Analysis, Prediction and Evaluation of Covid-19 Datasets Using Quanvolutional Neural Networks

Pinaki Sen, Alberto Maldonado Romo, Shek Lun Leung and Amandeep Singh Bhatia

pinakisen.eenita@gmail.com

Team Name: QTechnocrats

Analysis, Prediction and Evaluation of Covid-19 Datasets Using Quanvolutional Neural Networks

Outline

1. Introduction
2. Main Contributions
3. Quanvolutional Neural Networks
4. Methodology
5. Results & Discussion
6. Conclusion & Future Work

Introduction

- The Convolutional neural networks (CNNs) has an excellent performance in machine learning applications ranging from pattern recognition; from image processing to voice recognition due to its ability to extract features from the data in a hierarchical manner [1].
- The most beneficial aspect of CNNs is reducing the number of parameters in Artifical neural networks (ANNs), where the input propagates toward the deeper layers.
- For example, in image classification, the edge might be detected in the first layers, and then the simpler shapes in the second layers, and then the higher level features in the next layers as shown in Fig 1.

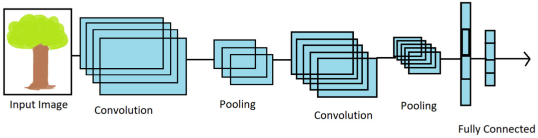

Figure 1: Architecture of Convolutional neural networks

Main Contributions

Quantum convolutional neural networks (QCNNs) extend the capabilities of CNNs by leveraging certain potentially powerful aspects of quantum computation. It operate on input data by locally transforming the data using a number of random quantum circuits [2].

- Motivated by the efficiency of classical convolutional neural networks, we have analyzed, predicted and evaluated the Covid-19 using Quanvolutional neural network (QNNs).
- We have performed binary classification of the covid-19 data set encoded in a quantum state. We have also investigated its performance by considering different parameters on the Pennylane's "default qubit" device.
- It has been shown that quantum circuits are able to model complex functional relationships, which is infeasible using polynomial-sized classical computational resources.

Quanvolutional Neural Networks (QNNs)

QNNs add a new type of transformational layer to the standard CNN architecture: the quantum convolutional (or quanvolutional) layer [3]. It is a made up of a group of N quantum filters, which operate much like their classical convolutional layer counterparts by producing features maps through locally transforming input data [4]. The process for transforming the classical data using quanvolutional filters is shown in Fig 2.

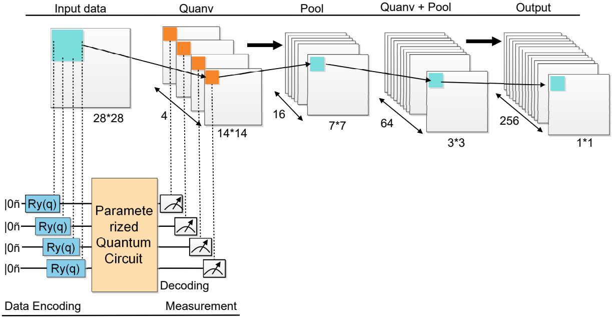

Figure 2: Transforming the classical data using quanvolutional filters.

Methodology

We considered a single quanvolutional filter uses a random quantum circuit q, which takes as input spatially-local subsections of images from dataset C_{vd}. We imported the Covid-19 dataset from Kaggle. Each input (ui) is a 2D matrix of size $n*n$ wherein $n > 1$. We initialized a PennyLane default.qubit device, simulating a system of 4 qubits. The quantum circuit consisting of:

- An embedding layer of local R_y rotations;
- A random parametrized quantum circuit of n layers;
- a final measurement in the computational basis, estimating the 4 expectation values.

The image is divided into squares of 2*2 pixels and each square is processed by the quantum circuit and finally 4 expectation values are mapped into 4 different channels of a single output pixel.

Results & Discussion

Below each input image, the 4 output channels generated by the quantum convolution are visualized in gray scale.
It can be clearly observed that some local distortion is introduced by the quantum kernel and down sampling the resolution.Although, the global shape of the image is preserved as it is as expected for a convolution layer.

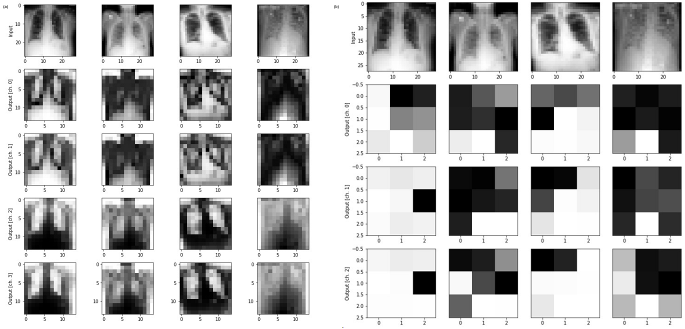

Figure 3: (a) Compressed images 14*14. (b) Quanvolutional neural network on Covid-19 dataset

Cont'd

Fig 4 (a-b) shows the accuracy around 70% and 76% for model$_1$ and model$_2$, respectively. Moreover, the cost is evaluated 0.774 as shown in Fig 4.

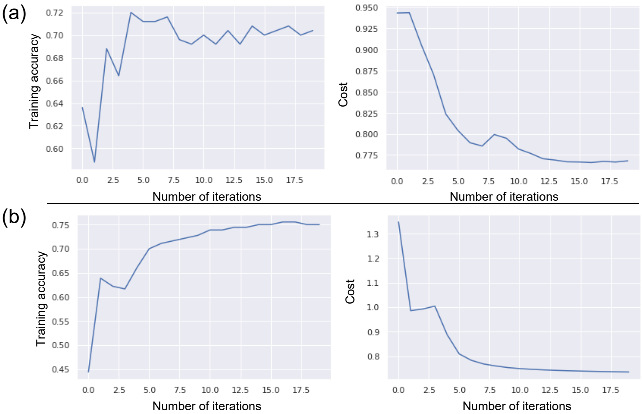

Figure 4: (a) Accuracy and cost of model$_1$. (b) Accuracy and cost of model$_2$

Conclusion & Future Work

The main benefit is that quantum circuit can generate highly complex kernels whose computation could be, at least in principle, classically intractable.

- The real x-ray images in the dataset is enough large to contain a lots of information. But due to lack of computational resources we reduced the size to 28x28 using openCV library, which may have suppressed a lot of important information. Later with the availability of more computational resources, we can use 256x256 dimensional image which can increase the accuracy of the model.
- After applying Quanvolution and flattening the data, we had 256 features of each image and 11 features are used by feature selection method due to lack of qubits.
- This work can be implemented on a real-time quantum computer with more number of available qubits and real-time simulation of the quantum circuit to get a feel of the quantum system. Moreover, we can experiment with training of four quanvolutional layers on the randomly generated image data with the availability of more qubits.

References I

[1] Saad Albawi, Tareq Abed Mohammed, and Saad Al-Zawi.
Understanding of a convolutional neural network.
In *2017 International Conference on Engineering and Technology (ICET)*, pages 1–6. Ieee, 2017.

[2] Maxwell Henderson, Samriddhi Shakya, Shashindra Pradhan, and Tristan Cook.
Quanvolutional neural networks: powering image recognition with quantum circuits.
Quantum Machine Intelligence, 2(1):1–9, 2020.

[3] Junhua Liu, Kwan Hui Lim, Kristin L Wood, Wei Huang, Chu Guo, and He-Liang Huang.
Hybrid quantum-classical convolutional neural networks.
arXiv preprint arXiv:1911.02998, 2019.

[4] Quanvolutional Neural Networks.
`https://pennylane.ai/qml/demos/tutorial_quanvolution.html`.
[Online; accessed 24-JFeb-2021].

Thank You