Deakin's Quantum ML Research: Quantum Federated Learning with Simple Data Encoding and Aggregation

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Abstract

Our work addresses the challenges of implementing QFL over distributed quantum networks by operationalizing data-encoding-driven QFL on IBM's quantum cloud platforms. Demonstrated with genomic datasets, our method accelerates QFL adoption, enabling efficient, privacy-preserving training while showcasing its transformative potential in quantum computing and advancing Deakin's leadership in this field. We invite collaboration and funding to further develop and scale our QFL methodology.[a]

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Three Ideas

1. Advance decentralized quantum model training with data privacy, addressing key challenges in cloud-based quantum platforms through innovative data-encoding-driven QFL
2. Investigate QML techniques for genomic sequence classification; explore feature maps to encode classic data to quantum data
3. Personalised QFL: pQFL framework design, theoretical analysis and experiments

QFL Algorithm

Procedure Initialize
Split the global genomic dataset (X, Y) into client-specific datasets $(x_i, y_i) \sim (X, Y)$, for $i = 1, \dots, n$
Initialize client weights θ_i and global weights θ_g
Procedure QFL Learning with Training
for $epoch = 1$ to I **do** ▷ *Iterate over epochs*
  Select a subset of m clients randomly from n clients
  for each client i in the selected subset **do**
  ▷ *Client-side training loop*
    Initialize client-specific quantum circuit Q_i
    Encode local client data x_i into quantum states X_{q_i}
    Train the quantum model by minimizing the local loss function and updating the weights:

$$\theta_i = \text{argmin}_{\theta_i} \mathcal{L}(f_{Q_i}(X_{q_i}), y_i)$$

  ▷ *Minimize the local loss function for each client i*
    Upload updated local weights θ_i to the server
  end for
  Server-side Aggregation:

Deakin's QFL

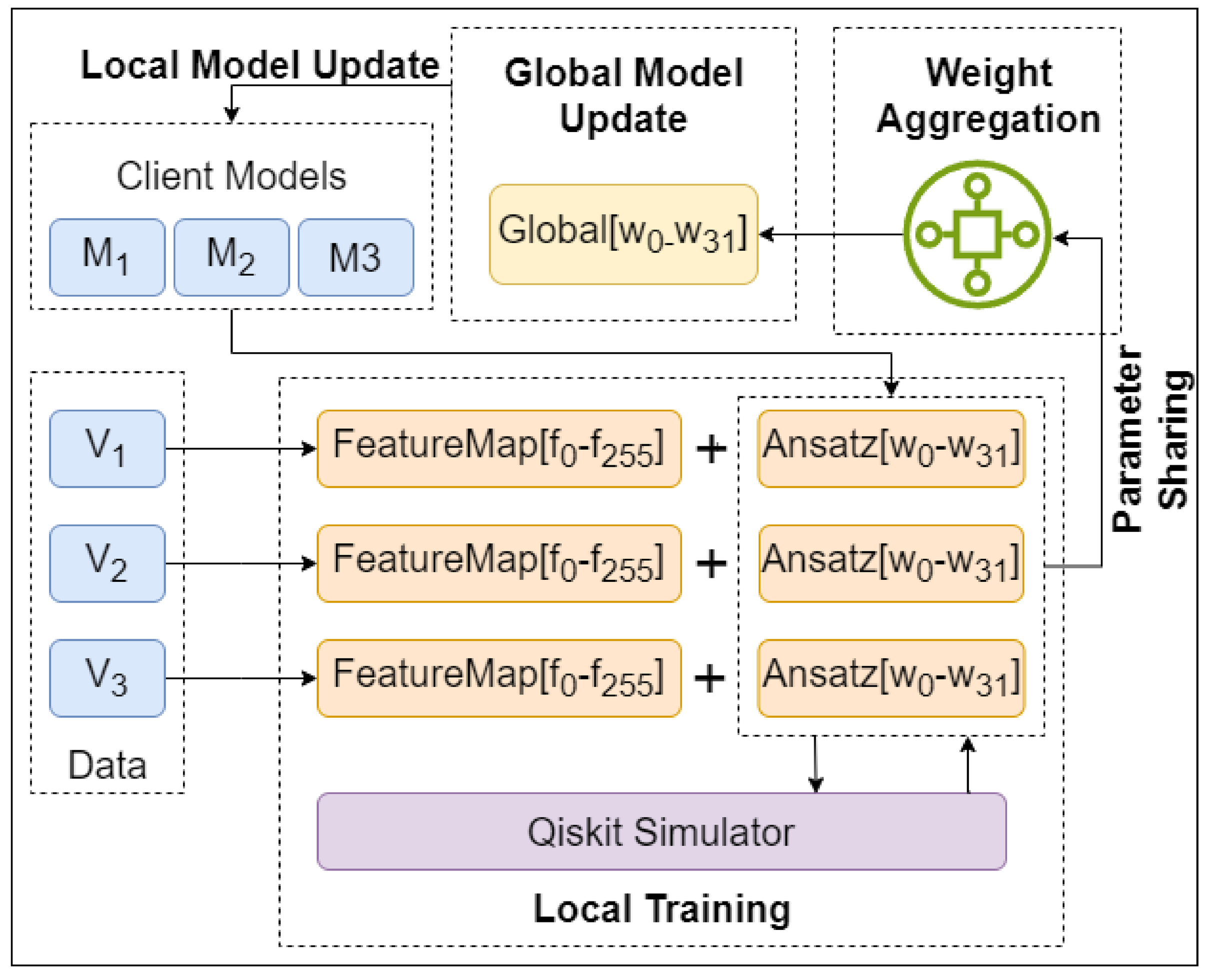


Figure 1: Local learning in the proposed QFL: consisting of several key components. The *feature map* ingests input data and encodes them into a quantum state. Following this, the *Ansatz* comes into play as a parameterized quantum circuit, its parameters being iteratively fed by the *Optimizer*–optimization objective function is driven by the outcomes from the *Sampler*.

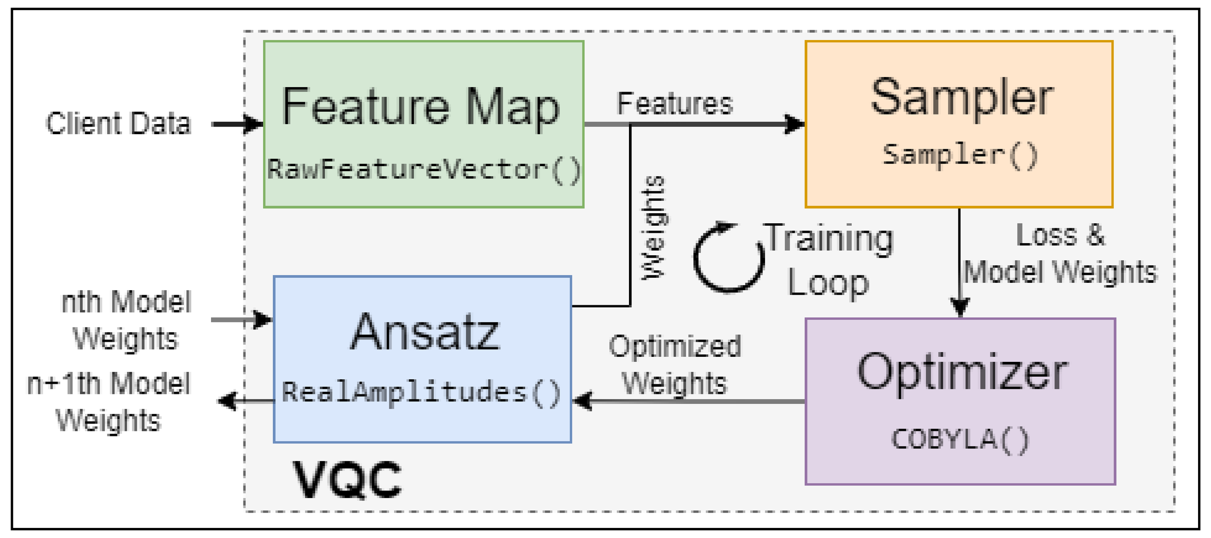


Figure 2: Local learning in the proposed QFL: consisting of several key components. The *feature map* ingests input data and encodes them into a quantum state. Following this, the *Ansatz* comes into play as a parameterized quantum circuit, its parameters being iteratively fed by the *Optimizer*–optimization objective function is driven by the outcomes from the *Sampler*.

Genomic Data Analysis

Algorithm 2 Pegasos-QSVC

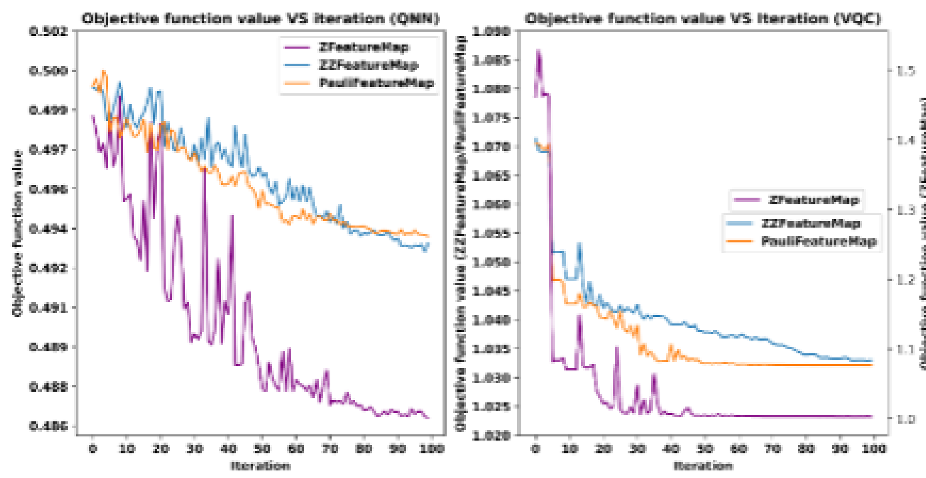
Encode data $\vec{x}_i$ into quantum states $\psi \leftarrow U_{\text{feature}}(\vec{x}_i, \theta)$.
Construct $C \rightarrow$ Compute kernel matrix K.
for $t = 1$ to T **do**
  Randomly select a subset of samples
  Compute $y_i\langle\vec{w}, \phi(\vec{x}_i)\rangle$ for each sample
  if $y_i\langle\vec{w}, \phi(\vec{x}_i)\rangle < 1$ **then** $\vec{w} \leftarrow (1-\eta\lambda)\vec{w} + \eta y_i \phi(\vec{x}_i)$
  else $\vec{w} \leftarrow (1-\eta\lambda)\vec{w}$
  end if
  Normalize $\vec{w}$: $\vec{w} \leftarrow \min\left(1, \frac{1/\sqrt{\lambda}}{\|\vec{w}\|}\right)\vec{w}$
end for
Prepare $\psi \leftarrow U_{\text{feature}}(\vec{x}_i, \theta)$.
return Decision function: $f(\vec{x}) = \text{sign}(\langle\vec{w}, \phi(\vec{x})\rangle)$.

Algorithm 3 Variational Quantum Classifier (VQC)

Encode data $\vec{x}_i$ into quantum states $\psi \leftarrow U_{\text{feature}}(\vec{x}_i)$.
Construct variational circuit: parameterized gates $U(\vec{\theta})$.
Apply $U(\vec{\theta})$ to the encoded states ψ.
Measurement $M \leftarrow \text{measure}_{\{|0\rangle,|1\rangle\}}(\psi)$
Compute the cost function $C(\vec{\theta})$.
while not converged **do**
  Use classical optimizer: $\vec{\theta} \leftarrow \text{optimize}(C(\vec{\theta}))$

Algorithm 4 Quantum Neural Network (QNN) Operation

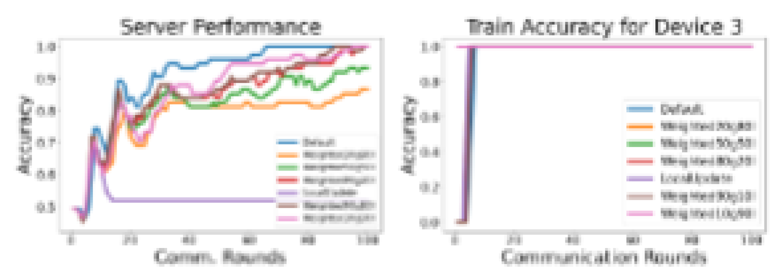
Encode $\vec{x}_i$ into quantum states: $\psi \leftarrow U_{\text{feature}}(\vec{x}_i)$.
for each layer l from 1 to L **do**
  Perform unitary transformation: $U_l(\theta_l)$
end for
Perform CNOT (or custom entangling gate)
Measure output qubits and obtain $|\Phi\rangle$
while $(E > \epsilon)$ **do**
  Renew θ (quantum gradient descent): $\theta = \theta - \eta\nabla_\theta E$
  $E = |expected\_output - measurement(\Phi)|^2$
end while



pQFL Algorithm

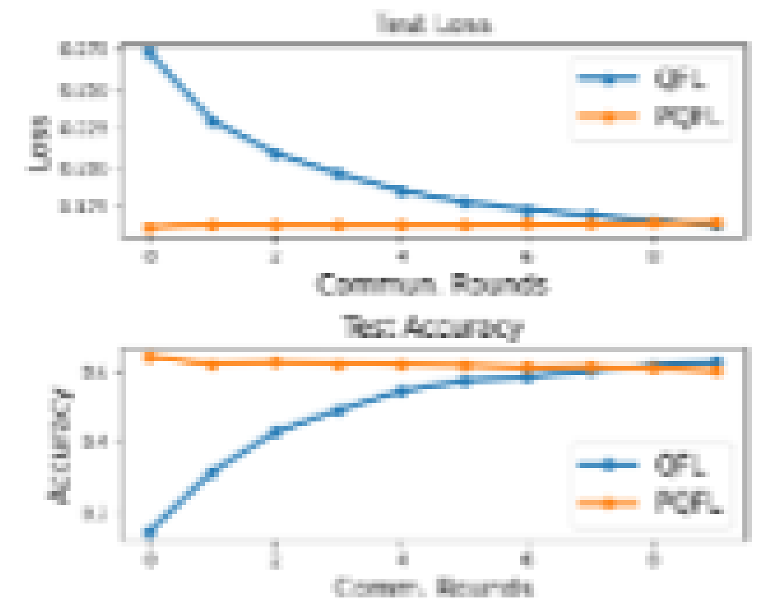
Input: N Devices $\{d_1, d_2, .., d_n\}$ with local datasets $\{D_1, D_2, ..., D_n\}$, Local models $\{\theta_1, \theta_2, ..., \theta_n\}$, weightage values g for global model and l for local model.
Output: Personalized Models θ_p, Global Model θ_{avg}.

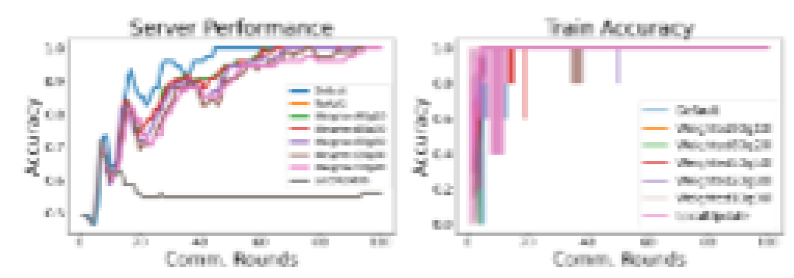
1: **procedure** Local Computation
2: $\theta_i = \frac{1}{m_i}\sum_{(x,y)\in D_i} L(\theta; |\psi\rangle, y)$
3: **procedure** Server Computation
4: Weighted: $\theta_p = (g.\sum_{i=1}^{n}\theta_i + l.\theta_i)/(g+l)$
5: Euclidean: if $ed_{avg} < ed_i, \theta_p = \theta_{avg}$
6: else $\theta_p = (\theta_i + \theta_{avg})/2$



(a) Server Accuracy **(b) Training Performance**

pQFL Insights





(a) Accuracy **(b) Training**

References

[1] Jacob Biamonte et al. 2017. Quantum machine learning. Nature.
[2] Gurung, Dev, and Shiva Raj Pokhrel. "A Personalized Quantum Federated Learning." Proceedings of the 8th Asia-Pacific Workshop on Networking. 2024.
[3] Mahdi Chehimi et al. 2024. Foundations of Quantum Federated Learning Over Classical and Quantum Networks. IEEE Network 38.
[4] Katarína Grešová et al. 2023. Genomic benchmarks: a collection of datasets for genomic sequence classification. BMC Genomic Data.
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Key Outcomes and Achievements

- A scalable, privacy-preserving QFL framework with innovative data encoding and aggregation methods.
- Demonstrated QFL's efficiency in genomic sequence classification using amplitude encoding.
- Proposed and validated a personalized QFL (pQFL) framework for tailored model training.
- Operationalized QFL on IBM's cloud quantum platforms, showcasing scalability and accessibility.