' from the 2024 paper.

This is the method we have chosen to implement this quantum circuit. Our main focus in this paper is to show a detailed and practical implementation so we'll skip the intuition and theory which comes with this. Next is to report the results by both of these models [Now uploaded on [GitHub](#)].⁸

Results

For our Classical CNN, we understand that with our cross entropy function and Adams Optimizer which are all well developed systems when it comes to CNN gives our Classical model a huge advantage.

⇒ **Accuracy:** $81.5 \pm 1\%$

⇒ **Epochs:** 300

Similarly for the same dataset and same architecture for our QCNN model. Note that this comparison is purely with our convolutional QCNN and is without the use of $\mathcal{R}(x)$ and $\mathcal{R}_2(x)$ blocks.

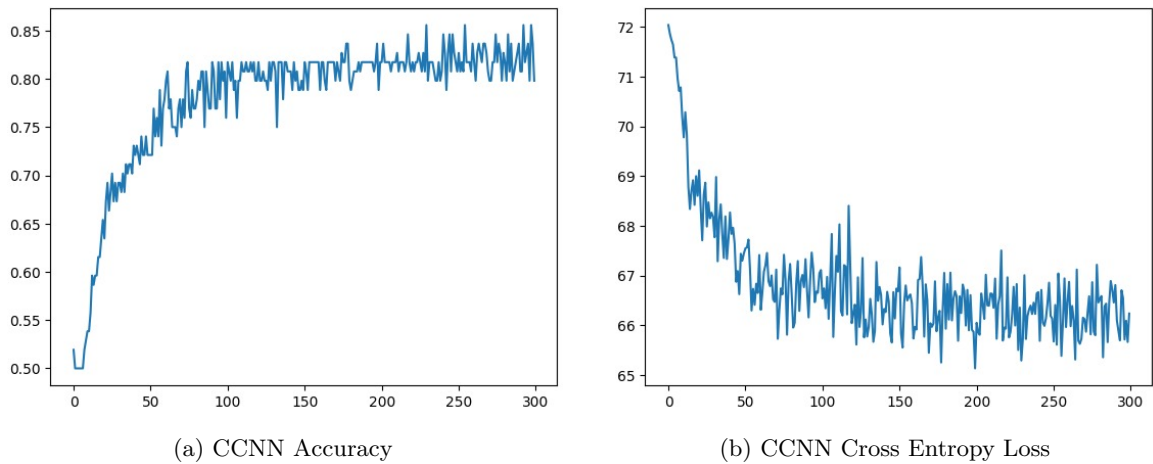
⇒ **Accuracy:** 77%

⇒ **Epochs:** 200

⁶insert ref COBYLA

⁷insert reference Zfeature map

⁸Please see the references for the theoretical aspect, you won't be disappointed!



Now, we use the ‘Residual-Blocks’ to see the difference between QCNN with and without the residual connection architecture.

Insert results of our residual block paper itegration...

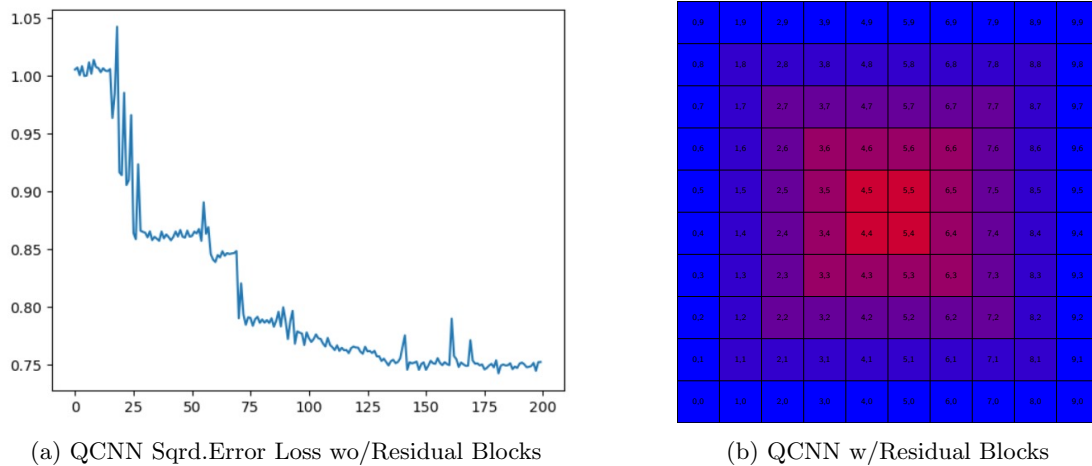


Figure 4: Results of Quantum CNN

Conclusion & Achievements

Our QCNN model reaches almost the same accuracy the CCNN reaches in 100 epochs. With more computing and time we might be able to replace CCNN with negligible decrease in performance. Also, the point to be noted is that our code is just simulating the qubits which makes it slower than if we had a actual quantum computer.

[illegible]

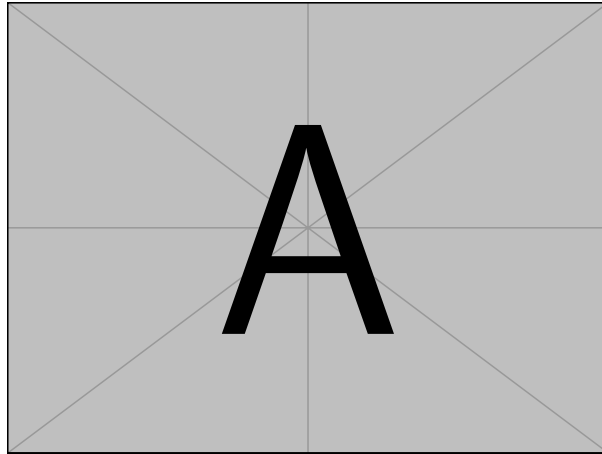


Figure 5: Placeholder

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Litrature Review & References:

- ref 1
- ref 2
- ref 3
- ref 4
- ref 5