FEDERATED QUANVOLUTIONAL NEURAL NETWORK: A NEW PARADIGM FOR COLLABORATIVE LEARNING

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ABSTRACT

In recent years, the concept of federated machine learning has been actively driven by scientists to ease the privacy concerns of data owners. It is a realistic goal to study the advanced computing ecosystem, which will be comprised of heterogeneous federated resources (i.e. classical and quantum). The federated hybrid quantum-classical algorithm called quanvolutional neural network is proposed with distributed training across edge devices. The hybrid algorithm requires small quantum circuits to produce meaningful features to classify COVID-19 and Medical MNIST machine learning datasets, which makes it ideal for NISQ era. The quantum federated learning approach trains a quantum algorithm across several decentralized servers holding local data samples without exchanging them.

QUANTUM FEDERATED LEARNING OPTIMIZATION

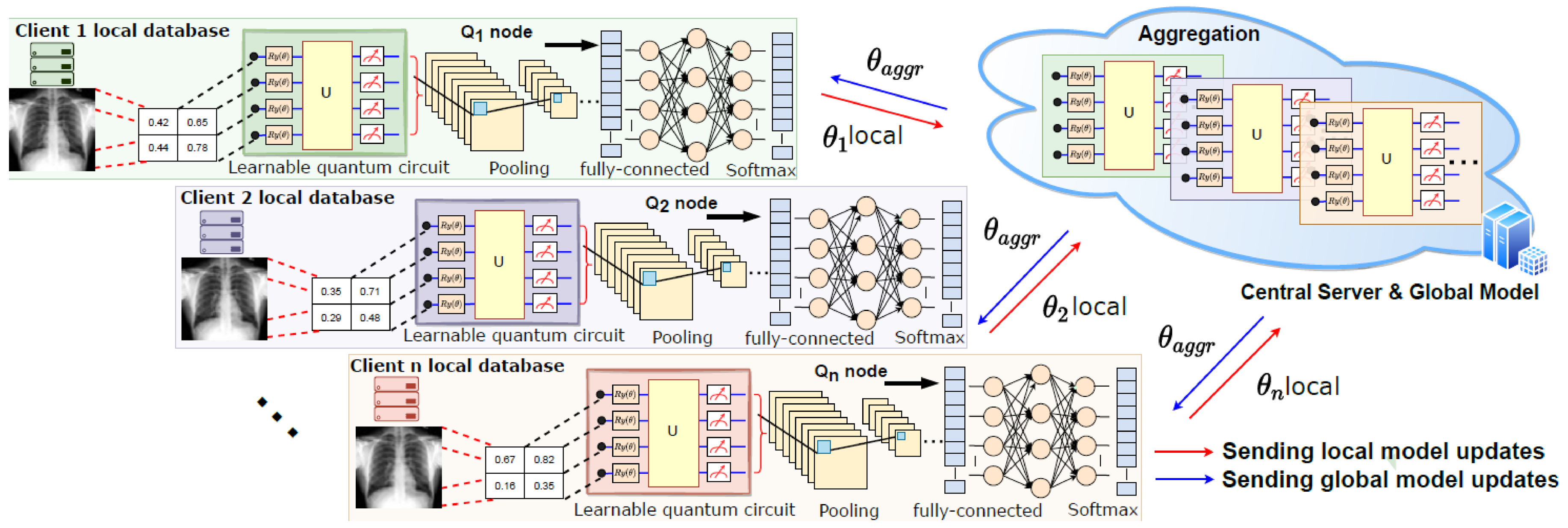

Figure 1: Example of a quantum federated learning framework based on quanvolutional neural network for an identification of chest related diseases collaboratively in healthcare sector

The concept of federated machine learning was introduced by Google in 2017 [1]. In this work, we explore the hybrid quantum-classical models [2] in federated settings. The collaborative training in federated quanvolutional neural network (FedQCNN) is achieved by the performing following steps:

- **A server-to-client broadcast step:** The central server broadcasts global model to all clients.
- **A local client update and upload step:** Each client k trains the current global model's parameters on their local data with a local SGD for optimization and sends back the gradients to central server. $g_k = \nabla_{\theta_k^r} F(\theta_k^r), \quad \theta_k^r = \theta_s^r - \eta g_k$
- **A server update step.** the central server then averages the local model parameters to update its global model by employing a federated averaging algorithm and sends the new set of parameters to all k clients for the next communication round [3].

MedNIST Non-IID1 dataset (97%)

Fed	C	E	B	QCNN
FedSGD		1	∞	1950
FedAVG	10	1	8	626 (3.11×)
FedAVG	10	5	8	49 (39.7×)
FedAVG	10	1	32	1750 (1.11×)
FedAVG	10	5	32	289 (6.74×)
FedAVG	20	1	8	286 (6.81×)
FedAVG	50	1	8	646 (3.01×)

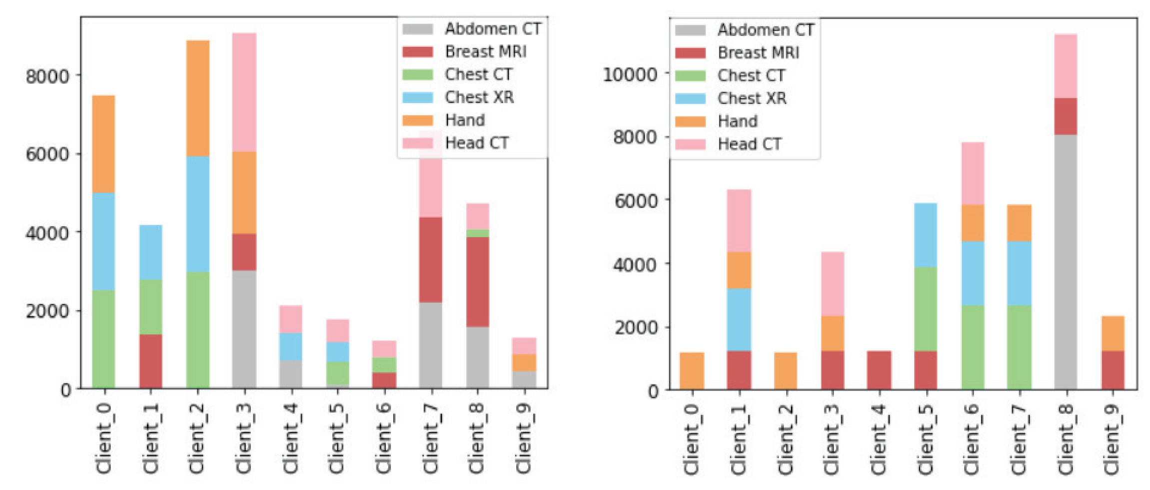

Figure 2: Non-identically independently distributed (Non-IID) dataset among 10 clients (in which each client should have samples from at least three classes) and real-world distribution (in which each client can have samples from any number of classes)

RESULTS & DISCUSSIONS

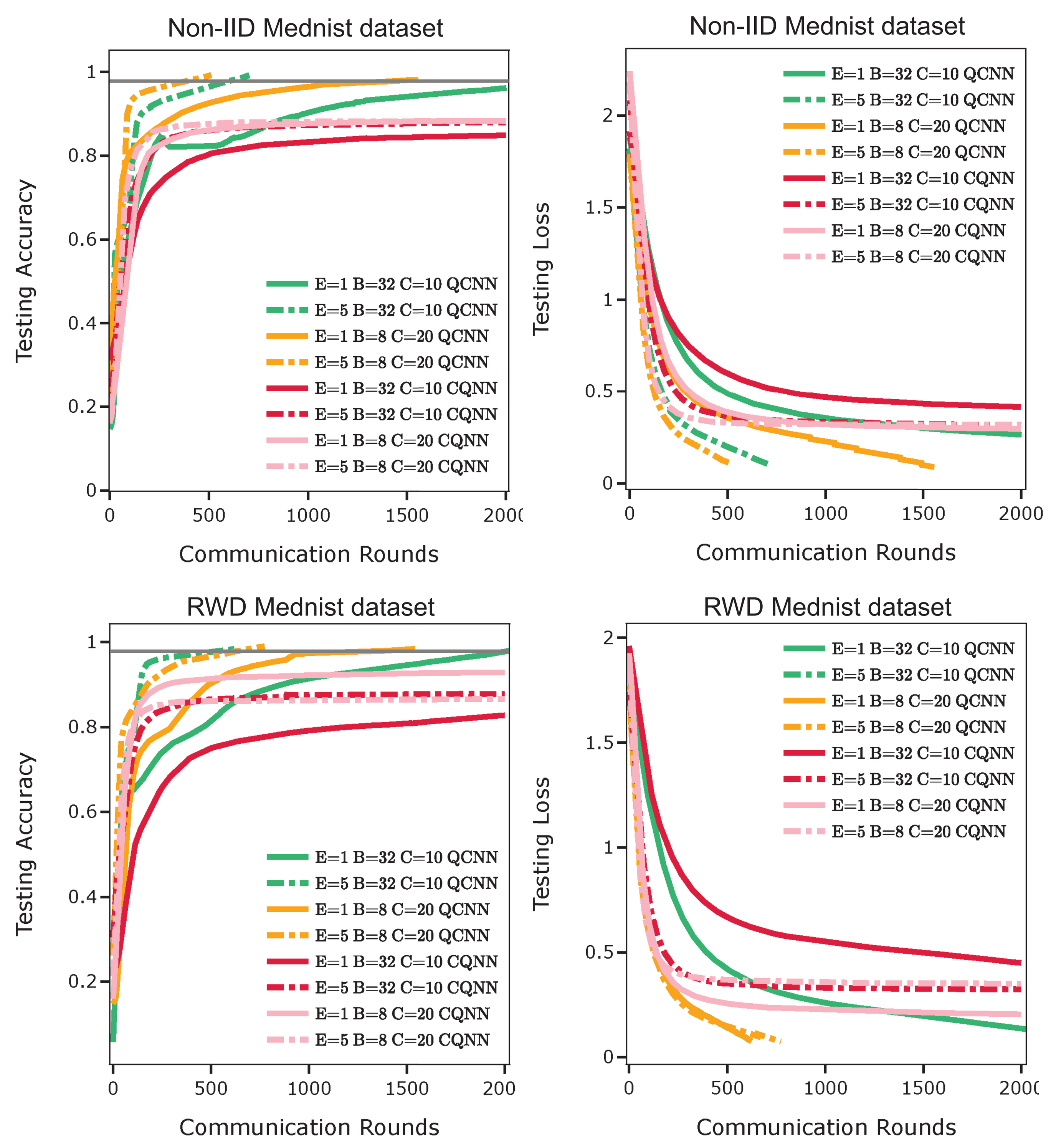

Figure 3: (a-b) shows the performance of FedQCNN and FedCQNN on Non-IID dataset, which is distributed among 10, 20 and 50 clients. It shows the effect o increasing batch-size, local epochs and clients.

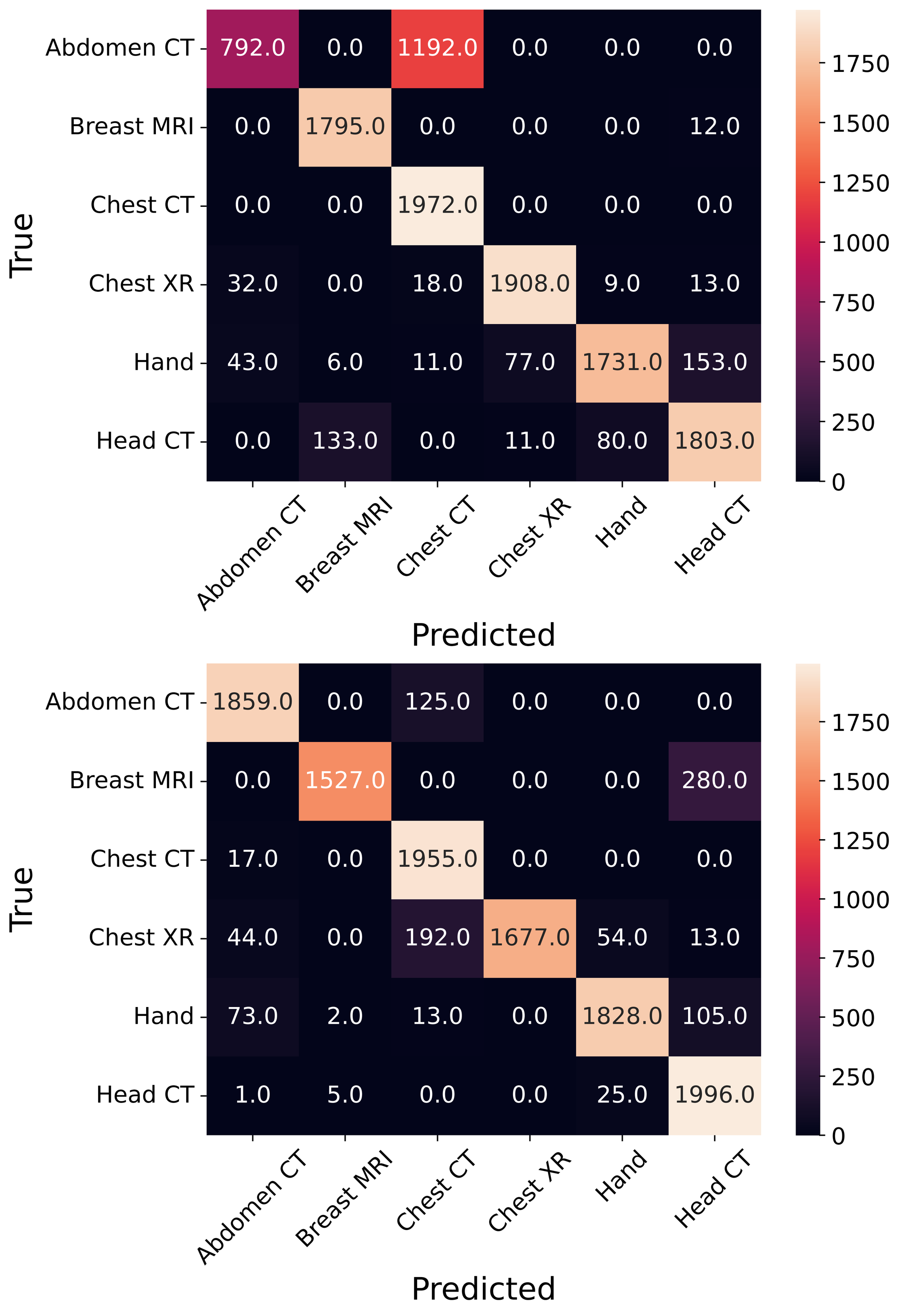

Figure 4: In real-world distribution with 20 clients, it has been investigated that FedQCNN is not able to classify chest CT class after 100 communication rounds with local epochs=1, batch-size=8 . But, on increasing local epochs=5, it shows a significant improvement.

CONCLUSION

In this work, we proposed a novel framework to train quanvolutional neural networks in federated learning settings. The FedCQNN takes fewer communication rounds for training as compared to the FedQCNN. While distributed quantum learning, the communication cost can be reduced by using small batch sizes or by adding more local SGD updates. The proposed algorithm help to distribute the computational resources on NISQ devices and preserving privacy.

REFERENCES

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