Supervised Learning using Hybrid Quantum-Classical Neural Networks

Gantiva Sneyder
Master in Computer Science Student
esgantivar@unal.edu.co

Toquica Hans
Master in Computer Science Student
hmtoquicac@unal.edu.co

Vega Diego
Master in Computer Science Student
davegav@unal.edu.co

Abstract

Deep learning has increasingly evolved in the past decades providing a new way to solve problems for analysis and automation. In parallel, quantum computing and quantum information have recently passed from theory to practical devices (and development interfaces provided for any user), this recent transformation is leading to increasing research in the field of quantum machine learning, and ergo the usage of quantum circuits in classical neural networks, called hybrid quantum-classical neural networks. One of the approaches of hybrid neural networks is the usage of convolutional quantum layers in the convolutional neural network (CNN) architectures. In this work a comparison between a common CNN and a hybrid CNN is done, in order to check what are the advantages of using a hybrid CNN instead of a good-old CNN.

Related Work

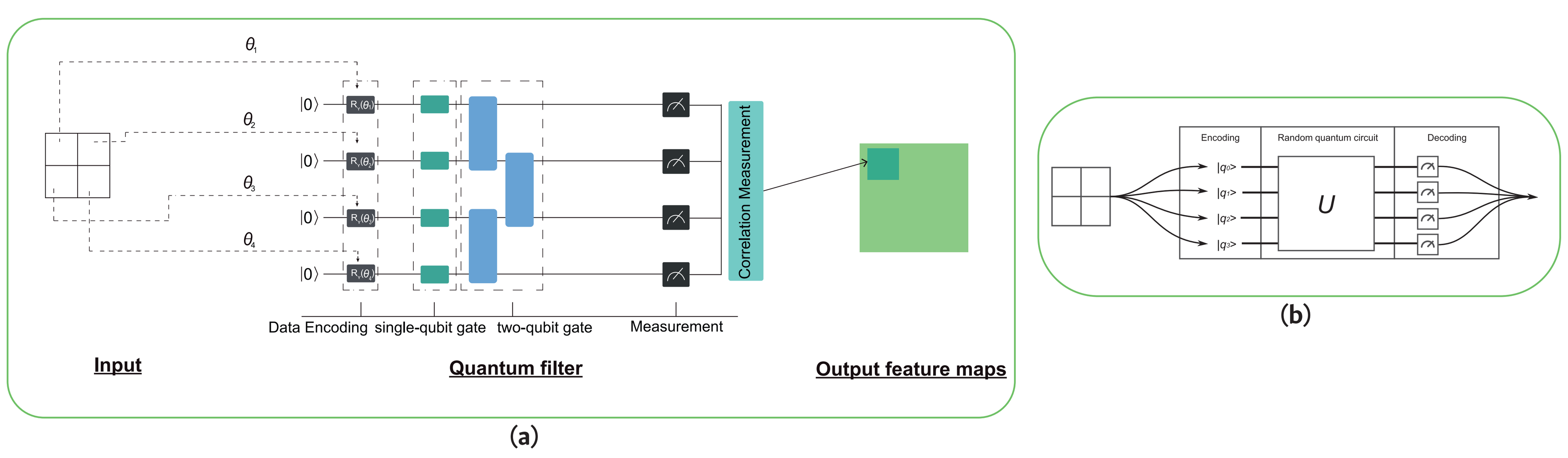

Fig 1. Different aproaches to quantum convolutional neural networks. Adapted from [3] and [4].

Dataset

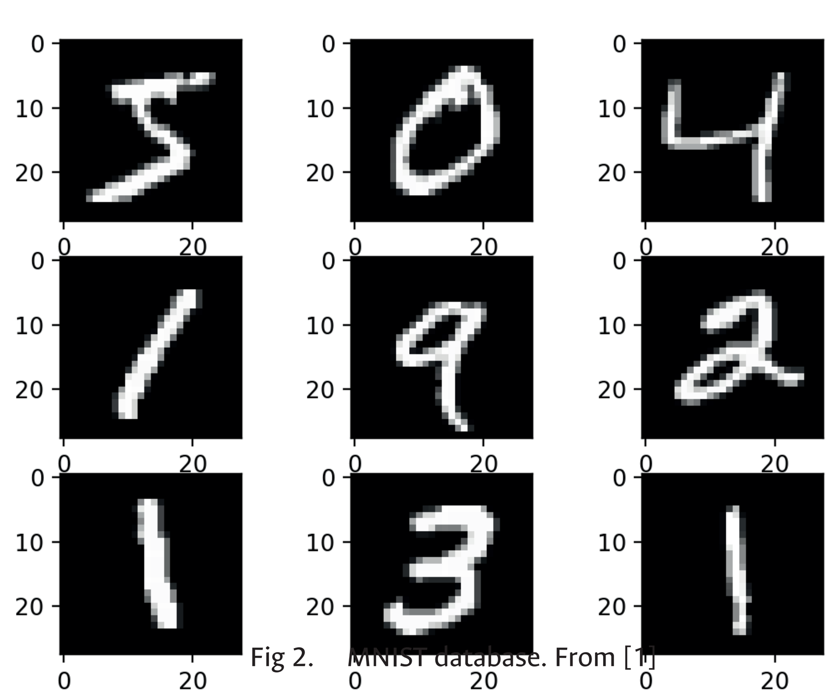

Fig 2. MNIST database. From [1]

The MNIST data set is composed of 60000 images for training and 10000 for validation, this dataset is about hand written digits from 0 to 9. The images have a dimension of 28 x 28 pixels, and each pixel can take a value between 0 and 255.
For our experimental setup we only use 10% of the dataset, 60 images of each class for training and 10 images of each class for test. The pixel's value is scaled between 0 and1.

Classical Model

We propose a classical neural network as baseline of the classification task, the architecture is composed by a Convolutional layer with filter parameter equal to 4, this filters are defined to enable the comparison with quantum proposal,the next ones are a flatten layer and finally a output layer with 10 units, this architecture is depicted in the figure 2.

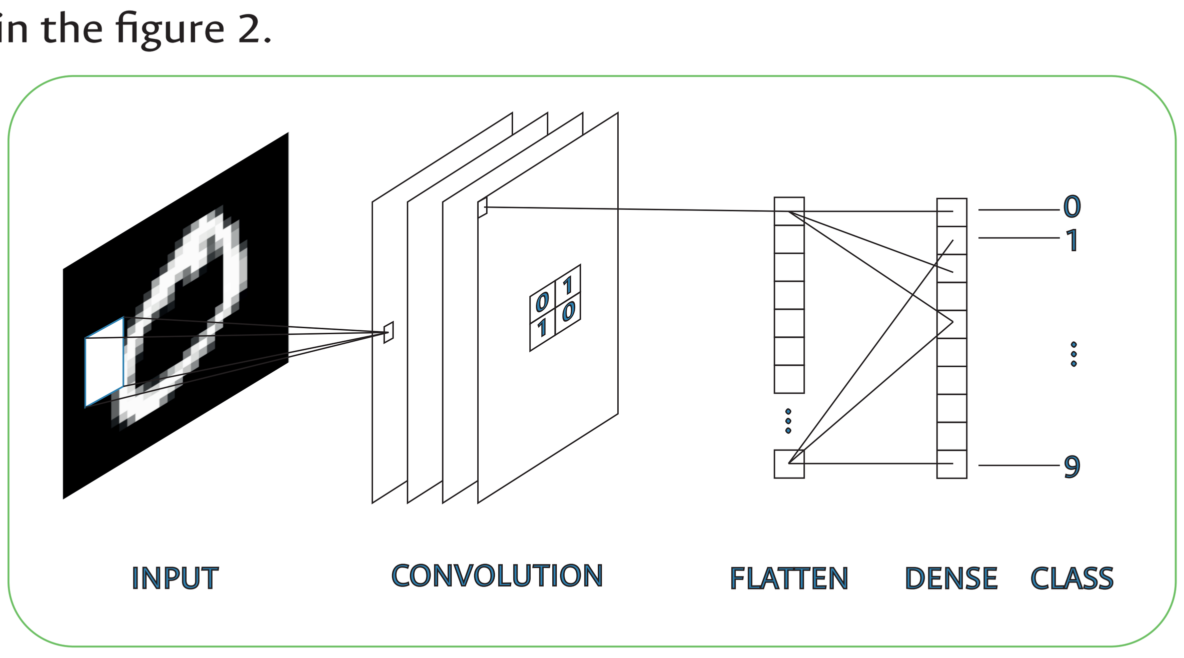

Fig 3. Structure of the classical neural network used.

Quantum Hybrid Model

For quantum architecture we propose two approaches: the classical architecture, which is presented in figure 3 and the quantum architecture that replaces the classical convolution with quantum convolution (QC). The QC consists on using a quantum circuit to extract features from raw data, the QC builds a kernel of 2 x 2 and uses this subset of data from images as parameters of the quantum circuit, the architecture is depicted in the figure 4. The classical approach encodes the parameters using a RotationY, and applies a Random Circuit, which is an utility from Pennylane that randomly chosen single qubit rotations and 2-qubit entangling gates, acting on randomly choses n-qubits. The outputs of this circuit are n classical values, result of applying quantum measurement over all qubits around Z-axis.
The second approach uses a custom quantum circuit as depicted in figure 5, the results of the kernel are used as a parameters of the operator that applies a rotation around Y-axis, these parameters are scaled by multiplying them by π, the output are n classical values product of quantum measurement over all qubits around Z axis.

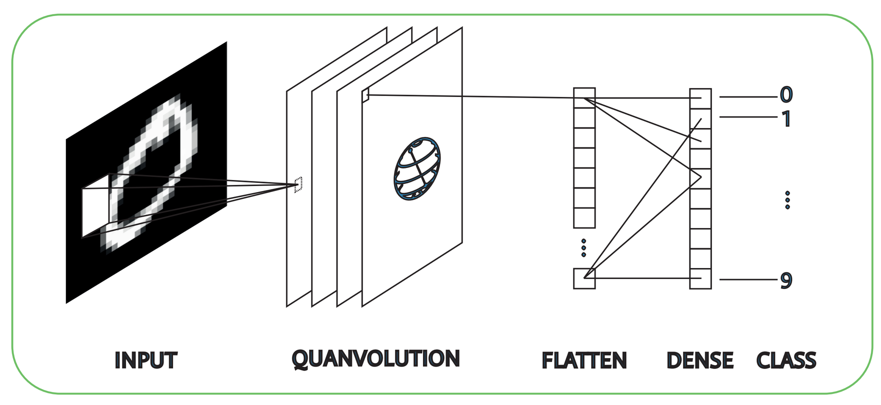

Fig 4. Structure of the hybrid quantum neural network used. Adapted from [3]

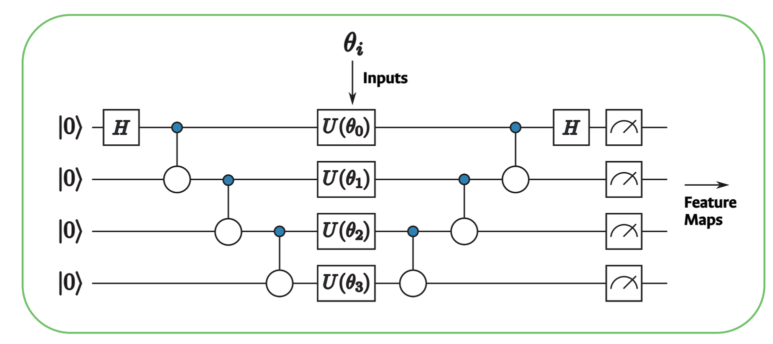

Fig 5. Quantum custom circuit of the neural hybrid network. Adapted from [3]

Results

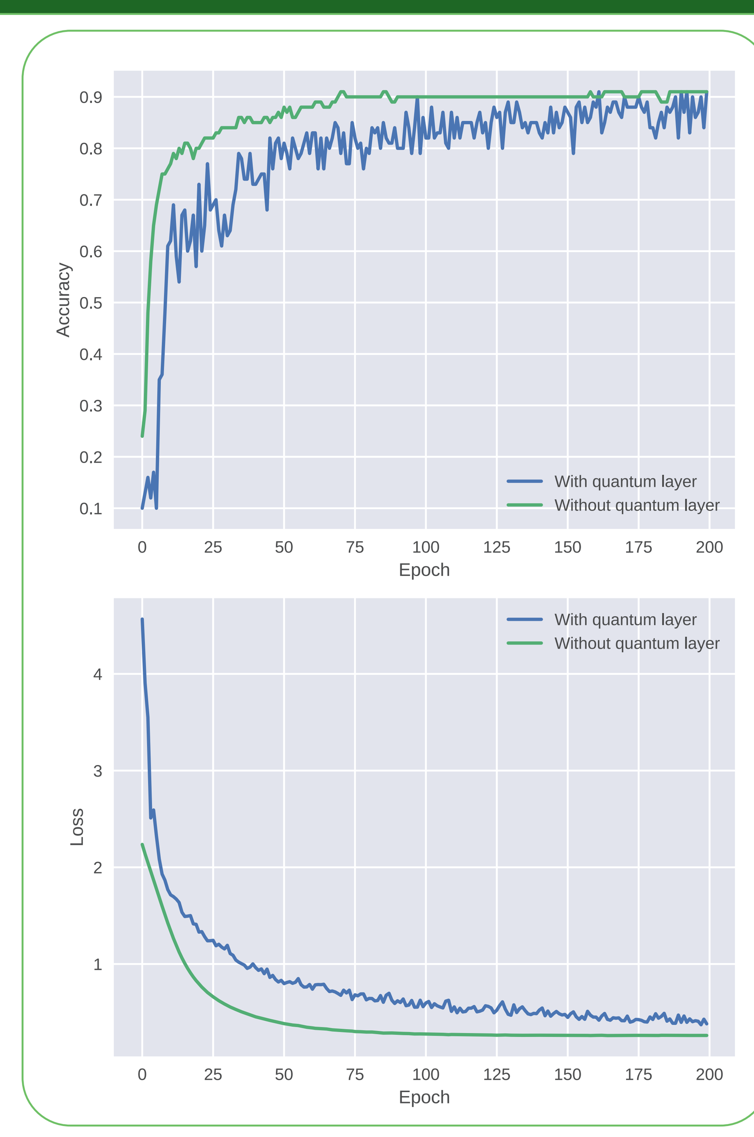

Fig 6. Results of quantum random circuit compared with classical model.

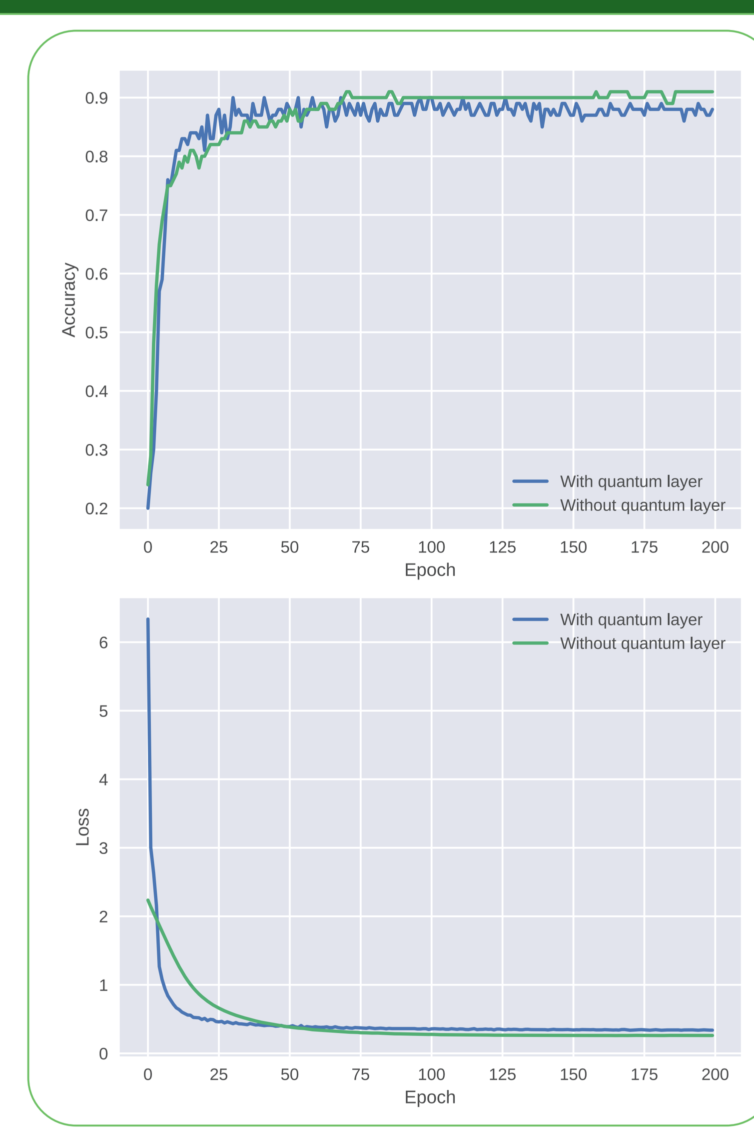

Fig 7. Results of quantum custom circuit compared with classical model.

Conclusions

- The results show that the quantum convolutional neural network that uses a Random circuit disposition, was not able to outperform the classical convolutional network. Despite the fact that the final values of the accuracy and loss of the models are the same, the speed of convergence is faster for the classical network. So in this case this model is not advised for this kind of classification problems.
- In the case of the quantum convolutional neural network that implements the Custom Circuit in contrast with the classical network, it is shown in the experiments that the models achieve approximately the same values of loss and accuracy, but the quantum approach has a higher speed of convergence during the initial stage. Therefore, the quantum model could be recommended for the initial stages of the training process of a classification problem.
- Taking into account the availability and cost of the quantum computing resources and the results of this work, we can conclude that it is not viable yet to use this kind of model due to lack of significant advantages in the network performance.

REFERENCES

[1] Brownlee, J., 2020. How To Develop A CNN For MNIST Handwritten Digit Classification. [online] Machine Learning Mastery. Available at: https://machinelearningmastery.com/how-to-develop-a-convolutional-neural-network-from-scratch-for-mnist-handwritten-digit-classification/ [Accessed 14 December 2020].

[2] TensorFlow. 2020. Fashion_Mnist | Tensorflow Datasets. [online] Available at: https://www.tensorflow.org/datasets/catalog/fashion_mnist [Accessed 14 December 2020].

[3] Henderson, M., Shakya, S., Pradhan, S., & Cook, T. (2020). Quanvolutional neural networks: powering image recognition with quantum circuits. Quantum Machine Intelligence, 2(1), 1-9.

[4] Liu, J., Lim, K. H., Wood, K. L., Huang, W., Guo, C., & Huang, H. L. (2019). Hybrid Quantum-Classical Convolutional Neural Networks. arXiv preprint arXiv:1911.02998.

VIDEO: https://www.youtube.com/watch?v=Y1bnPB2aj28

UNIVERSIDAD NACIONAL DE COLOMBIA