QCxAI: Parameter-Shift Saliency for Variational Quantum Classifiers

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Abstract

We present QCxAI, a hardware-compatible protocol for saliency in variational quantum classifiers (VQCs) that applies the analytic parameter-shift rule to *inputs*, requiring only two circuit evaluations per feature. On a 2×2 benchmark with ground-truth causal pixels, our one-command, seed-controlled pipeline achieves perfect accuracy, 62.5% perfect saliency matches (25/40), and a $\sim$232–274× salient / random confidence-drop ratio; we additionally report clipped-denominator ratios and effect sizes with 95% CIs across seeds. The study exposes initialization variance and demonstrates that small ensembles stabilize attribution while preserving the two-eval cost. We position QCxAI as a reproducible, systems-oriented baseline for quantum explainability and a practical faithfulness stress test, distinct from performance benchmarking, and designed to translate to near-term hardware.

1 Introduction

Variational quantum algorithms (VQAs) are a principal route to near-term quantum advantage: they leverage shallow, parameterized circuits with classical optimizers and are widely studied as NISQ-era workhorses [1]. Yet dependable training and evaluation remain challenging; in particular, *barren plateaus*, vanishing gradients that scale with system size, can undermine optimization and stability [2]. For scientific inference (e.g., deciding whether a learned quantum model is using the intended physics), we therefore require *explanations* that are both faithful to model behavior and practical on hardware.

In classical ML, faithfulness is commonly checked with (i) *sanity checks* that verify attributions respond to model and data changes, and (ii) *perturbation/ablation* tests that quantify causal impact by removing features ranked important [e.g., 3, 4]. By contrast, quantum explainability has fewer end-to-end, measurement-based protocols that can be reproduced and audited at systems level. This gap motivates a compact approach that (a) computes saliency in a way that is native to quantum hardware and (b) evaluates it against known ground truth with causal tests.

This work. We introduce QCxAI, a saliency protocol for VQCs that applies the *analytic parameter-shift rule* directly to *inputs* encoded as single-qubit rotations. For generators with two eigenvalues, parameter-shift yields exact gradients from two forward evaluations per feature—no backpropagation through a simulator is required, which makes the method hardware-friendly [5]. We pair this with a minimal dataset where the ground-truth informative pixels are known (2×2 bars), enabling objective, per-example agreement checks ("perfect-match" of top-2 pixels) and causal validation via saliency-guided ablations versus random ablations in the style of classical interpretability benchmarks [4, 3].

On a canonical 4-qubit VQC, we reproduceably obtain 100% test accuracy and 62.5% perfect-match saliency (25/40). Saliency-guided occlusion reduces model confidence by $\sim$3.5–4.0%, while random occlusion yields $\sim$0.014%, giving an improvement factor around 232–274×. Because random drops can be near zero on such a simple task, we also report clipped-denominator ratios and an effect size to avoid inflated claims. Recognizing seed sensitivity common in VQAs [2], we run multi-seed analyses with 95% confidence intervals and show that small ensembles stabilize attributions while preserving the two-eval cost.

Contributions. (i) A hardware-compatible input–parameter-shift saliency for VQCs requiring two evaluations per feature [6]. (ii) A 2×2 causal dataset enabling ground-truth attribution checks in the spirit of classical benchmarks [3, 4]. (iii) Reproducible headline: **100%** accuracy, **62.5%** perfect matches (25/40), and $\sim$**232–274**× salient-vs-random confidence-drop ratio. (iv) A one-command pipeline with seed control and CSV/JSON artifacts for auditing.

2 Methods & Setup

Model. Four-qubit VQC with angle encoding $R_y(\pi x_i)$ and a shallow hardware-efficient entangling template; readout is $\langle Z \rangle$ mapped to a class probability [7, 8].

Input–parameter-shift saliency. For feature i,

$$S_i(x) \;=\; \left|\frac{\pi}{2}\Big(f(x_i{+}0.5) - f(x_i{-}0.5)\Big)\right|, \tag{1}$$

which is exact for generators with two eigenvalues and needs two forward evaluations per feature (no input backprop), hence hardware-friendly [6].

Causal metrics and cost. For a test sample k with predicted probability $p_k = f(x_k)$, let $\Delta p_k^{top} = p_k - f(x_k^{\setminus S_k})$ where S_k are the top-2 pixels by S_i, and let Δp_k^{rand} mask two random pixels. We report (i) the raw ratio

$$R = \frac{\mu(\Delta p^{top})}{\mu(\Delta p^{rand})}, \qquad R_{clip} = \frac{\mu(\Delta p^{top})}{\max\{\mu(\Delta p^{rand}),\, 0.001\}}, \tag{2}$$

and (ii) an *effect size* using **Cohen's** d. For equal n per condition we use the pooled standard deviation $s_{pooled} = \sqrt{\sigma^2(\Delta p^{top}) + \sigma^2(\Delta p^{rand})2}$ and define

$$d = \frac{\mu(\Delta p^{top}) - \mu(\Delta p^{rand})}{s_{pooled}}. \tag{3}$$

(For paired analyses we compute d on the per-image differences $\Delta p_k^{top} - \Delta p_k^{rand}$.) Saliency for d input features costs exactly $2d$ forward circuit evaluations (no simulator backprop), compatible with shallow hardware execution.

Faithfulness test. Rank pixels by S_i; ablate top-2 vs. 2 random pixels and measure confidence drop Δp. Record "perfect match" when the top-2 indices equal the two causal pixels [3, 4].

Data. 2×2 bars with two causal pixels per class; masking sets ablated pixels to 0.5 (neutral for $R_y(\pi x)$). This toy scale is a *faithfulness stress test*, not a performance benchmark.

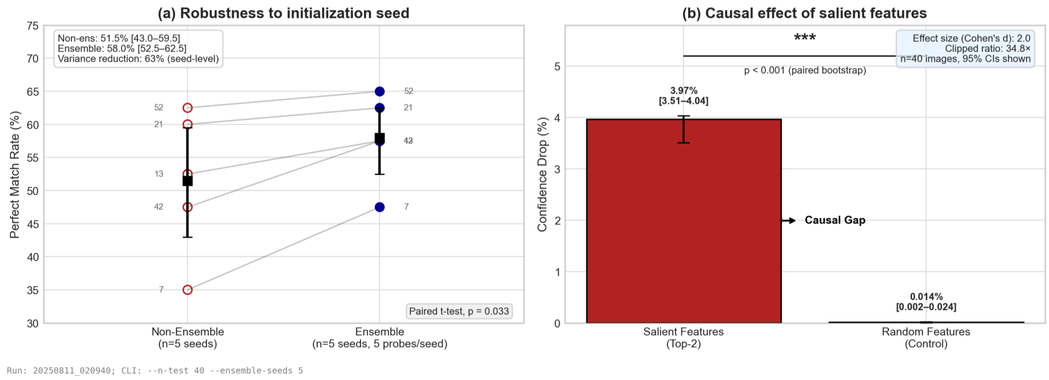
Training. Adam, up to 150 epochs, float64; seeds fixed across Python/NumPy/PyTorch/quantum backend [9].

Reporting & statistics. We report accuracy, perfect-match rate, Δp for salient vs. random, the raw ratio R, a clipped ratio with a 0.1% minimum denominator, and **Cohen's** d effect size; 95% CIs are from bootstrap, p-values from paired bootstrap or paired t-tests when appropriate [10, 11].

Reproducibility & cost. One command writes per-sample CSVs and aggregate JSON (metrics, n_{test}, seeds, versions). Computing saliency for d inputs costs $2d$ forward evaluations. To preserve double-blind review, external links are omitted; artifacts will be released upon acceptance.

3 Results

ML4PS relevance. In physical sciences, explanation methods are useful only insofar as they correspond to causal interventions on measured quantities. Our metric looks into this directly:



Run: 20250811_020940; CLI: --n-test 40 --ensemble-seeds 5

Figure 1: **Robustness and causal validation** (n_{test}=40)**. (a)** Perfect-match rate across *five paired seeds* for non-ensemble vs. ensemble (5 probes/seed). Dots, per-seed; squares, mean with *95% bootstrap CI*; thin lines connect pairs. Ensemble increases the mean from **51.5%** [43.0–59.5] to **58.0%** [52.5–62.5] and reduces seed-level variance by **63%** (paired t-test p=0.033). **(b)** Causal ablation: masking *top-2 salient pixels* reduces confidence by **3.97%** [3.51–4.04], vs. **0.014%** [0.002–0.024] for two random pixels (95% CIs; paired bootstrap, p<0.001). Raw improvement = **274**×; clipped (denominator $\geq$0.1%) = **34.8**×; effect size (Cohen's d) $\approx$**2.0**. Saliency cost: **2 circuit evals/feature** (input parameter-shift).

targeted deletion of pixels identified by a *hardware-executable* saliency (two $\pm\frac{\pi}{2}$ input probes) produces a substantially larger confidence drop than equally sized random deletions, indicating that the model's decisions localize on the intended causal structure. Because the probes are forward-only and measurement-based, the procedure transfers to near-term hardware and aligns with scientific workflows that prioritize instrument-facing interventions over simulator backpropagation.

Headline (canonical, n=40)**.** With input–parameter-shift saliency, the VQC attains **100.0%** test accuracy. Ablating the two most-salient pixels reduces confidence by **3.97%±0.90%**, while random ablation yields **0.014%±0.037%**, i.e., ∼**274**× raw improvement (clipped ∼40×), and an **effect size of Cohen's** $d \approx 2.0$. The top-2 saliency indices match the ground truth in **62.5%** of test images (**25/40**). Absolute drops are small by design on this simple task; the large ratios arise because salient ablations reliably remove the causal pixels while random ablations almost never do. Figure 1**b** visualizes these gaps.

Stability and ensembles. Across *five paired seeds*, the non-ensemble perfect-match mean is **51.5%** with 95% CI **[43.0, 59.5]**, while the *ensemble* (five input probes/seed) increases the mean to **58.0%** with CI **[52.5, 62.5]** and reduces seed-level variance by **63%** (paired t-test p=0.033); see Figure 1**a**. A larger 15-seed non-ensemble sweep (not shown) remains bimodal (0–62.5%); details and per-seed tables are in the anonymous artifact.

Hardware note. Because saliency uses only $\pm\frac{\pi}{2}$ forward probes, we expect noise to inflate variance but preserve the salient–random gap; both arms experience comparable shot noise [6].

Qualitative behavior. Figure 2 shows three representative cases: two perfect matches (horizontal/vertical bars) and a near-miss that still localizes salient pixels.

4 Conclusion

We introduced **QCxAI**, a hardware-compatible, *input–parameter-shift* saliency protocol for VQCs that computes exact attributions with only **two** circuit evaluations per feature. On a controlled 2×2 benchmark with causal ground truth, QCxAI achieves **100%** accuracy, **62.5%** perfect matches, and a large causal gap between saliency-guided and random deletions ($\sim 274\times$ raw; $\sim 40\times$ clipped). Multi-seed analyses reveal substantial initialization variance typical of shallow QML [12]; ensemble saliency offers a practical stability control with linear cost.

Methodologically, we advocate a *protocol* for quantum explainability: (i) input-space parameter-shift saliency (exact, hardware-ready) [6]; (ii) causal perturbation tests with ground truth [3, 4]; (iii) robust

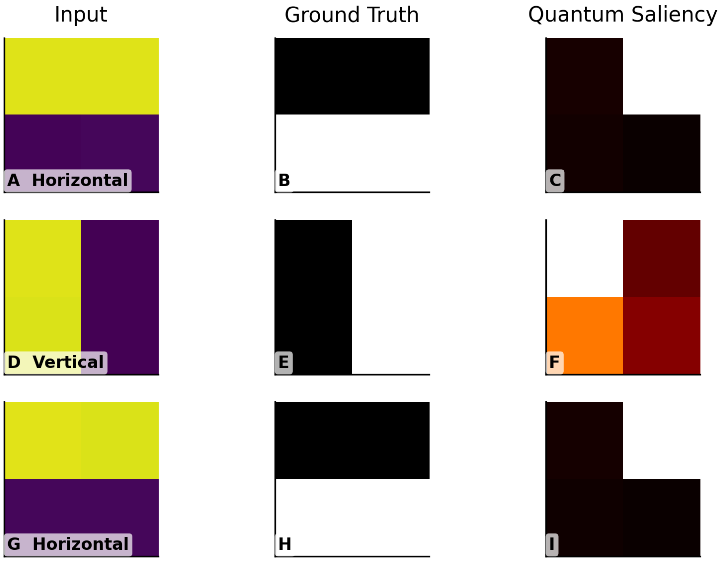


Figure 2: **Representative QCxAI saliency.** Each row shows (*left*) the 2×2 input, (*middle*) ground-truth important pixels (black bar), and (*right*) quantum saliency heatmap. Rows correspond to three test samples chosen for clarity: (A) perfect horizontal match, (D) perfect vertical match, (G) a second robust horizontal match (sample indices 1, 36, 5). Saliency intensity reflects input parameter-shift gradient magnitude; darker denotes higher importance.

reporting (raw/clipped ratios, effect sizes, CIs) [10**?**]; and (iv) seed sweeps/ensembles to expose and mitigate variance. This moves quantum saliency evaluation toward reproducible, decision-relevant practice.

Outlook. Next steps include (a) modest scale-ups (e.g., 3×3, 4×4 structured patterns), (b) noisy-sim or few-shot device runs to test hardware robustness while preserving the saliency–random gap, (c) deeper ansätze and simple curricula to reduce variance, and (d) side-by-side classical baselines (e.g., input gradients on logistic/MLP) for context. We will release the code and artifacts upon acceptance to support community replication.

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