

Dual-Head Hybrid Quantum Classical Framework for Neuroimaging Based Dementia Detection

Sounak Bhowmik and Himanshu Thapliyal

Cybersecurity and Quantum Biomedical Interdisciplinary Technologies (Cy-QuBIT) Lab,
Dept. of Electrical and Computer Engineering, Southern Methodist University, Dallas, TX, USA

Contact Authors: sbhowmik@smu.edu, hthapliyal@smu.edu

INTRODUCTION & MOTIVATION

- Neuroimaging-based models are widely used for detecting ADRD.
- They vary in performance and reliability.
- Classical and quantum AI models have individual limitations.
- We present, *A hybrid quantum-classical approach to boost performance; a dual head joint optimization strategy.*

High-dimensional MRI

Brain scans contain subtle spatial patterns that are difficult to encode directly on limited-qubit devices.

Small Clinical Dataset

ADRD neuroimaging datasets are limited and can be sensitive to preprocessing, feature extraction, and random initialization.

Hybrid Uncertainty

Prior comparisons show final metrics, but do not fully explain whether quantum and classical objectives cooperate.

PRIMARY CONTRIBUTIONS

¹ Dual-head architecture

Shared CNN features feed a classical dense head and a variational quantum (VQC) head.

² λ -weighted training

A single objective sweeps between classical-only, quantum-only, and hybrid regimes, controlled by λ .

³ Baselines

Results are compared with a pure QNN and a prior quantum transfer learning baseline.

⁴ Behavior analysis

The λ -loss curve shows whether objectives compete or remain compatible.

TRAINING STRATEGY

Two-stage training isolates the interaction between classical and quantum objectives

Stage I - Classical backbone

- ResNet-style CNN trained from scratch
- 40 epochs using Adam
- Input MRI data resized to 128×128 grayscale
- Backbone learns MRI-specific spatial features

Stage II - Dual heads

- Backbone frozen
- Feature projection to dimensions equal to the available number of qubits.
- Classical dense head and 12-qubit VQC
- 80 iterations using λ -weighted loss

JOINT OBJECTIVE

A broad low-loss λ region would show that the two heads cooperate during training.

$$L_{\text{total}} = \lambda L_{\text{classical}} + (1 - \lambda) L_{\text{quantum}}$$

$\lambda = 0$

Quantum-only optimization

$0 < \lambda < 1$

Hybrid classical-quantum objective

$\lambda = 1$

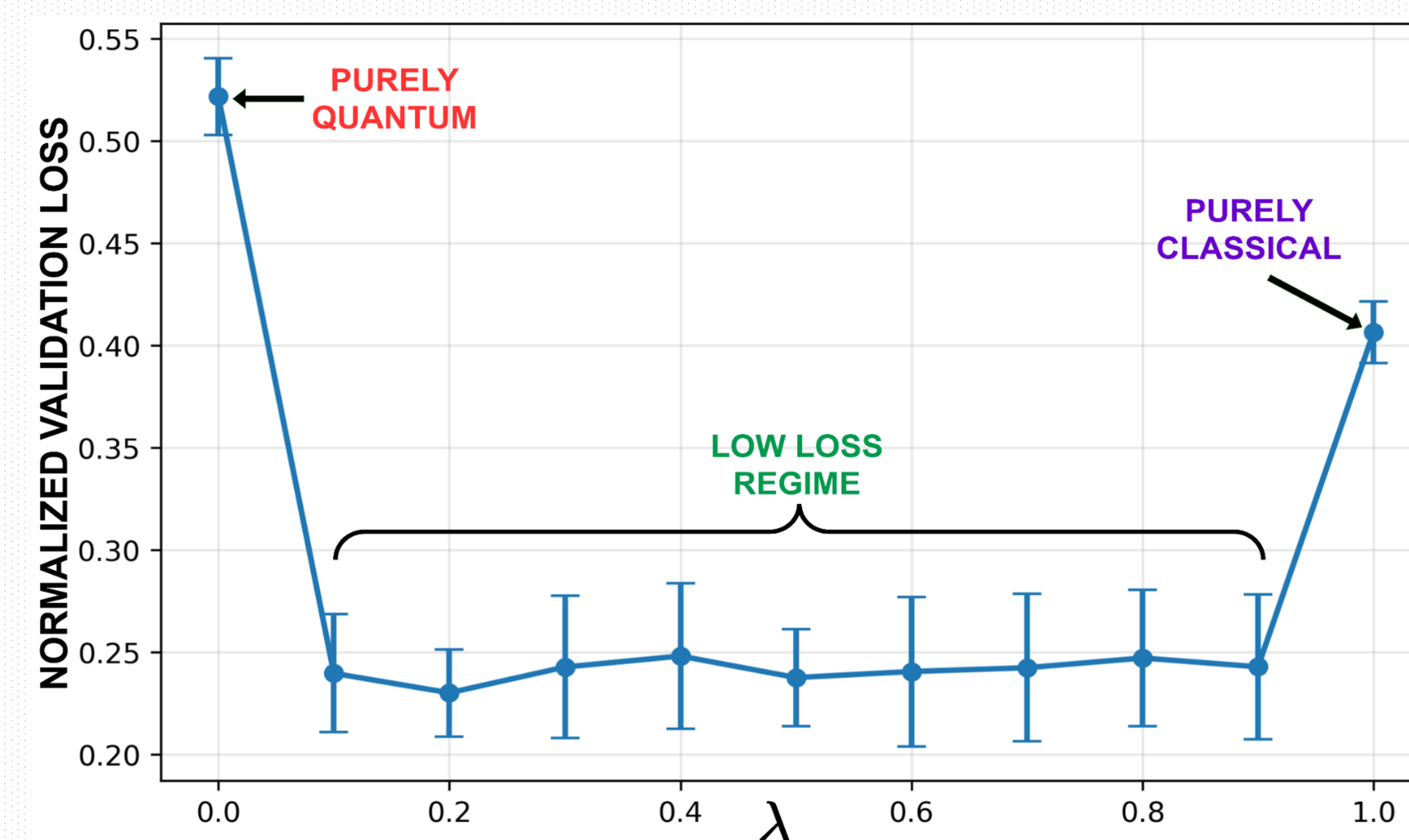
Classical-only optimization

Interpretation rule: if objectives conflict, validation loss should sharply degrade across λ ; if compatible, intermediate values should stay low.

Quantum-only and classical-only endpoints have higher validation loss.

Intermediate λ settings form a broad low-loss region, with the lowest point near $\lambda \approx 0.2$.

λ -SWEEP



RESULTS

Metric	Pure QNN	QTL	Classical head	Quantum ideal	Quantum noisy
Accuracy	0.5909	0.9394	0.9913	0.9913	0.9396
Precision	0.5695	0.9652	0.9816	0.9816	0.8842
Recall	0.6693	0.9412	1.0000	1.0000	1.0000
F1-score	0.6153	0.9487	0.9952	0.9952	0.9385
AUC	0.6539	0.9745	0.9913	0.9913	0.9879

0.9913
accuracy for both ideal heads

0.9396
noisy quantum-head accuracy

0.9952
F1-score for both ideal heads

OBSERVATIONS

Observation	Implication
Pure QNN is weak	Feature compression can remove clinically relevant spatial information from MRI images.
Joint heads are strong	The frozen CNN backbone provides a compact representation that both heads can use.
Noisy quantum degrades	Noise remains a critical practical constraint, especially for precision and accuracy.
λ sweep is stable	Classical and quantum objectives can be jointly optimized without a sharp trade-off.

CONCLUSION

The paper supports hybrid quantum-classical optimization as a practical near-term direction.

Stable

Intermediate λ values form a **broad low-loss region** across random initializations.

Accurate

Both heads reached **0.9913** accuracy and **0.9952** F1-score.

Realistic

Quantum modules remain **sensitive to noise** during practical hardware limitations.

