Hybrid Quantum-Classical Neural Network for Semantic Segmentation

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***Abstract*—Hybrid quantum-classical neural networks are a increasingly popular approach to apply the advantages of quantum computing to machine learning problems. In this project, We apply a hybrid quantum-classical neural network to semantic segmentation: recognizing the footpath from the rest of image.**

***Index Terms*—Machine Learning, Quantum Computing, Semantic Segmentation, Neural Networks**

I. Introduction

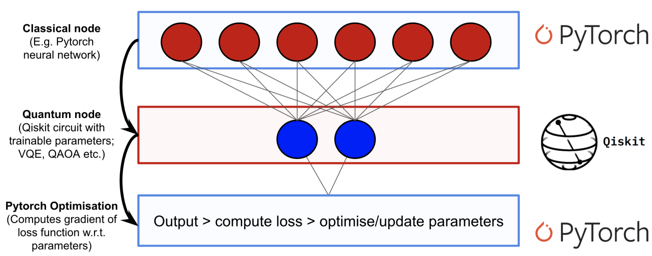

Figure 1: Diagram of Hybrid Classic-Quantum Neural Network structure using Qiskit and PyTorch Source: [1]

Quantum Computing is becoming both a cheaper and more accessible technology through the introduction of tools such as NISQ (noisy intermediate-scale quantum) and cloud quantum computing [2]. Quantum computing also possesses a unique advantage over traditional computing as rather than using traditional bits that possess binary values of 0 or 1 quantum bits exist on a Bloch sphere taking values between 0 or 1 with the superposition state of 2^n possible outcomes at any given time [3]. Combined with quantum properties such as superposition and entanglement we can utilize this quantum advantage [4]. As such, there is a growing interest into utilizing quantum computing for machine learning problems, including those performed by neural networks. While there is a growing interest in pure quantum neural networks, there is also a growing interest in hybrid classical-quantum neural networks. Utilizing both quantum and classical layers, these algorithms can be friendly to NISQs whose noise can be detrimental to other quantum algorithms [5]. Furthermore, they can tackle problems and models that may be challenging for a traditional classical computer but easy for a quantum computers [6].

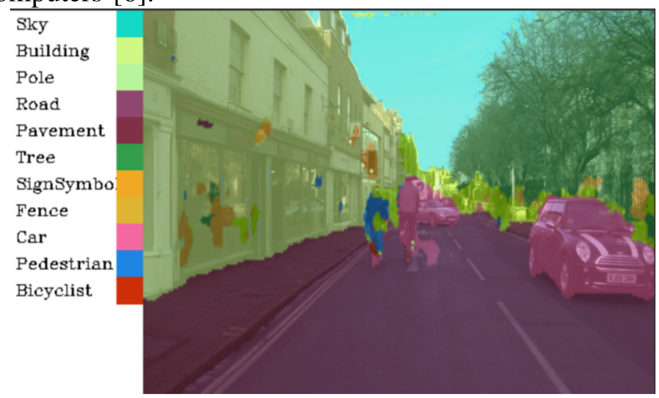

Figure 2: Example of Semantic Segmentation on street: [7]

Semantic segmentation is one such popular task which hybrid machine learning models could be applied to. Semantic segmentation is a computer vision task where each pixel of a input image is assigned a class value. It differs from instance segmentation as those of the same class would be given the same class label rather than different labels for each instance of a class. Semantic segmentation is applicable in tasks such as autonomous vehicles, augmented reality, and medical image diagnosis [8]. The accuracy of an algorithm solving Semantic Segmentation is given through the IOU values for each class: IOU = True Positives / (True Positives + False Positives + False Negatives). Two important IOU values are the mean IOU value for all classes or the frequency weighted IOU which calculates the mean IOU with weighted importance based on frequency of class. By taking the mean or frequency weighted value of IOU one can calculate the accuracy of semantic segmentation.

II. Related Work

Similar work with image segmentation and hybrid quantum systems has been done. There is research done on segmentation using hybrid quantum systems. However, they are not neural nets. Segmentation of surface cracks was done with a hybrid network for image classification and a K-means algorithm for segmentation

[9]. Medical data with binary classification for tumor or non-tumor classification used a SHS 256 algorithm as well as a 2 bit quantum circuit for classification, followed by a segCNN for segmentation [10]. There is also research done on hybrid quantum neural networks for classification. There was classification of COVID-19 x-ray lungs with a hybrid CNN with a Convolutional layer at the start of the neural network [11]. Also, there was classification of photovoltaic faults using a hybrid two layer QNN [12].

III. Method

Figure 3: Example pictures of Bangladesh footpaths and corresponding masks to the footpaths dataset Source: [13]

For this project images containing of footpaths in the streets of Bangladesh were used [13]. Each image contained a corresponding mask of the footpath. To segment the data I utilized a hybrid classical-quantum neural network to detect the footpath from the rest of the image. For the classical portion of the hybrid neural-network, I used the segnet implementation by Divam Gupta [7]. Segnet is a semantic segmentation neural network which works through two networks: encoding and decoding network. The encoder network reduces the image to a lower resolution while the decoder network up-scales the image back to the original resolution [14]. The decoding network up-scales through pooling indices computed in the max pooling layers in the corresponding encoding layer. Through this approach learning is not necessary for decoding, making training faster [15]. All optimization was carried out using a Adam optimizer and the learning rate was set to .01.

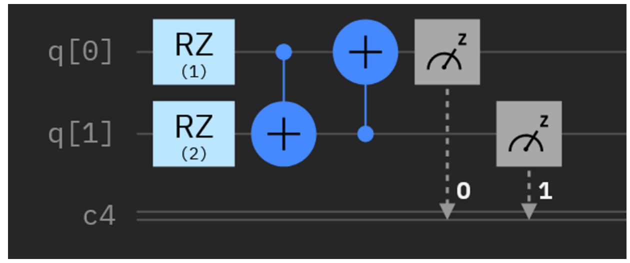

Figure 4: Quantum Circuit

For the quantum portion of the neural network a quantum circuit was used. The quantum circuit consisted of a angle embedding followed by a basic entanglement and Pauli Z measurement for both qubits. The basic entanglement works through CNOT gates that connect both of the qubits. In a CNOT gate one qubit acts as a control which remains static and the other qubit the target, which changes based on the control. By using two CNOT gates we entangle both the qubits. This quantum circuit was simulated using a Pennylane simulator as through initial testing significant change in performance was not observed with using a Qiskit simulator vs a Pennylane simulator. The network was first tested with only the classical portion. Next, the final classical softmax layer was replaced with a quantum circuit. Afterwards the network was tested with a quantum circuit before the final classical softmax layer. This was also tested with different dataset sizes, 800 training images and 2 epochs, 400 training images and 5 epochs. Both times 200 images were used as the testing dataset.

IV. Result

Model	Runtime on Ryzen 5 PRO 6 core CPU(Hours)	Frequency Weighted IU (200 Test Images)	Mean IU (200 Test Images)
Traditional Segnet, 800 Images, 2 epochs	1	0.7884	0.7685
Segnet with Quantum Circuit + Softmax, 800 images, 2 epochs	9	0.7665	0.7421
Segnet with only Quantum Circuit, 800 images, 2 epochs	7	0.3795	0.3417
Traditional Segnet, 400 Images, 5 epochs	4	0.7638	0.7368
Segnet with Quantum Circuit + Softmax, 400 images, 5 epochs	26	0.7312	0.7019
Segnet with only Quantum Circuit, 400 images, 5 epochs	22	0.4554	0.4242

Figure 5: Table of all results

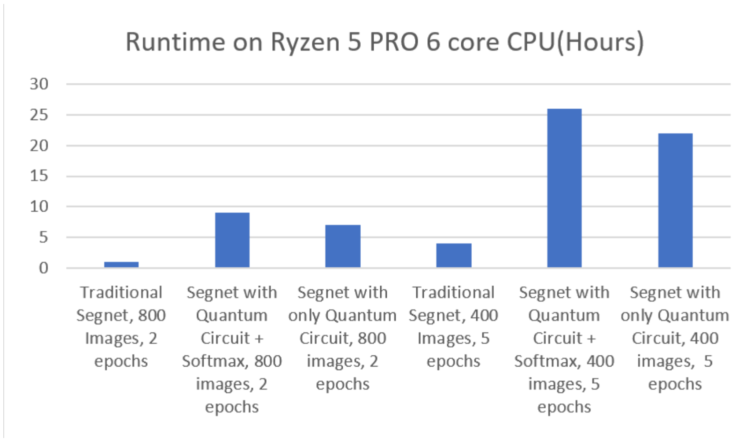

Figure 6: Table of runtimes on ryzen CPU

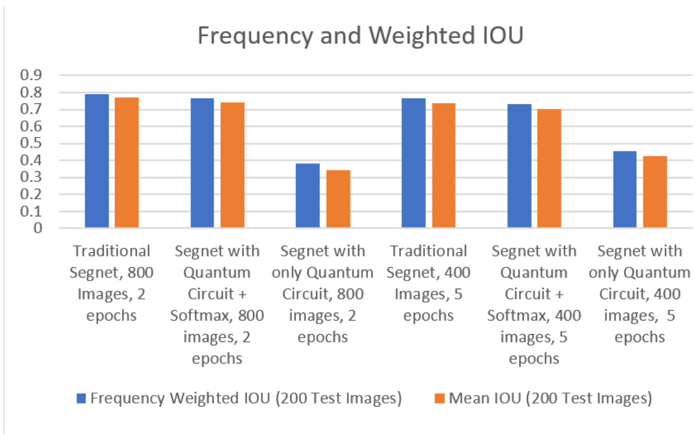

Figure 7: Table of Frequency Weighted and Mean IOU

Overall there was a lower frequency and mean IOU with the hybrid segnet than with the traditional segnet. Furthermore, run-time for the hybrid segnet was significantly increased. The difference between the traditional segnet compared to the softmax + quantum circuit segnet was small for both IOU values with only about .03 difference for both mean and frequency IOU. For both traditional and hybrid segnet with softmax, difference between IOU values between hybrid and traditional segnet increased when more epochs were run but less images. However, when running with just quantum circuit and no softmax, accuracy increased with more epochs and less images.

V. Conclusion Future Work

Overall I received lower accuracy with the hybrid segnet than the traditional segnet with significant increased runtime. The increased runtime was expected as simulating a quantum circuit is computationally intensive. However, the reduced accuracy was unexpected. Quantum computing is still in its early stages and finding improvements through quantum computing is difficult. There may be a few reasons for this: the training image size is not large enough. The quantum circuit was not optimized, using a basic entanglement rather than a circuit designed for semantic segmentation or even semantic segmentation of the specific data set. Hybrid models with optimized quantum circuits perform better than unoptimized quantum circuits [16] [12]. Furthermore, the fact that it was a binary classification, the advantages of quantum may be less identifiable compared to a classification with more classes. Lastly, while the dataset tested was Bangladesh footpaths, Kitti vision dataset is a more standard and more useful dataset to test on. These are all angles that can be improved on for future work.

Acknowledgment

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References

[1] "Hybrid quantum-classical neural networks with pytorch and qiskit," Apr 2022. [Online]. Available: https://qiskit.org/textbook/ch-machine-learning/machine-learning-qiskit-pytorch.html

[2] J. Preskill, "Quantum computing in the nisq era and beyond," *Quantum*, vol. 2, p. 79, 2018.

[3] D. Ristè, M. P. Da Silva, C. A. Ryan, A. W. Cross, A. D. Córcoles, J. A. Smolin, J. M. Gambetta, J. M. Chow, and B. R. Johnson, "Demonstration of quantum advantage in machine learning," *npj Quantum Information*, vol. 3, no. 1, pp. 1–5, 2017.

[4] G. S. Uehara, A. Spanias, and W. Clark, "Quantum information processing algorithms with emphasis on machine learning," in *2021 12th International Conference on Information, Intelligence, Systems & Applications (IISA)*. IEEE, 2021, pp. 1–11.

[5] J. Liu, K. H. Lim, K. L. Wood, W. Huang, C. Guo, and H.-L. Huang, "Hybrid quantum-classical convolutional neural networks," *Science China Physics, Mechanics & Astronomy*, vol. 64, no. 9, pp. 1–8, 2021.

[6] R. Divya and J. D. Peter, "Quantum machine learning: A comprehensive review on optimization of machine learning algorithms," in *2021 Fourth International Conference on Microelectronics, Signals & Systems (ICMSS)*. IEEE, 2021, pp. 1–6.

[7] Divamgupta, "Image segmentation keras : Implementation of segnet, fcn, unet, pspnet and other models in keras," https://github.com/divamgupta/image-segmentation-keras, 2013.

[8] A. Garcia-Garcia, S. Orts-Escolano, S. Oprea, V. Villena-Martinez, and J. Garcia-Rodriguez, "A review on deep learning techniques applied to semantic segmentation," *arXiv preprint arXiv:1704.06857*, 2017.

[9] S. Pramanik, M. G. Chandra, C. Sridhar, A. Kulkarni, P. Sahoo, V. C. DV, H. Sharma, A. Paliwal, V. Navelkar, S. Poojary *et al.*, "A quantum-classical hybrid method for image classification and segmentation," *arXiv preprint arXiv:2109.14431*, 2021.

[10] J. Amin, M. A. Anjum, N. Gul, and M. Sharif, "A secure two-qubit quantum model for segmentation and classification of brain tumor using mri images based on blockchain," *Neural Computing and Applications*, pp. 1–14, 2022.

[11] E. H. Houssein, Z. Abohashima, M. Elhoseny, and W. M. Mohamed, "Hybrid quantum-classical convolutional neural network model for covid-19 prediction using chest x-ray images," *Journal of Computational Design and Engineering*, vol. 9, no. 2, pp. 343–363, 2022.

[12] G. Uehara, S. Rao, M. Dobson, C. Tepedelenlioglu, and A. Spanias, "Quantum neural network parameter estimation for photovoltaic fault detection," in *2021 12th International Conference on Information, Intelligence, Systems & Applications (IISA)*. IEEE, 2021, pp. 1–7.

[13] M. Mamun, A. Al, and I. Kadir, "Footpath image dataset: Annotated footpath images of bangladesh," 2020.

[14] V. Badrinarayanan, A. Handa, and R. Cipolla, "Segnet: A deep convolutional encoder-decoder architecture for robust semantic pixel-wise labelling," *arXiv preprint arXiv:1505.07293*, 2015.

[15] V. Badrinarayanan, A. Kendall, and R. Cipolla, "Segnet: A deep convolutional encoder-decoder architecture for image segmentation," *IEEE transactions on pattern analysis and machine intelligence*, vol. 39, no. 12, pp. 2481–2495, 2017.

[16] M. Dobson, G. S. Uehara, and A. Spanias, "Quantum neural network benchmarking with mnist dataset."