A Precise Classification of Medical Images with a Cost-Efficient Quantum-Classical Hybrid Neural Network

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***Abstract*—This work discusses a cost-efficient hybrid quantum-classical neural network for classification of medical images. By embedding a 4-qubit variational quantum circuit (VQC) within a compact convolution neural network (CNN), the hybrid model achieves the accuracy of deep classical networks (99.89%) with much less parameters and faster training than ResNet-18 and VGG-16 model. Compared to a conventional CNN that shows the best training speed, the hybrid still remains even more parameter-efficient with similar speed, confirming its potential for real-time medical diagnostics in resource-constrained conditions.**

***Index Terms*—Quantum Machine Learning, Hybrid Neural Networks, Medical Imaging, Parameter Efficiency**

I. Introduction

Deep learning models such as convolution neural networks (CNNs) [1], ResNet-18 [2], and VGG-16 [3] excel in handling medical images but generally demand millions of parameters and expensive computational costs, limiting their utilization in edge devices. Various techniques in quantum machine learning (QML) has been studied to pursue for the chance to tackle the resource limit of classical approaches. Their performance with respect to the state-of-the-art classical models, however, has not yet been rigorously understood in general as previous studies mainly focused on presenting reviews of diverse approaches in QML with an analysis on their scaling challenges stemming from limits in quantum resources [4], [5], tested the performance on small datasets [6], [7], and discussed the performance only with respect to simple CNNs [7].

In this work, we particularly aim to carefully examine the performance of hybrid quantum-classical models for QML [5], [7], which have attracted keen interests from researchers due to their potential for cost-efficient operations in noise-intermediate-scale quantum (NISQ) environments. For a large set of medical images ($\sim$59K), we conduct rigorous training processes with 4-qubit variational quantum circuits (VQCs) and clearly demonstrate the benefit of our hybrid QML model from the perspective of the model performance, against the well known classical ML models including ResNet-18 [2] and VGG-16 [3].

II. Methodology

Hybrid QML Model: The hybrid model employed in this work is developed with the Pennylane software development kit [8], where its data encoder and VQCs are simply implemented with the built-in subroutine `AngleEmbedding` and the `StronglyEntanglingLayers`, respectively. Other properties of the hybrid model are based on the work reported by Liu $et\ al.$ [7].

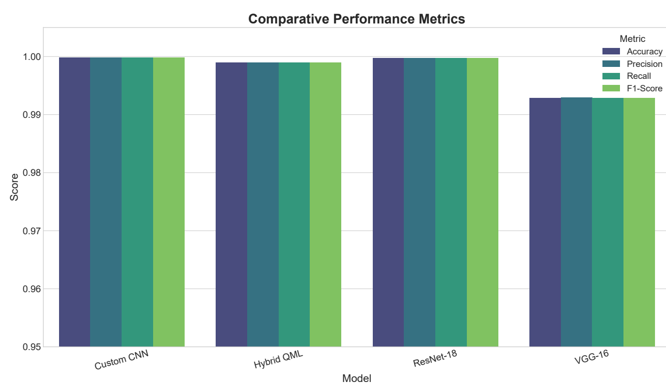

Fig. 1: Comparative performance metrics of all models: the accuracy and the precision of image classification, the recall and the F1-score.

Training Setup: The large dataset we use consists of 58,954 x-ray images [9], being classified into 6 modalities: AbdomenCT, BreastMRI, CXR, ChestCT, Hand, and HeadCT. To training our hybrid model with these data, we use the Adam optimizer (a built-in optimizer of Pennylane) with a learning rate of 0.001 and a batch size of 32, 10 epochs, and the Categorical Cross-Entropy loss function. All calculations were performed on a MacBook Air with an Apple M1 chip (8-core CPU, 7-core GPU, 16-core Neural Engine), 8GB unified memory, and 256GB SSD.

III. Results and Discussion

Table I and Figure 1 show the performance obtained with benchmark tests, where the model performance is assessed with the accuracy and the precision of classification, the number of associated parameters, the speed of training, the recall, and the F1-score. Results clearly highlight the remarkable cost-efficiency of the hybrid QML model in classification of medical images. In particular, the hybrid QML model offers fairly nice accuracy with much less parameters when compared to the three classical models considered in this work. One remarkable point of the results that must be emphasized, is the benefit in computing speed. Although the 4-qubit hybrid model is executed in a classical PC, the training speed is $\sim$10$\times$ and $\sim$50$\times$ better than that of ResNet-18 and VGG-16, respectively.

TABLE I: Model Performance Comparison

Model	Acc.	Params	Time (s)	Prec.	F1
CNN	99.98	0.53M	457	0.9999	0.9999
Hybrid QML	99.89	0.04M	533	0.9990	0.9990
ResNet-18	99.97	11.17M	5568	0.9998	0.9998
VGG-16	99.28	134.28M	24631	0.9930	0.9929

Figure 2 shows the convergence behavior of the training process conducted with various models, indicating our hybrid model, which uses the smallest number of parameters, converges quite fast although its initial accuracy (at the first epoch) turns out be the worst among all the tested cases. Figure 3 show the confusion matrix of our hybrid model and indicates that the accuracy of classification is perfect for AbdomenCT, BreastMRI, ChestCT and HeadCT images. Figure 4 shows one of previously unseen Chest X-Ray (CXR) images that is successfully classified with our model, indicating the practicality of the hybrid QML.

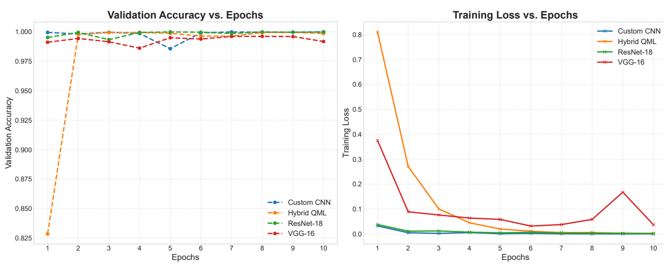

Fig. 2: Learning dynamics that shows validation accuracy and training loss per epoch of each model. In spite of the worst initial accuracy, the hybrid model converges quite fast compared to its classical counterparts.

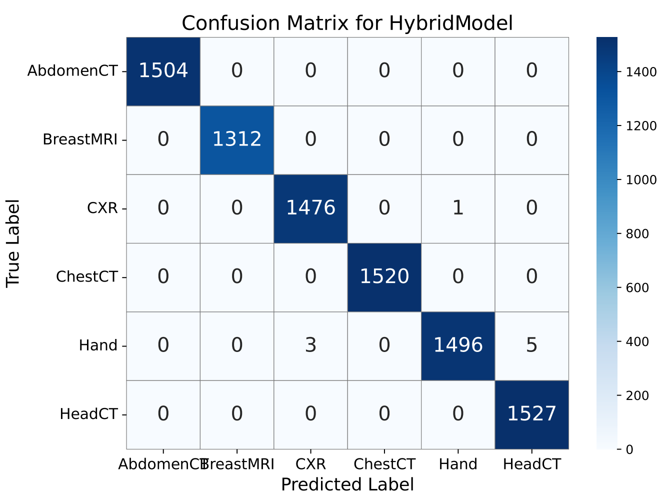

Fig. 3: The confusion matrix of the hybrid model demonstrating the perfect accuracy in classification of AbdomenCT, BreastMRI, ChestCT and HeadCT images.

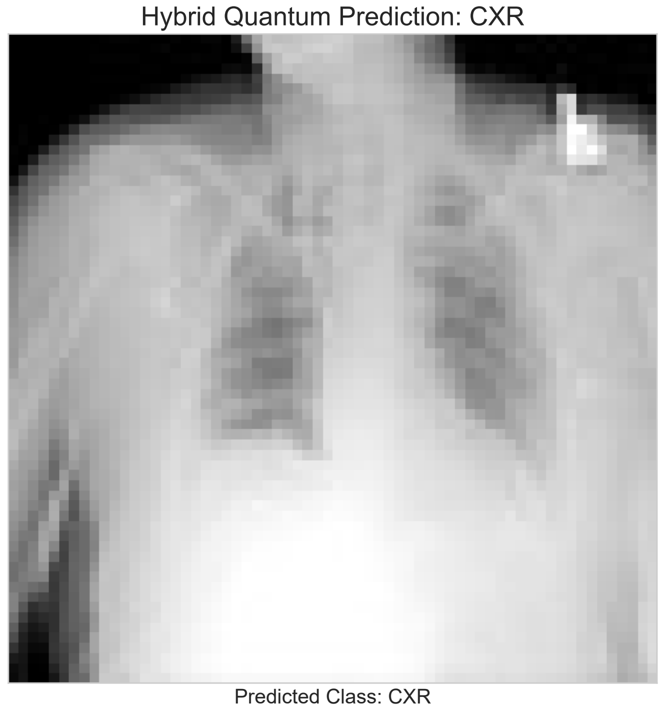

Fig. 4: One of chest X-Ray (CXR) images that is previously unseen but is successfully classified with the hybrid model.

IV. Conclusion

This work demonstrates that a lightweight hybrid quantum-classical model matches the accuracy of ResNet-18, VGG-16, and CNN with a much less computing cost. It achieves 99.89% accuracy with just 0.04M parameters, training 10$\times$ faster than ResNet-18 and 46$\times$ faster than VGG-16, highlighting the practical efficiency improvements enabled by quantum networks for real-time and resource-constrained medical diagnostics.

Acknowledgment

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