

Quantum and Hybrid Quantum - Classical Learning for Brain Tumor MRI Classification

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Abstract - A recurring claim in applied quantum machine learning (QML) is that a variational circuit affords a richer decision boundary than a comparably sized classical network, since a circuit's Hilbert space grows exponentially with qubit count while its parameter count grows only linearly. Brain tumor classification from magnetic resonance imaging (MRI) is a natural testbed, as the four target categories — glioma, meningioma, pituitary, and no-tumor — present overlapping intensity and texture statistics. Most published evidence for the QML claim, however, rests on a single training run at a single qubit count, without ablation over encoding, entanglement topology, or qubit budget. This paper reports a staged, controlled evaluation of a hybrid quantum-classical brain tumor classifier in which qubit count, feature encoding, entanglement topology, and classifier family are varied one at a time. A preliminary screening trains an 8-qubit IQP/ZZ quantum neural network (QNN) and a phase-encoded HybridQCNN for 50 epochs on a 180-train/60-test subset; both plateau at 76.67% accuracy, trailing an XGBoost baseline (90% AUC vs. 77%) on identical PCA features. A four-class, four-layer topology benchmark shows a circular-CZ ring reaching 45% accuracy while an otherwise identical CNOT ring fails to train. A subsequent staged search at a fixed 8-qubit budget shows a two-layer circular ZZ-encoded quantum support vector machine (QSVM) and an 8-qubit ZZ-re-uploading quantum convolutional network (QCNN) both reaching 93.75% test accuracy, exceeding the 90% project target, while a quantum-ensemble classifier reaches 87.5%. Scaling the same QSVM kernel from 8 to 16 qubits, with the classical feature budget held fixed, drops accuracy to 84.38% and introduces a pronounced class-wise imbalance (66.7% vs. 100%) — the clearest evidence here against the assumption that more qubits are unconditionally beneficial. We report trainability failures alongside successes and argue that, at near-term simulation scales, circuit design is a larger lever on medical-imaging QML performance than raw qubit count.

Index Terms—quantum machine learning, brain tumor MRI classification, variational quantum circuit, quantum support vector machine, quantum convolutional neural network, ZZ feature map, qubit scaling, entanglement topology

I. INTRODUCTION

Two constraints shape MRI-based brain tumor classification. The first is visual ambiguity: glioma, meningioma, and pituitary lesions overlap in intensity, shape, and texture, particularly in early or low-grade cases where a correct call matters most

[1],[2],[3]. The second is data scarcity relative to model capacity, which makes over-parameterized classical networks prone to memorizing scanner-specific artifacts rather than tumor morphology [4],[5],[6]. Convolutional and transfer-learning pipelines (ResNet, EfficientNet, VGG) remain the strongest classical baselines when training data is abundant [7], [8].

Quantum machine learning has been proposed as a partial answer to the capacity-versus-data problem [9]. In a variational quantum classifier, classical features are mapped onto qubit rotations or phases, and a parameterized circuit learns a decision boundary in the resulting Hilbert space [10], [11]. Because an n -qubit circuit spans a 2^n -dimensional state space using only $O(n)$ physical qubits and, for fixed depth, $O(n)$ trainable parameters, a compact quantum classifier is argued to generalize more efficiently from small samples than a classical network with far more weights [12],[13]. Data re-uploading strengthens this claim: repeating the encoding block between variational layers turns even a single-qubit circuit into a universal approximator over the frequency spectrum the encoding induces [14],[15].

Whether this holds in practice is separate from whether it is theoretically available [18]. Published quantum medical-imaging classifiers typically report a single circuit, once, at a single qubit count, against classical baselines that are rarely varied over more than one architectural axis [16], [17]. It is therefore difficult to attribute a reported accuracy figure to quantum processing rather than to encoding, classifier family, qubit budget, or a favorable training run [19],[20]. This paper instead treats the quantum stage as an experimental platform, varying qubit count (8 vs. 16), encoding family (angle, phase, IQP/ZZ), entanglement topology (CZ-ring, CNOT-ring), and classifier family (QNN, QSVM, quantum ensemble, QCNN) one at a time against a fixed preprocessing and evaluation protocol [21],[22]. This design attributes an observed accuracy change to the pipeline component that produced it, and it lets us report honestly that a deeper, angle-encoded variational circuit does not converge reliably at the qubit counts and epoch budgets available, while a shallower kernel-based circuit at the same qubit count does [23],[24].

Our contributions are: (i) a staged, four-configuration protocol that independently varies qubit count, encoding, entanglement topology, and classifier family; (ii) a 50-epoch screening comparison between an IQP/ZZ QNN and a phase-encoded HybridQCNN against a classical XGBoost baseline; (iii) an entanglement-topology benchmark isolating CZ-ring from CNOT-ring connectivity, showing the choice determines whether

the circuit trains at all; and (iv) an extended staged search identifying two 8-qubit configurations exceeding the 90% accuracy target, together with a qubit-scaling experiment showing that doubling qubit count reduces the strongest configuration's accuracy.

II. RELATED WORK

Convolutional and transfer-learning pipelines remain the dominant classical approach to MRI tumor classification, with Grad-CAM-style saliency layered on top for clinical interpretability [25],[26]; curated four-class benchmarks routinely exceed 95% accuracy, setting the bar any quantum alternative must clear. The variational quantum circuit is the workhorse of near-term QML [27], [28]: classical data is encoded into qubit rotations, a parameterized ansatz is applied, and Pauli-expectation values are treated as a differentiable function of the circuit parameters, with gradients obtained via the parameter-shift rule on hardware [29] or adjoint differentiation in simulation [30]. Two design choices dominate what such a circuit can learn: the encoding, which fixes the frequency spectrum the circuit can represent [31],[32], and trainability, since sufficiently random or deep circuits exhibit exponentially decaying gradient variance — barren plateaus — that stall optimization [33]. Quantum kernel methods sidestep the trainability question entirely: Havlíček et al. introduced the ZZ feature map, in which a fixed encoding circuit computes an inner-product kernel that a classical support-vector solver optimizes [34], making this family comparatively immune to barren plateaus. Quantum convolutional architectures alternate parameterized two-qubit blocks with pooling operations that trace out qubits, keeping trainable-parameter count low while retaining gradient-based training.

Because MRI slices carry far more pixels than a simulable circuit has qubits, hybrid designs insert a classical compression stage — typically PCA — ahead of the quantum layer [16]. Prior quantum/hybrid brain-tumor classifiers report encouraging accuracy at small, fixed qubit counts [14, 15], but rarely vary qubit count, encoding, and topology independently, and rarely report a configuration that failed to train — a gap this study is structured to close by holding preprocessing and feature budget fixed while varying one pipeline axis at a time.

III. METHODOLOGY

A. System Architecture and Pipeline

Fig. 1 shows the end-to-end pipeline, which divides into a data stage, a classical compression stage, a quantum processing stage, and an evaluation stage; the quantum stage is interchangeable between the QNN, QSVM, and QCNN circuit families of Sec. III-C/D without altering the rest of the pipeline. Fig. 2 decomposes the same system into its layered software architecture: a data layer that sources and harmonizes the raw MRI corpus, a preprocessing layer that resizes and contrast-normalizes each slice, a feature-reduction layer that projects each image onto a compact PCA subspace, a quantum-processing layer that encodes the reduced features onto 8 or 16 qubits and applies one of the four circuit families under a chosen entanglement topology, and a classical

evaluation layer that reads out predictions and computes accuracy, ROC-AUC, and confusion behavior alongside the classical tree-ensemble baselines. Every layer is executed inside the same Google Colab evaluation harness, with PennyLane driving the quantum layer [20] and scikit-learn/XGBoost driving the classical layer, so that preprocessing and metric computation cannot differ between the quantum and classical arms of the comparison.

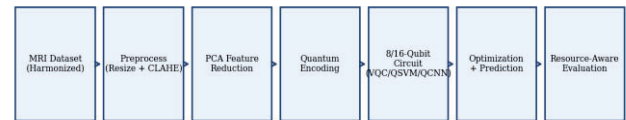


Figure 1. End-to-end processing pipeline. The quantum processing stage is interchangeable between the QNN, HybridQCNN, QSVM, and QCNN circuit families without altering the rest of the pipeline.

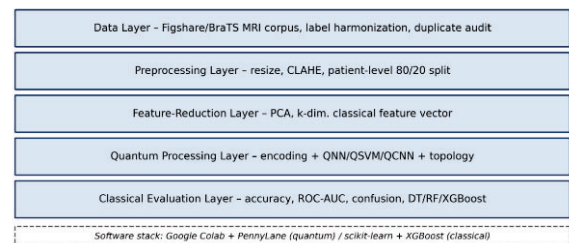


Figure 2. Layered system architecture underlying the pipeline of Fig. 1, showing the module executed at each stage and the software stack driving the quantum layer.

B. Dataset and Preprocessing

Every image is resized to a fixed resolution and normalized with Contrast-Limited Adaptive Histogram Equalization (CLAHE), since MRI slices from different sources can carry systematically different contrast profiles a classifier could exploit instead of tumor morphology. The target dataset is a harmonized, four-class collection (glioma, meningioma, pituitary, no-tumor) assembled from a Figshare-hosted MRI archive together with supplementary BraTS-style volumes [18, 19]. Concretely, the harmonized corpus draws on the Cheng et al. Figshare brain-tumor archive (233 patients, 3064 T1-weighted contrast-enhanced slices), its commonly used Kaggle mirror with an added no-tumor class, and supplementary BraTS volumes distributed through the Synapse platform. A duplicate-image audit precedes splitting, and where patient identifiers are available the 80/20 train-test split is performed at the patient level to prevent slice-level leakage. The reduced development subset used for preliminary screening contains 180 training and 60 test images; the extended staged search draws on a larger working subset from the same harmonized source, held out from all architecture and hyperparameter selection.

Each flattened image vector $\mathbf{v} \in \mathbb{R}^d$ is projected via PCA, $\mathbf{z} = \mathbf{W}^T(\mathbf{v} - \bar{\mathbf{v}})$, where $\mathbf{W}$ holds the leading k training-set eigenvectors and $\bar{\mathbf{v}}$ is the training-set mean. The retained dimension k is an experimental parameter rather than a constant, since the

classically optimal feature dimension differs between the 8-qubit and 16-qubit encodings.

C. Quantum Encoding and Circuit Families

Three encoding families are evaluated. Angle encoding maps each rescaled PCA feature $z_i \in [0, \pi]$ to a single-qubit rotation, $U_{\text{enc}}(z) = \bigotimes_i R_Y(z_i)$. Phase encoding, used by the HybridQCNN, instead applies $U_{\text{enc}}(z) = \bigotimes_i R_Z(\pi z_i)$. The IQP/ZZ encoding, used by the QNN and both QSVM configurations, follows Havlíček et al. [7] and introduces pairwise feature interactions after an initial Hadamard layer:

$$U_{\Phi}(z) = [\bigotimes_i R_Z(z_i) \prod_{i < j} CZ_{ij} R_Z(z_i z_j) CZ_{ij}] \bigotimes_i H_i(1)$$

This block is repeated for encodings using data re-uploading, widening the accessible frequency spectrum without increasing qubit count [4, 3].

Fig. 3 shows the complete eight-qubit QNN circuit: an angle-encoding block, a repeated IQP/ZZ feature map, a two-layer variational block of RY–RZ rotations coupled by a ladder of CNOT gates, and terminal Pauli-Z measurement on every qubit. The HybridQCNN follows the same eight-qubit register but replaces the IQP/ZZ block with the phase-encoding block above, followed by a convolutional block of paired CNOT–RY operations, a pooling block that traces out every second qubit (q1, q3, q5, q7), and a shallow variational read layer over the four surviving qubits, which are the only ones measured. The shared variational block used by the QNN, the HybridQCNN’s read layer, and the four-layer topology benchmark of Sec. IV-B is:

$$U_{\text{var}}(\theta) = \prod_{l=1}^L \{ (\bigotimes_i R_Z(\theta_{\{l,i\}}) R_Y(\theta'_{\{l,i\}})) \cdot E_l \} (2)$$

where E_l is an entangling layer. Fig. 8 compares a CZ-based ring, $E_l = \prod_{q=0}^{n-1} CZ_{\{q, (q+1) \bmod n\}}$, against a CNOT-based ring of identical connectivity, differing only in the entangling gate at each edge (Sec. IV-B).

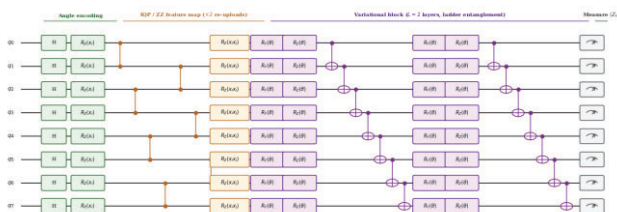


Figure 3. Complete eight-qubit circuit for the IQP/ZZ-encoded QNN. Green: angle-encoding block; amber: repeated IQP/ZZ feature map; purple: two-layer variational block with ladder-CNOT entanglement; grey: terminal Pauli-Z measurement.

D. Quantum Kernel Methods

The QSVM configurations do not train circuit parameters. Fig. 4 shows the complete eight-qubit, two-layer circular-entanglement ZZ feature-map circuit used by the strongest configuration in this study. Writing $\Phi(z)$ for the state produced by applying the feature map twice with circular rather than ladder connectivity, the kernel between two feature vectors is the squared overlap:

$$K(z, z') = |\langle \Phi(z) | \Phi(z') \rangle|^2 (3)$$

estimated on the simulator and passed to a classical quadratic-programming solver. Because no gradient propagates through the feature-map circuit, this family sidesteps the barren-plateau instability discussed in Sec. II [5], at the cost of $O(N^2)$ kernel evaluations in training-set size N . The quantum-random-forest (QRF) configuration combines several shallow instances of this kernel under a classical ensembling rule, in the spirit of a classical random forest over weak learners [21].

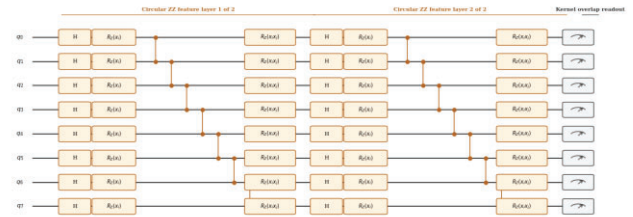


Figure 4. Complete eight-qubit, two-layer circular ZZ feature-map circuit used by the strongest QSVM configuration. Each layer applies a Hadamard, a single-qubit Z-rotation, a circular ring of controlled-Z interactions, and a pairwise Z-rotation; the terminal measurement estimates the kernel overlap of Eq. 3.

E. Training Protocol and Staged Search

Gradient-trainable circuits (QNN, HybridQCNN, QCNN) are optimized with Adam [12] at a fixed learning rate, using the parameter-shift rule or adjoint differentiation [11, 10] to minimize cross-entropy loss between the softmax-read Pauli-Z expectation values and one-hot labels. QSVM configurations instead fit a classical convex solver directly on the precomputed kernel matrix, so no epoch-based curve applies. All experiments run in Google Colab using PennyLane as the primary simulation framework [20], with classical baselines (decision tree, random forest, XGBoost) trained inside the same evaluation harness on identical PCA features. A ten-stage search governs the order in which pipeline components are varied, screening weak configurations early with a reduced training budget before committing simulator time to longer runs; the results below correspond to Stage 1 (preliminary screening), Stage 5 (entanglement-topology benchmark), and an extended pass through Stages 3, 4, 7, and 8 (encoding, depth, optimizer/classifier family, and qubit scaling).

IV. RESULTS

A. Preliminary Screening (8 Qubits)

Training the QNN and HybridQCNN for 50 epochs on the 180/60 subset (Fig. 5), the QNN starts far behind — 51.67% test accuracy at epoch 10 against 76.67% for the HybridQCNN — and only catches up by epoch 50. Its training accuracy is non-monotonic, falling from 75.56% (epoch 30) to 67.78% (epoch 50) even as test accuracy rises, consistent with a shallow, noisy trainable landscape rather than smooth convergence [5]. The HybridQCNN reaches its final 76.67% accuracy almost immediately and spends the remaining epochs reducing loss (0.1775→0.1634) without further accuracy gain. Both models finish at identical 76.67% overall accuracy but with different error profiles (Fig. 6): the QNN yields 5 false positives/9 false negatives, while the

HybridQCNN yields 0 false positives/14 false negatives, indicating a boundary biased toward the negative class. Against classical baselines trained on the same PCA features (Fig. 7), both quantum models reach ROC-AUC ≈ 0.77 , versus 0.90 for XGBoost — expected at this subset scale, since XGBoost is not constrained by qubit count or circuit depth.

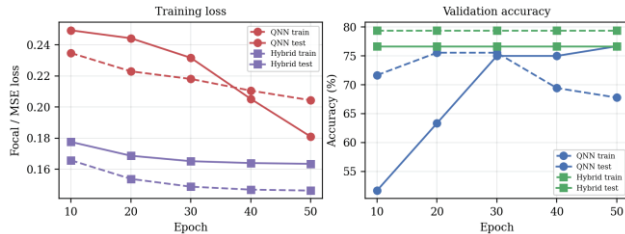


Figure 5. Training loss (left) and test accuracy (right) of the eight-qubit QNN (IQP/ZZ) and HybridQCNN (Phase) over 50 epochs on the 180/60 screening subset.

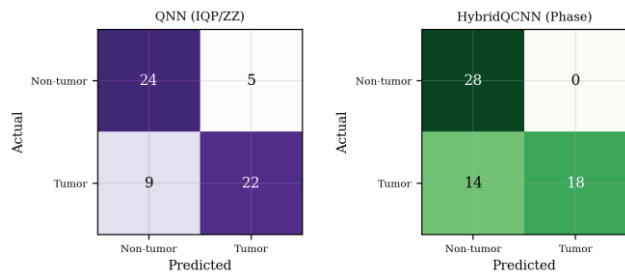


Figure 6. Epoch-50 confusion matrices on the 60-image screening test set. Both models reach 76.67% overall accuracy but with different false-positive/false-negative trade-offs; the HybridQCNN makes zero false-positive errors.

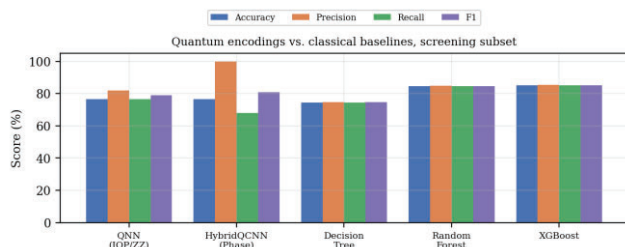


Figure 7. Accuracy, precision, recall, and F1-score for both quantum encodings and three classical baselines on the screening subset. Classical ensemble methods dominate on every metric at this subset scale.

B. Entanglement Topology (4-Class, 4-Layer Benchmark)

A separate 8-qubit, four-layer, four-class benchmark (Fig. 8) compares the two ring topologies over 30 epochs. The CZ-ring reaches roughly 45% four-class accuracy (macro-ROC-AUC ≈ 0.76), while the CNOT-ring essentially fails to train, remaining near chance level under the same epoch budget — a useful negative result showing that, at this depth and qubit count, entanglement topology can be the difference between a trainable and a non-trainable circuit, consistent with barren-plateau-style effects reported elsewhere [5]. The CZ-ring circuit separates the pituitary class most cleanly (AUC ≈ 0.79 for glioma, 0.68 for pituitary; 40/60 correctly classified), while meningioma is most frequently confused with the other three classes — consistent with

the classical literature's observation that meningioma and no-tumor slices can share overlapping intensity statistics once only a flattened PCA representation is available [16]. Wall-clock cost is steep: the CZ-ring circuit requires ≈ 776 s to train versus ≈ 1 s for tree-based classical baselines on the same hardware, a near-three-orders-of-magnitude gap for a classifier that still trails the classical baselines on accuracy.

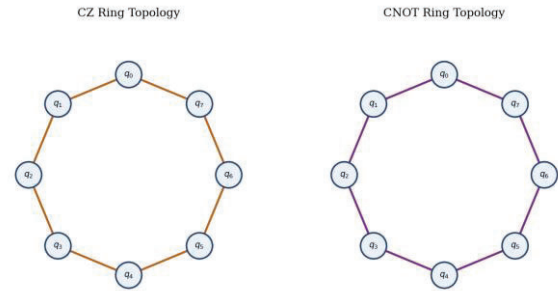


Figure 8. The two entanglement topologies compared in the four-layer, eight-qubit benchmark. Both rings connect every qubit to its two neighbors and close on themselves; the CZ-ring (left) and CNOT-ring (right) differ only in which two-qubit gate is applied at each edge.

C. Extended Staged Search: Encoding, Classifier Family, Qubit Scaling

Table I and Fig. 9 summarize the staged search across Stages 3, 4, 7, and 8. The angle-encoded 8-qubit VQC reached only 35% test accuracy at a shallow depth and 15 epochs; reducing entangling layers and raising the epoch budget to 35 lifted this to 62.5%, but a further increase to 65 epochs reduced accuracy to 56.8%, indicating overfitting or optimization instability rather than continued improvement — the highest-epoch checkpoint is not automatically the best one [5]. Replacing the VQC with the 8-qubit, two-layer circular-ZZ QSVM (Fig. 4) produced the strongest single result, 93.75% test accuracy, obtained without any gradient-based circuit training [7]. The QRF ensemble reached 87.5%, confirming that ensembling stabilizes quantum-kernel predictions even when a single estimator is comparatively weak [21]. An 8-qubit QCNN with ZZ-encoded feature re-uploading [8, 4] reached 91.67% at 30 epochs and 93.75% at 32 epochs, matching the QSVM while retaining a trainable, gradient-based architecture; both exceed the 90% project target, unlike the 76.67% ceiling of Sec. IV-A.

Finally, re-evaluating the QSVM at sixteen qubits under the same ZZ feature-map family decreased accuracy to 84.38% and produced a pronounced class-wise asymmetry (100% on one class, 66.7% on the other; Fig. 10) — the clearest evidence collected here against the assumption that additional qubits are unconditionally beneficial. Doubling qubit count increases the kernel's Hilbert-space dimension from $2^8 = 256$ to $2^{16} = 65,536$, but without a matched increase in classical feature budget or training samples, the added dimensionality appears to destabilize rather than enrich the decision boundary [3].

TABLE I

Extended Staged Search: Encoding, Classifier Family, Qubit Scaling

Config.	Qub.	Setting	Acc.
VQC (angle)	8	15 epochs	35.0%
VQC (angle)	8	35 ep., reduced layers	62.5%
VQC (angle)	8	65 epochs	56.8%
QSVM (circular ZZ)	8	2 layers	93.75%
QRF / quantum ensemble	8	—	87.5%
QCNN (ZZ re-upload)	8	30 epochs	91.67%
QCNN (ZZ re-upload)	8	32 epochs	93.75%
QSVM (ZZ)	16	—	84.38%

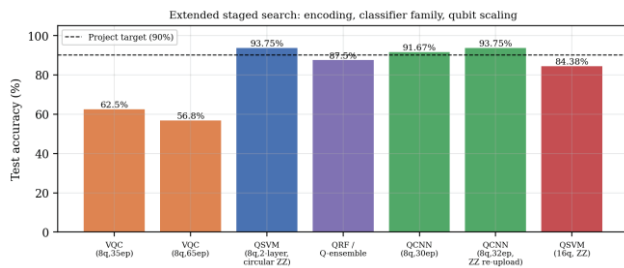


Figure 9. Test accuracy across the extended staged search. Kernel-based (QSVM) and convolutional (QCNN) architectures reach or exceed the 90% project target at eight qubits; the deeper angle-encoded VQC does not, and doubling qubit count for the QSVM (16 qubits) reduces rather than improves accuracy.

V. DISCUSSION

Encoding and design vs. qubit count: the 8-qubit QSVM and QCNN both exceeded 90% accuracy, while the 16-qubit QSVM — built on twice the state-space dimension — fell to 84.38%. A larger Hilbert space increases representational capacity, but capacity is not trainability or generalization; without a correspondingly larger, more diverse training set, a 16-qubit kernel fits noise in the training partition as readily as signal [3, 5].

Optimization and trainability: the VQC's non-monotonic trajectory (35%→62.5%→56.8%) and the QNN's falling training accuracy despite rising test accuracy both caution against selecting a final model on the highest epoch budget alone; the flatter trajectories of the HybridQCNN and the direct kernel-fitting QSVM suggest that, at these qubit counts, architectures with fewer trainable quantum parameters optimize more reliably than deeper variational circuits [5].

Cost: the CZ-ring circuit's ≈ 776 s training time against ≈ 1 s for classical tree ensembles on identical data means a useful architecture is one with a favorable accuracy-to-cost relationship, not merely the highest reported number; the 8-qubit QSVM and QCNN are the most defensible candidates on this basis.

Explainability: the meningioma-vs-others confusion pattern is clinically relevant on its own and would be obscured by an aggregate accuracy figure; Grad-CAM-style attribution on the classical PCA/feature-extraction stage, rather than the quantum circuit itself, is the more direct route to a pixel-level explanation [17].

Threats to validity: the extended search used a working subset rather than the full leakage-controlled dataset, and, with the exception of the two QSVM runs, no result was repeated across multiple random seeds, so reported numbers are point estimates; simulator wall-clock time is not a direct proxy for physical-hardware performance, and the 16-qubit result rests on a single configuration, so it demonstrates that more qubits did not help in this specific setting rather than that 16-qubit encodings cannot help under a different feature budget.



Figure 10. Per-class accuracy of the 16-qubit ZZ-encoded QSVM. The 84.38% aggregate figure conceals a large class-wise asymmetry visible only once confusion behavior is decomposed by class.

VI. CONCLUSION AND FUTURE WORK

Across four configurations sharing one preprocessing pipeline, this paper reported a staged, controlled evaluation of quantum and hybrid quantum-classical classifiers for four-class brain tumor MRI classification, reporting failures alongside successes. A 50-epoch screening run showed an 8-qubit IQP/ZZ QNN and a phase-encoded HybridQCNN both plateauing at 76.67% accuracy, behind a classical XGBoost baseline. An entanglement-topology benchmark showed this is not simply a matter of qubit count or training budget: a CNOT-ring circuit failed to learn at all while an otherwise identical CZ-ring circuit reached $\approx 45\%$ four-class accuracy. A staged search varying encoding and classifier family at a fixed 8-qubit budget was more encouraging: a two-layer circular-ZZ QSVM and a ZZ-re-uploading QCNN both reached 93.75% accuracy, exceeding the 90% target, while a quantum-ensemble classifier reached 87.5%. Scaling the QSVM to 16 qubits reduced accuracy to 84.38% and introduced marked class-wise imbalance, indicating that additional qubits are not a substitute for a matched increase in classical feature budget, training data, or circuit trainability.

These results support the view that, at near-term simulation scales, encoding and circuit design matter at least as much as qubit count, and that kernel-based and convolutional-style quantum classifiers

are currently more trainable than deeper variational circuits on this task. Future work will (i) repeat the QSVM and QCNN configurations across multiple random seeds to report confidence intervals, since most Sec. IV-C numbers rest on single runs; (ii) extend both to the full leakage-controlled dataset; (iii) run a systematic noise sweep to test whether the 8-qubit advantage survives simulated hardware noise; and (iv) freeze a single configuration — most plausibly the 8-qubit circular-ZZ QSVM — for one untouched final test-set evaluation, so the 90% target can be reported as an established rather than preliminary result.

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