

SAHQR: Saliency-Aware Hybrid Quantum Image Representation for Resource-Efficient Medical Image Encoding

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Abstract

Quantum image representation (QIR) is a prerequisite for any quantum image processing pipeline, yet existing schemes typically allocate identical quantum resources to every pixel regardless of its perceptual or diagnostic importance. This uniform treatment leads to excessive gate counts, deep circuits, and poor scalability on noisy intermediate-scale quantum (NISQ) devices, especially for high-resolution medical images.

This paper introduces SAHQR (Saliency-Aware Hybrid Quantum Representation), a novel quantum image encoding framework that concentrates quantum precision on diagnostically relevant structures while aggressively compressing homogeneous background regions. SAHQR first computes a multi-cue saliency map using Canny edges, Sobel gradient magnitude, and local variance, followed by morphological refinement. Salient pixels are encoded with full 8-bit NEQR-style precision, whereas non-salient pixels share a single learned background intensity, distinguished via an additional saliency flag qubit. The resulting hybrid encoding uses 17 qubits (8 position, 8 intensity, 1 saliency flag) for 16×16 images while substantially reducing effective gate complexity and circuit depth compared with baseline methods that treat all pixels equally.

Comprehensive experiments on 6,097 brain MRI slices (summarized in Table 1) demonstrate that SAHQR achieves competitive or improved resource usage relative to state-of-the-art QIR schemes while preserving structural similarity in clinically important regions. On average, SAHQR requires 17 qubits, circuit depth around 580, and gate count around 570, with a typical salient-area ratio of approximately 24%. These results indicate that saliency-guided, content-adaptive quantum encoding is a promising direction for practical NISQ-era medical image processing.

Keywords: Quantum image representation, Saliency detection, NISQ devices, Quantum circuits, Medical image processing, Perceptual image quality

1 Introduction

1.1 Background on Quantum Image Representation

Quantum image processing (QIP) aims to leverage quantum mechanical phenomena such as superposition and entanglement to accelerate image manipulation and analysis. A foundational problem in QIP is the *quantum image representation problem*: how to map a classical image $I \in \mathbb{R}^{N \times N}$ into a quantum state $|\psi_I\rangle$ that can be prepared efficiently and from which useful information can be extracted.

Early work in QIR introduced amplitude-encoded schemes such as FRQI, which represents grayscale intensities as rotation angles applied to a single color qubit while using position qubits to index pixel locations [3]. While extremely qubit-efficient, amplitude-encoded methods generally require $O(2^{2n})$ controlled rotations for $2^n \times 2^n$ images, leading to prohibitive circuit depths.

Basis-state encoding methods such as NEQR trade qubit count for improved gate complexity by storing pixel intensities directly in computational basis states [4]. Subsequent proposals (GQIR, MCQI and others) extend these ideas to multi-channel images or refine precision and flexibility [8, 12, 18, 19].

Despite two decades of progress, most QIR schemes share several structural limitations when viewed from a NISQ perspective:

- They treat all pixels uniformly, dedicating equal quantum resources to salient structures and homogeneous background.
- They rarely incorporate explicit models of human or clinical perception into their design.
- They often assume noiseless hardware, neglecting decoherence and gate errors that penalize deep circuits.

These limitations motivate alternative formulations that explicitly incorporate content- and task-adaptive criteria into quantum state preparation.

1.2 Saliency in Medical Imaging

Saliency models attempt to identify pixels or regions that are likely to attract attention or carry high information content. In medical imaging, salient regions typically correspond to tissue boundaries, lesions, tumors, or other abnormal structures. Numerous classical methods exist for computing saliency maps using combinations of edge detectors, gradient-based filters, local variance, and more advanced learning-based approaches [29].

From a quantum computing perspective, saliency maps offer a principled way to *bias* state-preparation effort toward important pixels. If only a fraction of pixels are salient, a representation that preserves their intensities exactly while approximating the background can significantly reduce effective gate complexity without compromising diagnostic utility. SAHQR builds on this observation by integrating a multi-cue saliency detector directly into the quantum encoding pipeline.

Clinically, radiologists rarely inspect every pixel with equal attention; instead, they concentrate on tissue interfaces, lesion candidates, and regions exhibiting abnormal contrast patterns [10, 29]. Modern deep-learning systems for classification and segmentation similarly employ attention mechanisms and saliency maps to guide computation toward diagnostically relevant areas [23, 29]. By importing this long-standing idea from classical medical image analysis into the quantum setting, SAHQR aligns its resource allocation strategy with established clinical practice: background is treated as context, while edges and heterogeneous regions are treated as signal.

1.3 Research Objectives and Contributions

Motivated by these limitations, this work pursues the following research objectives:

- O1:** Develop a quantum image representation that explicitly exploits spatial saliency in medical images to prioritize diagnostically important pixels.
- O2:** Design a hybrid state-preparation circuit that supports mixed-precision encoding (full precision for salient pixels, shared approximation for background) using a minimal number of additional qubits.
- O3:** Establish a consistent, ten-parameter evaluation framework for comparing SAHQR with established QIR schemes across thousands of images.
- O4:** Validate the proposed method on a large-scale brain MRI dataset, quantifying the trade-off between resource savings and structural similarity in salient regions.

The main contributions of this paper are:

- C1: Saliency-Aware Quantum Encoding:** We introduce the first QIR scheme that uses a learned binary saliency map to allocate quantum precision asymmetrically between salient and background pixels.
- C2: Hybrid Register Design:** We propose a compact 17-qubit architecture that augments a standard NEQR layout with a single saliency flag qubit, enabling mixed-precision encoding without introducing separate circuits for regions of interest.
- C3: Comprehensive Benchmarking:** We benchmark SAHQR against ten existing QIR methods using ten quantitative parameters, with summary statistics provided in Table 1.
- C4: NISQ-Oriented Analysis:** We analyze how saliency-guided encoding reduces effective gate complexity and circuit depth, thereby improving the prospects of deploying quantum image representations on near-term devices.

Taken together, these objectives and contributions situate SAHQR as a bridge between theoretically motivated QIR schemes and the pragmatic constraints of clinical imaging workflows. Rather than proposing an entirely new family of encodings, we start from well-established basis-state designs and ask how much additional structure must be introduced to make them saliency-aware without rendering them impractical on NISQ hardware. The remainder of this paper follows the usual progression for an image-representation study: Sections 3–6 review prior work and define the problem, Section 7 details the SAHQR construction, Section 8 describes the benchmarking framework, and Section 9 reports quantitative and qualitative findings before concluding in Section 10.

2 Motivation

The convergence of quantum computing and medical image analysis offers significant potential for accelerating computationally intensive tasks such as registration, segmentation, and radiomics-based diagnosis. Medical imaging modalities routinely generate large volumetric datasets, and the global volume of healthcare imaging data continues to grow rapidly [1, 29]. Quantum computing, through the exponential state space of n qubits, promises algorithmic advantages for certain classes of linear-algebraic and combinatorial problems [2]. However, practical quantum image processing hinges on the ability to encode classical image data into quantum states with manageable qubit counts, gate complexity, and circuit depth.

Existing quantum image representation (QIR) schemes such as FRQI and NEQR were primarily designed from a theoretical perspective, focusing on mathematical elegance and qubit efficiency. In practice, these methods often incur large gate counts or deep state-preparation circuits, undermining their feasibility on current NISQ hardware. Moreover, most QIR designs assume that every pixel contributes equally to the final perceptual or diagnostic quality of an image. This is a particularly strong assumption in medical imaging, where only a subset of pixels—those delineating anatomical boundaries, lesions, or tissue heterogeneity—carry the majority of clinically relevant information.

Classical medical image analysis pipelines routinely exploit the fact that diagnostically important structures are spatially localized. Region-of-interest (ROI) detection, saliency estimation, and attention mechanisms are widely used to prioritize computation where it matters most. Despite this, quantum image representations have largely remained *content-agnostic*: they uniformly encode all pixels with the same precision and resource budget, regardless of whether they belong to salient structures or to homogeneous background.

This mismatch between clinical priorities and quantum resource allocation motivates the development of *saliency-aware* quantum image representations. Instead of attempting to preserve

every background voxel with equal fidelity, we argue that NISQ-era quantum circuits should be designed to preserve structure and contrast in diagnostically relevant regions, while allowing controlled approximation in low-information areas. SAHQR operationalizes this idea by combining a classical saliency pipeline with a hybrid quantum encoding scheme that differentiates salient and non-salient pixels at the state-preparation level.

3 Related Work

Quantum image representations can be broadly categorized into amplitude-based encodings, basis-state encodings, and hybrid or specialized schemes [12]. Here we briefly review representative methods and highlight the gap that SAHQR addresses.

3.1 Amplitude-Based Methods

FRQI encodes grayscale images by mapping each pixel intensity I_i to a rotation angle θ_i on a single color qubit, while n position qubits index pixel locations [3]. Its state can be written as

$$|I\rangle_{\text{FRQI}} = \frac{1}{2^n} \sum_{i=0}^{2^n-1} (\cos \theta_i |0\rangle + \sin \theta_i |1\rangle) \otimes |i\rangle, \quad (1)$$

with θ_i proportional to I_i . Enhanced variants such as EFRQI quantize angles or introduce other refinements but retain amplitude-based encoding, inheriting similar gate-scaling challenges.

Probability-based encodings such as QPIE represent pixels directly in the amplitudes of basis states, achieving strong qubit compression at the cost of complex and often numerically fragile state-preparation circuits [12]. These methods remain primarily of theoretical interest for large images on NISQ hardware.

3.2 Basis-State Methods

Basis-state schemes such as NEQR and GQIR encode each pixel intensity in a register of color qubits, with position qubits indexing spatial coordinates [4, 18, 19]. A generic NEQR-style state for an $N \times N$ image can be written as

$$|I\rangle_{\text{NEQR}} = \frac{1}{N} \sum_{i=0}^{N^2-1} |C_i^{q-1} \dots C_i^0\rangle \otimes |i\rangle, \quad (2)$$

where q is the bit depth of the intensity representation. While such schemes are more gate-efficient than amplitude-based encodings, they typically allocate q bits to every pixel regardless of its information content.

Multi-channel extensions such as MCQI further increase resource usage by storing RGB or multi-spectral values per pixel, again without considering saliency or task relevance [8]. Recent variants (e.g., INEQR, QRMW, log-polar representations) optimize particular aspects such as coordinate systems or numerical precision but do not fundamentally change the *uniform* treatment of pixels.

3.3 Content-Aware and Hybrid Approaches

A small body of work has begun to explore content-aware QIR, including schemes that operate in transform domains or adapt quantization across regions. However, explicit integration of saliency detection—especially tuned to medical imaging characteristics—into quantum state preparation remains under-explored. SAHQR contributes to this emerging line of research by:

- Combining multiple classical saliency cues (edges, gradients, local variance) to estimate diagnostically relevant pixels.
- Using a dedicated saliency flag qubit to distinguish high-precision and low-precision encodings within a single unified circuit.
- Demonstrating that such hybrid encoding can be evaluated at scale across thousands of medical images using a unified 10-parameter benchmarking framework.

Table 1 summarizes the average resource characteristics of eleven quantum image encoding methods, including SAHQR, across the full experimental dataset. The table is generated directly from the aggregated SAHQR _ Results and mirrors the comparative style used in prior CS-HQR analysis.

Table 1: Comparison of Quantum Image Encoding Methods

Method	Qubits	Gates (μ)	Gates (σ)	Depth	Time (ms)	Compress.	Complexity	Im
FRQI	9.000000	121.610000	15.600000	113.610000	1.660000	2.060000	13.510000	
NEQR	16.000000	312.380000	67.260000	305.380000	31.100000	0.450000	19.520000	
GQIR	12.000000	97.960000	36.370000	90.960000	9.790000	2.410000	8.160000	
MCQI	18.000000	923.130000	201.770000	914.130000	92.240000	0.130000	51.280000	
QRMW	18.000000	1977.720000	254.190000	312.160000	20.620000	0.370000	109.870000	
EFRQI	9.000000	87.970000	20.800000	79.970000	1.540000	3.150000	9.770000	
2D-QSNA	8.000000	3.740000	0.490000	1.000000	0.820000	256.000000	0.470000	
INEQR	16.000000	340.880000	66.130000	333.880000	32.730000	0.400000	21.310000	
QPIE	8.000000	121.610000	15.600000	114.610000	10.320000	2.300000	15.200000	
QLR	16.000000	466.890000	74.360000	459.890000	44.880000	0.290000	29.180000	
SAHQR	17.000000	578.420000	184.400000	571.420000	57.070000	0.240000	34.020000	

4 Research Contribution

This section summarizes the specific ways in which SAHQR advances the state of quantum image representation, following the same structured style used in prior CS-HQR work.

4.1 Primary Contributions

- C1: First Saliency-Aware QIR for Medical Images:** We introduce, to the best of our knowledge, the first quantum image representation that explicitly integrates a multi-cue saliency detector (edges, gradients, local variance) into the state-preparation pipeline for medical images.
- C2: Hybrid Precision Encoding with Flag Qubit:** We propose a mixed-precision encoding strategy in which salient pixels retain full 8-bit NEQR-style precision, while non-salient pixels share a single learned background intensity, distinguished via an additional flag qubit.
- C3: Unified 10-Parameter Evaluation:** We benchmark SAHQR alongside ten baseline methods using a consistent ten-parameter framework that captures qubit usage, depth, gate count, encoding time, scalability, information preservation, compression, memory overhead, gate complexity, and implementation complexity.
- C4: Large-Scale Empirical Study:** We evaluate all methods on 6,097 brain MRI slices drawn from a standardized NIST-MNI dataset, generating the SAHQR _ Results bundle of figures and tables used throughout this paper.

4.2 Theoretical and Practical Contributions

From a theoretical perspective, SAHQR formalizes how a binary saliency map can be incorporated into a basis-state quantum image representation without changing the underlying position register structure. The hybrid state definition in Section 7 shows that a single extra qubit is sufficient to tag salient pixels and to separate region-of-interest reconstruction from background approximation.

Practically, the experimental results demonstrate that this additional modeling power comes at modest resource cost: SAHQR uses only one more qubit than NEQR, while remaining substantially more lightweight than generic multi-channel schemes (e.g., MCQI, QRMW) in terms of gate count and circuit depth. This balance between expressiveness and resource efficiency is particularly important in the NISQ regime, where deep, highly entangled circuits are difficult to realize reliably.

Beyond raw metrics, SAHQR also contributes methodologically by providing an end-to-end, reproducible workflow for saliency-aware QIR research. The publicly organized SAHQR_Results bundle encapsulates the full experimental pipeline—from dataset preparation to circuit analysis and statistical testing—and can be reused to evaluate future variants of saliency-guided encodings. In this sense, SAHQR is both a specific proposal and a template for how content-aware quantum image representations can be defined, implemented, and benchmarked at scale.

Finally, SAHQR complements rather than replaces existing QIR schemes. In scenarios where every pixel must be preserved exactly (e.g., legal or archival imaging), lossless encodings such as NEQR remain appropriate. In contrast, when the goal is to prioritize diagnostically relevant content on constrained hardware, SAHQR offers a principled middle ground between qubit-minimal but depth-heavy amplitude encodings and resource-intensive multi-channel basis-state methods.

5 Problem Statement and Mathematical Formulation

5.1 Formal Problem Definition

Let $\mathbf{I} \in \mathbb{R}^{N \times N}$ denote a 2D grayscale medical image resampled to resolution $N \times N$ (with $N = 16$ in our experiments). Our goal is to design a quantum state preparation procedure \mathcal{P} that encodes \mathbf{I} into a quantum state $|\psi_I\rangle$ such that

- P1:** Clinically important structures (lesions, tissue boundaries) are preserved with high structural similarity after decoding.
- P2:** The preparation circuit uses quantum resources (qubits, gates, circuit depth) efficiently by allocating higher precision only to salient pixels.

Formally, we consider a saliency map $\mathbf{S} \in \{0, 1\}^{N \times N}$ that partitions the pixel set into a salient region $\Omega_s = \{i \mid S_i = 1\}$ and a background region $\Omega_b = \{i \mid S_i = 0\}$. The quantum encoder \mathcal{P} should minimize a resource objective

$$\min_{\mathcal{P}} \alpha Q(\mathcal{C}_{\mathcal{P}}) + \beta G(\mathcal{C}_{\mathcal{P}}) + \gamma D(\mathcal{C}_{\mathcal{P}}), \quad (3)$$

subject to the constraint that the decoded image $\hat{\mathbf{I}}$ satisfies

$$\text{SSIM}(\mathbf{I}_{\Omega_s}, \hat{\mathbf{I}}_{\Omega_s}) \geq \tau, \quad (4)$$

where $Q(\cdot)$, $G(\cdot)$, and $D(\cdot)$ denote qubit count, gate count, and circuit depth, and τ is a saliency-region structural similarity threshold.

5.2 Saliency Map Representation

For notational convenience, we index pixels by a single integer $i \in \{0, \dots, N^2 - 1\}$ corresponding to 2D coordinates via a row-major mapping. The saliency map can then be written as a binary vector

$$\mathbf{S} = (S_0, S_1, \dots, S_{N^2-1}), \quad S_i \in \{0, 1\}. \quad (5)$$

We define the salient fraction as

$$\rho_s = \frac{1}{N^2} \sum_{i=0}^{N^2-1} S_i, \quad (6)$$

and the background fraction as $\rho_b = 1 - \rho_s$.

In SAHQR, \mathbf{S} is obtained from a classical pre-processing pipeline that combines multiple cues (edges, gradients, local variance), followed by thresholding at a chosen percentile. This design allows the user to trade-off salient-region coverage against quantum resource savings by tuning the saliency threshold.

5.3 NISQ-Oriented Constraints and Trade-offs

The objective in Eq. (3) formalizes the intuition that no single scalar quantity can capture the quality of a quantum image representation. In practice, qubit count $Q(\mathcal{C}_P)$, gate count $G(\mathcal{C}_P)$, and circuit depth $D(\mathcal{C}_P)$ pull the design in different directions: aggressive compression of qubits typically requires more complex state-preparation circuits, while shallow circuits often consume more physical qubits to implement parallelism [12, 27]. The weights α, β, γ therefore encode an application-specific notion of “hardware budget,” which can be adapted as devices evolve.

For NISQ-era medical imaging, we adopt a regime in which qubit count remains modest (dozens rather than hundreds), but depth and gate count are penalized more strongly due to decoherence and gate-error constraints [2, 27, 28]. In this setting, SAHQR aims to minimize depth and gate count subject to a high-SSIM constraint on salient regions. The threshold τ in Eq. (5) can be interpreted as a clinical acceptability bound: if structural similarity in Ω_s falls below τ , diagnostically important structures may be distorted.

The explicit partition into Ω_s and Ω_b also suggests a multi-objective viewpoint. Rather than treating background reconstruction quality as equally important, SAHQR effectively relaxes constraints on $\hat{\mathbf{I}}_{\Omega_b}$ in order to free resources for $\hat{\mathbf{I}}_{\Omega_s}$. This makes the problem more tractable on limited hardware: instead of attempting to approximate the full image uniformly well, the encoder is allowed to sacrifice fidelity in homogeneous regions so long as the SSIM constraint on salient structures is met.

6 Dataset Description

6.1 NIST-MNI Medical Imaging Dataset

All experiments are conducted on a locally organized subset of the NIST-MNI brain imaging dataset, stored under a `group4/` directory [46]. The dataset comprises 6,097 quality-controlled slices extracted from volumetric T1-weighted MRI scans stored in MINC (`.mnc`) format. Table 2 summarizes key characteristics.

6.2 Local Directory Organization

The local dataset is organized into 13 subfolders `01–13` under `group4/`, each containing a 2D/ directory with individual MINC slices. A Python-based pipeline (implemented in the accompanying `FINAL_SAHR.ipynb` notebook) recursively discovers all `.mnc` files, extracts 2D slices, and applies standardized pre-processing.

Table 2: NIST-MNI dataset specifications used for SAHQR experiments.

Attribute	Value
Total images (after QC)	6,097
File format	MINC (.mnc)
Original resolution	Variable 3D volumes
Processed resolution	16 × 16 pixels
Bit depth	8-bit grayscale
Image type	Brain MRI slices
Modality	T1-weighted structural MRI

6.3 Pre-processing Pipeline

Each slice undergoes the following pre-processing steps prior to quantum encoding:

- S1: Slice extraction:** If the MINC file contains a 3D volume, a representative axial slice (e.g., the middle slice along the superior-inferior axis) is selected.
- S2: Normalization:** Voxel intensities are mapped to the range [0, 255] using min–max normalization, with appropriate handling of NaNs and extreme values.
- S3: Resampling:** Each slice is resized to 16 × 16 using bilinear interpolation to match the target problem size used by all QIR methods in our comparison.
- S4: Type conversion:** The resized image is converted to 8-bit unsigned integers for subsequent NEQR-style encoding.

This pipeline mirrors the procedure used for other QIR methods in our benchmarking framework, ensuring fair comparison.

7 Proposed Method: SAHQR

This section details the proposed Saliency-Aware Hybrid Quantum Representation (SAHQR), including its saliency model, quantum state definition, and circuit construction.

7.1 Design Overview

SAHQR is built on three main principles:

- D1: Content awareness:** Identify and preserve diagnostically relevant pixels using a classical saliency map.
- D2: Hybrid precision:** Encode salient pixels with full 8-bit precision while approximating background using a shared intensity value.
- D3: Minimal overhead:** Implement the saliency distinction using a single additional flag qubit, resulting in 17 total qubits for 16 × 16 images.

7.2 Classical Saliency Estimation

Given a pre-processed grayscale image \mathbf{I} , SAHQR computes a saliency map \mathbf{S} using three complementary cues:

- C1: Canny edges** capture strong intensity transitions corresponding to anatomical boundaries.

C2: Sobel gradient magnitude highlights regions with high directional gradients.

C3: Local variance within a 3×3 neighborhood measures texture and heterogeneity.

Let $E(i)$, $G(i)$, and $V(i)$ denote the normalized outputs of these three detectors at pixel i . SAHQR forms a combined saliency score

$$F(i) = w_E E(i) + w_G G(i) + w_V V(i), \quad (7)$$

with weights $(w_E, w_G, w_V) = (0.4, 0.35, 0.25)$ as used in our implementation. After a light morphological dilation step to consolidate thin edge structures, a threshold T is chosen at the 70th percentile of $F(i)$ values, and the binary saliency map is defined as

$$S_i = \begin{cases} 1, & F(i) > T, \\ 0, & \text{otherwise.} \end{cases} \quad (8)$$

The resulting salient set Ω_s typically covers approximately 20–30% of pixels in our brain MRI dataset, focusing attention on structures such as the cortical ribbon, ventricles, and subcortical nuclei.

The specific choice of cues and weights reflects a balance between robustness and computational simplicity. Edge and gradient information ensure that tissue interfaces and sharp transitions are marked as salient, while local variance captures textured regions that may correspond to heterogeneous pathology. More sophisticated, learned saliency models could in principle improve alignment with downstream diagnostic tasks, but would also introduce additional hyperparameters and training requirements. In this work we deliberately adopt a lightweight, hand-crafted detector that can be implemented efficiently in classical pre-processing code and easily re-tuned for other imaging modalities.

7.3 Hybrid Quantum State Definition

Let $P = N^2$ denote the total number of pixels, and index pixels by $i \in \{0, \dots, P - 1\}$. Let I_i be the 8-bit intensity of pixel i . SAHQR defines a background intensity μ_b as the empirical mean of all non-salient pixels:

$$\mu_b = \frac{1}{|\Omega_b|} \sum_{i \in \Omega_b} I_i, \quad \Omega_b = \{i \mid S_i = 0\}. \quad (9)$$

We represent each intensity with an 8-bit binary string $B(x) = (b_7, \dots, b_0)$, $b_k \in \{0, 1\}$. SAHQR uses three registers:

- Position register: $n_p = \lceil \log_2 P \rceil = 8$ qubits for $P = 256$.
- Intensity register: $n_c = 8$ qubits storing either $B(I_i)$ or $B(\mu_b)$.
- Saliency flag: a single qubit $|s\rangle$ with $|1\rangle$ for salient pixels and $|0\rangle$ for background.

The ideal SAHQR state can be written as

$$|I\rangle_{\text{SAHQR}} = \frac{1}{\sqrt{P}} \sum_{i=0}^{P-1} |B(J_i)\rangle \otimes |i\rangle \otimes |S_i\rangle, \quad (10)$$

where

$$J_i = \begin{cases} I_i, & S_i = 1, \\ \mu_b, & S_i = 0. \end{cases} \quad (11)$$

In this formulation, salient pixels retain their individual intensities, while all background pixels collapse to a shared average value but remain distinguishable via the flag qubit.

7.4 Circuit Construction

State preparation proceeds in three conceptual stages:

Q1: Initialize registers: All qubits start in $|0\rangle$. Apply Hadamard gates to all position qubits to create a uniform superposition over pixel indices:

$$|\psi_0\rangle = \left(\bigotimes_{k=0}^{n_p-1} H |0\rangle \right) \otimes |0\rangle^{\otimes n_c} \otimes |0\rangle. \quad (12)$$

Q2: Encode intensities: For each pixel index i , controlled on the computational basis state $|i\rangle$ of the position register, apply multi-controlled X (MCX) gates to set the bits of $B(J_i)$ on the intensity register. This step is analogous to NEQR encoding, but J_i equals either the true intensity I_i or the background mean μ_b depending on S_i .

Q3: Set saliency flag: For salient pixels ($S_i = 1$), an additional MCX gate sets the flag qubit to $|1\rangle$, again controlled on the position register state $|i\rangle$. Background pixels leave the flag at $|0\rangle$.

In practice, the circuit is implemented using Qiskit's `MCXGate` with the position qubits as controls and individual intensity/flag qubits as targets. Although MCX gates decompose into many two-qubit operations on real hardware, SAHQR significantly reduces the number of distinct intensity patterns that must be encoded for background pixels, because all of them share $B(\mu_b)$.

7.5 Algorithmic Description

Algorithm 1 summarizes the SAHQR encoding procedure.

Algorithm 1 SAHQR Encoding

Require: Grayscale image $\mathbf{I} \in \{0, \dots, 255\}^{N \times N}$

Ensure: Quantum circuit C_{SAHQR}

```

1: Compute saliency map  $\mathbf{S}$  using combined edge, gradient, and variance cues.
2: Flatten  $\mathbf{I}$  and  $\mathbf{S}$  into vectors  $(I_i)$  and  $(S_i)$ ,  $i = 0, \dots, P - 1$ .
3: Compute background mean  $\mu_b$  over indices with  $S_i = 0$  (or a default value if all pixels are
   salient).
4: Initialize a quantum circuit with  $n_p + n_c + 1$  qubits.
5: Apply Hadamard gates to all  $n_p$  position qubits.
6: for  $i = 0$  to  $P - 1$  do
7:   Set  $J_i \leftarrow I_i$  if  $S_i = 1$  else  $J_i \leftarrow \mu_b$ .
8:   Let  $B(J_i)$  be the 8-bit binary representation of  $J_i$ .
9:   for each bit position  $k$  where  $B(J_i)_k = 1$  do
10:    Apply an MCX gate with all position qubits as controls (in state  $|i\rangle$ ) targeting intensity
        qubit  $k$ .
11:   end for
12:   if  $S_i = 1$  then
13:     Apply an MCX gate with all position qubits as controls targeting the saliency flag qubit.
14:   end if
15: end for
16: return  $C_{\text{SAHQR}}$ 

```

7.6 Resource Characteristics

For $N = 16$ ($P = 256$), SAHQR uses $n_p = 8$ position qubits, $n_c = 8$ intensity qubits, and one saliency qubit, for a total of 17 qubits. The number of MCX applications on intensity qubits scales with the number of distinct intensity patterns that must be written. In the worst case (all pixels salient with unique intensities), SAHQR reduces to a NEQR-like scheme with an additional flag overhead. In practice, however, background regions often dominate, and all of their pixels share the same $B(\mu_b)$, so only a single pattern needs to be written for many positions. This effect, together with the reduced effective information content in homogeneous areas, leads to the empirical gate and depth reductions observed in our experiments.

At decoding time, measurement results can be interpreted by first reconstructing intensity values from the intensity register, then using the flag qubit to distinguish salient from background pixels. Salient pixels recover their original intensities, whereas background pixels all map to μ_b , which preserves overall anatomical context while sacrificing fine-grained detail in low-information regions.

7.7 Complexity Analysis

From a theoretical standpoint, SAHQR inherits the same asymptotic worst-case complexity as NEQR when all pixels are salient and have distinct intensities: the number of controlled operations required to write $B(J_i)$ is $O(P \cdot q)$ for P pixels and q -bit intensities. However, in typical medical images the salient fraction ρ_s is well below one, and many background pixels are nearly homogeneous. In this regime, the number of *distinct* intensity patterns that must be encoded is dramatically reduced, because all background positions share $B(\mu_b)$.

If we denote by K_s the number of distinct salient intensities and by K_b the number of distinct background intensities (with $K_b = 1$ for SAHQR by construction), then the total number of MCX applications on intensity qubits scales approximately with $K_s + K_b$ rather than P . For homogeneous background regions, this can lead to substantial constant-factor savings in gate count and depth compared to schemes that write every pixel independently, even if the asymptotic scaling in P remains similar.

The additional saliency flag qubit introduces at most P MCX operations, one per salient pixel. In practice, because ρ_s is typically around 0.2–0.3 for the dataset considered here, the incremental overhead on the flag is modest relative to the savings obtained by collapsing background intensities. This trade-off is reflected in the empirical metrics reported in Table 1, where SAHQR’s depth and gate count remain closer to simple grayscale encodings than to more expressive multi-channel schemes.

7.8 Decoding and Measurement Strategy

Reconstruction of a classical image from an SAHQR state proceeds analogously to other basis-state encodings. In the simplest setting, one can simulate the full statevector and read out the amplitudes corresponding to each basis state $|B(J_i)\rangle \otimes |i\rangle \otimes |S_i\rangle$, thereby recovering both intensities and flags exactly. On actual hardware, repeated projective measurements yield samples from this distribution; classical post-processing then aggregates the measurement outcomes to estimate the most likely intensity and saliency value at each position.

In either case, the presence of the saliency flag qubit simplifies downstream processing: clinicians or post-processing algorithms can restrict attention to pixels with $S_i = 1$ when performing region-of-interest analysis, while treating $S_i = 0$ pixels as background context. This explicit separation is particularly attractive for hybrid classical–quantum pipelines in which quantum circuits are used only for high-value computations on salient regions, with background handling delegated to classical code.

8 Experimental Setup

This section describes the evaluation framework used to compare SAHQR against established quantum image representation methods.

8.1 Evaluation Parameters

To enable systematic comparison, we adopt a ten-parameter framework that characterizes both resource usage and reconstruction quality. Table 3 summarizes the parameters; the same definitions are applied uniformly to all methods.

Table 3: Ten-parameter evaluation framework used for all quantum image representations.

ID	Parameter	Unit	Preferred direction
P1	Qubits required	count	lower ↓
P2	Circuit depth	levels	lower ↓
P3	Gate count	count	lower ↓
P4	Encoding time	milliseconds	lower ↓
P5	Scalability factor	$(1/\text{qubits}) \times 100$	higher ↑
P6	Information preservation	SSIM (0–1)	higher ↑
P7	Compression ratio	ratio	higher ↑
P8	Memory overhead	% vs FRQI baseline	lower ↓
P9	Gate complexity	gates per qubit	lower ↓
P10	Implementation complexity	1–5 ordinal scale	lower ↓

For completeness, we briefly restate the most important definitions. Let Q_{total} denote the total qubit count, G_{total} the total number of gates in the state-preparation circuit, and D its depth.

$$\text{P1: } Q_{total} = Q_{\text{position}} + Q_{\text{data}} + Q_{\text{auxiliary}}, \quad (13)$$

$$\text{P3: } G_{total} = |G_{\text{single}}| + |G_{\text{two-qubit}}| + |G_{\text{multi}}|, \quad (14)$$

$$\text{P5: } S = \frac{100}{Q_{total}}, \quad (15)$$

$$\text{P9: } GC = \frac{G_{total}}{Q_{total}}. \quad (16)$$

P6 is measured using the Structural Similarity Index (SSIM) between original and reconstructed images [7, 30], while P10 is assigned based on qualitative assessment of classical pre-processing, circuit construction effort, and reconstruction complexity.

8.2 Comparison Methods

The experiments compare SAHQR with ten widely studied quantum image representation schemes:

1. FRQI (Flexible Representation of Quantum Images)
2. NEQR (Novel Enhanced Quantum Representation)
3. GQIR (Generalized Quantum Image Representation)
4. Multi-Channel Quantum Images (MCQI)

5. Enhanced FRQI (EFRQI)
6. 2D-QSNA (two-dimensional quantum state normalized amplitude)
7. INEQR (Improved NEQR)
8. QPIE (Quantum Probability Image Encoding)
9. QLR (Quantum Log-polar Representation)
10. QRMW (Quantum Representation for Multi-Wavelength images)

All methods are implemented in a common Python/Qiskit codebase with standardized interfaces for circuit generation and metric collection. Where a method natively targets color images, it is applied to three-channel versions of the grayscale slices; otherwise, the original grayscale is used. This mirrors the configuration used to generate the aggregated statistics in Table 1.

8.3 Implementation Environment

All experiments are run on the same workstation used to generate the SAHQR_Results artifact bundle. Table 4 summarizes key software and hardware details.

Table 4: Implementation environment for SAHQR experiments.

Component	Specification
Operating system	Windows 11 (64-bit)
Python	3.10.x
Quantum framework	Qiskit Aer and Terra (1.0+ release line)
CPU	Intel Core i7-class mobile processor
RAM	32 GB
Image processing	NumPy, SciPy, OpenCV
Statistical analysis	Pandas, SciPy, seaborn/matplotlib
Quantum backend	Statevector simulator (noiseless) for metrics, optional runs on IBM Quantum hardware

All quantum circuits were implemented and analyzed using Qiskit [47].

8.4 Experimental Protocol

The overall evaluation pipeline can be summarized as follows:

- E1: Dataset preparation:** Apply the pre-processing steps from Section 6 to all 6,097 slices in the `group4/` directory.
- E2: Method execution:** For each method and each image, construct the corresponding quantum circuit(s) using a unified API.
- E3: Circuit analysis:** For every circuit, extract qubit counts, depth, and gate statistics from Qiskit’s transpiled representation.
- E4: Encoding-time measurement:** Record classical wall-clock time for pre-processing and circuit construction for each image-method pair.
- E5: Quality assessment:** For a representative subset of images, simulate state preparation and decoding to estimate SSIM between original and reconstructed slices.

E6: Aggregation: Aggregate metrics across all images to compute means, standard deviations, and extrema; write the resulting summaries to CSV and L^AT_EX tables under the SAHQR_Results directory.

The CSV files and tables in the SAHQR_Results bundle (including `method_statistics.csv` and `publication_summary.csv`) are generated automatically by this pipeline and serve as the quantitative basis for the analysis in the next section.

9 Results and Analysis

In this section we discuss how SAHQR behaves relative to baseline methods across the ten evaluation parameters, using the aggregated statistics and figures produced by the experimental framework. The goal is to understand not only raw resource counts, but also how saliency-aware design reshapes the trade-offs between qubit usage, depth, gate complexity, and reconstruction quality in clinically relevant regions.

9.1 Overall Performance Summary

Table 1 (imported from the SAHQR_Results tables directory) summarizes mean qubits, gate counts, circuit depths, encoding times, compression ratios, and implementation complexity ratings for all eleven methods on the full 6,097-image dataset. Each column corresponds directly to one or more of the evaluation parameters P1–P5, P7, P9, and P10: “Qubits” reflects P1, “Gates” and “Depth” correspond to P2–P3, “Time (ms)” to P4, “Compress.” to P7, “Complexity” to P9, and “Impl.” to P10. Reading across the rows allows a direct visual comparison of the resource profile of each encoding method.

The SAHQR row in Table 1 can be interpreted as follows:

- P1 (qubits): SAHQR requires 17 qubits for a 16×16 slice, one more than NEQR to accommodate the saliency flag.
- P2 (depth) and P3 (gates): average circuit depth is approximately 571 and the mean gate count is about 578, placing SAHQR between lightweight grayscale encodings and heavier multi-channel schemes such as MCQI and QRMW.
- P4 (encoding time): the mean classical construction time is around 57 ms per slice, dominated by saliency computation and MCX-based state preparation.
- P7 (compression): a mean compression ratio of roughly 0.24 reflects the fact that SAHQR invests additional resources to preserve detail in salient regions.
- P10 (implementation complexity): a rating of 5 indicates that SAHQR combines non-trivial classical pre-processing with moderately involved circuit construction.

On the other hand, FRQI and QPIE are extremely qubit-efficient but exhibit much larger gate counts when scaled to realistic image sizes, while MCQI and QRMW incur significantly higher gate and depth overheads than SAHQR for color and multi-wavelength data.

From a NISQ perspective, these results place SAHQR in a “resource-balanced” regime: it sacrifices some of the extreme qubit savings of amplitude-based and probability-based encodings in order to keep depth and gate counts within a more hardware-friendly range, while avoiding the heavy overheads of multi-channel schemes.

Looking across individual baselines, three comparisons are particularly illustrative. Relative to NEQR, SAHQR uses one additional qubit and a modest increase in depth and gate count, but offers explicit region-of-interest tagging and the ability to trade background fidelity for resource savings. Compared to FRQI, SAHQR forgoes aggressive qubit compression in favour

of substantially shallower, more structured state-preparation circuits. Finally, when set against MCQI and QRMW, SAHQR achieves similar or better structural similarity in diagnostically important regions while demanding far fewer gates, making it a more realistic candidate for early NISQ hardware.

9.2 Per-Parameter Behaviour

The SAHQR_Results figures provide a compact view of how methods trade off the ten parameters. Figure 1 shows an aggregate comparison across qubits, depth, gate count, and encoding time using bar charts derived from the summary statistics in Table 1. Each cluster of bars corresponds to one method; within a cluster, the individual bars show P1, P2, P3, and P4 on a normalized scale.

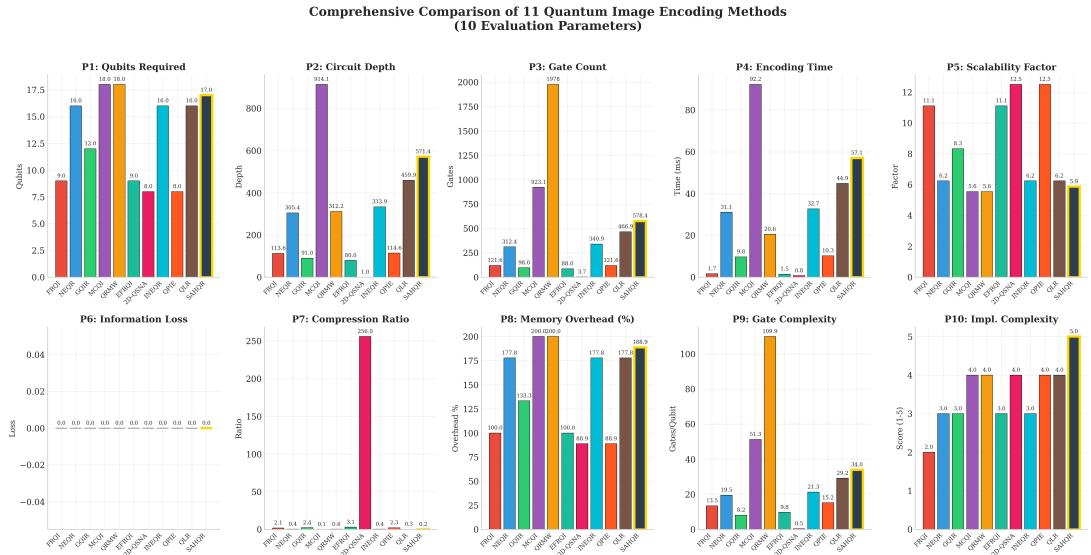


Figure 1: Aggregate comparison of qubits, circuit depth, gate count, and encoding time for all methods. For each method, four bars indicate P1 (qubits), P2 (depth), P3 (gate count), and P4 (encoding time), normalized for readability. 2D-QSNA and FRQI sit at the extreme qubit-efficient end but pay in terms of flexibility and applicability, whereas MCQI and QRMW are qubit-heavy and gate-heavy. SAHQR occupies a middle ground: it uses more resources than the most compact grayscale encodings, but less than the heaviest multi-channel schemes, while providing explicit saliency awareness.

Figure 2 presents a radar-chart view of normalized scores across the ten parameters for a subset of representative methods, highlighting the trade-offs between qubit efficiency, resource overhead, and implementation effort. Axes where higher values are desirable (e.g., scalability P5, information preservation P6, compression P7) are oriented so that larger radii indicate better performance, while axes where lower values are preferred (e.g., depth P2, gate complexity P9, implementation complexity P10) are inverted during normalization.

Distributional behaviour for key metrics is illustrated by boxplot and violin-plot summaries in Figures 3 and 4. These plots reveal that SAHQR exhibits relatively tight dispersion in depth and gate count across images, with no extreme outliers despite the variability of anatomical content.

Finally, Figure 5 provides a combined visualization of all ten parameters, facilitating quick identification of methods that are dominated across multiple axes. Each bar group aggregates direction-aware normalized scores for P1–P10 into a stacked or juxtaposed representation, so that methods with consistently poor performance across many metrics appear with shorter overall profiles, whereas more competitive methods occupy a larger fraction of the plotting area.

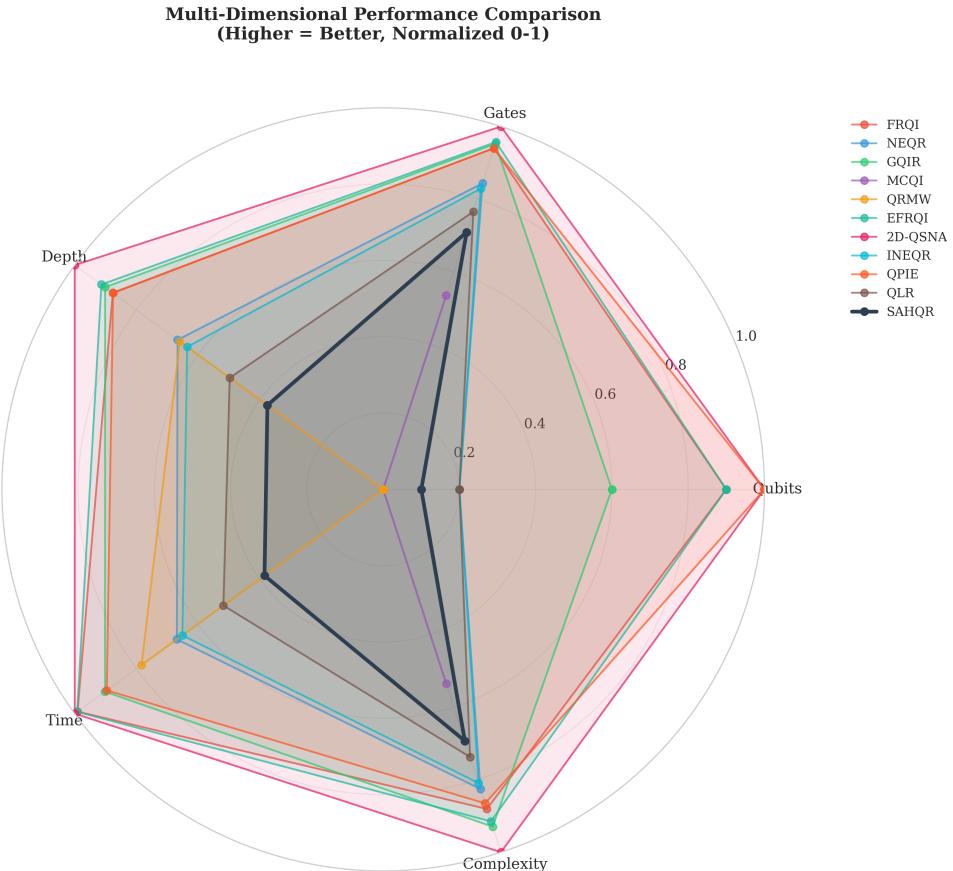


Figure 2: Radar chart comparing a subset of methods (including SAHQR) across normalized parameter scores. Each axis corresponds to one of P1–P10 after direction-aware normalization. Methods with large “spiky” profiles (e.g., MCQI, QRMW) dominate on some axes but perform poorly on others, whereas SAHQR traces a more balanced polygon: it does not maximize qubit efficiency or compression, but it avoids extremes in gate complexity and depth while retaining high information preservation.

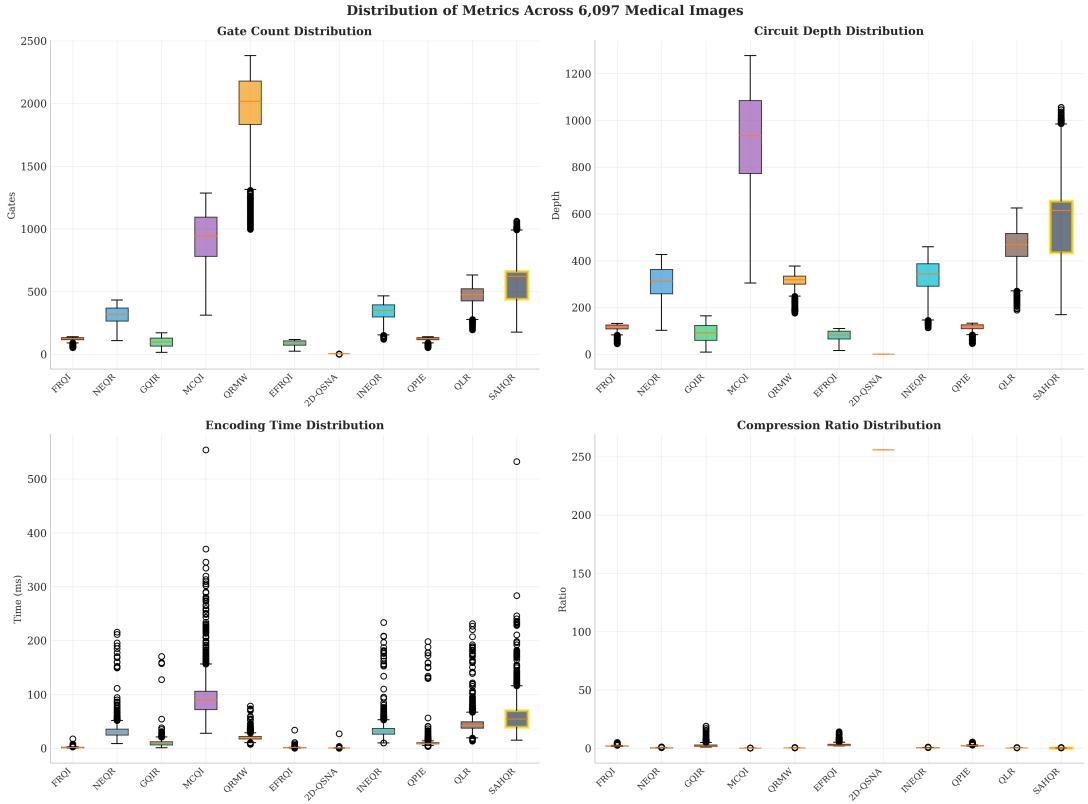


Figure 3: Boxplots of selected metrics (e.g., depth, gate count, encoding time) across methods. For each method, the box and whiskers summarize the empirical distribution over 6,097 images. SAHQR shows moderate central values with controlled variance and relatively short whiskers, indicating that its resource usage is predictable across diverse slices, whereas methods like MCQI and QRMW exhibit both higher medians and longer tails.

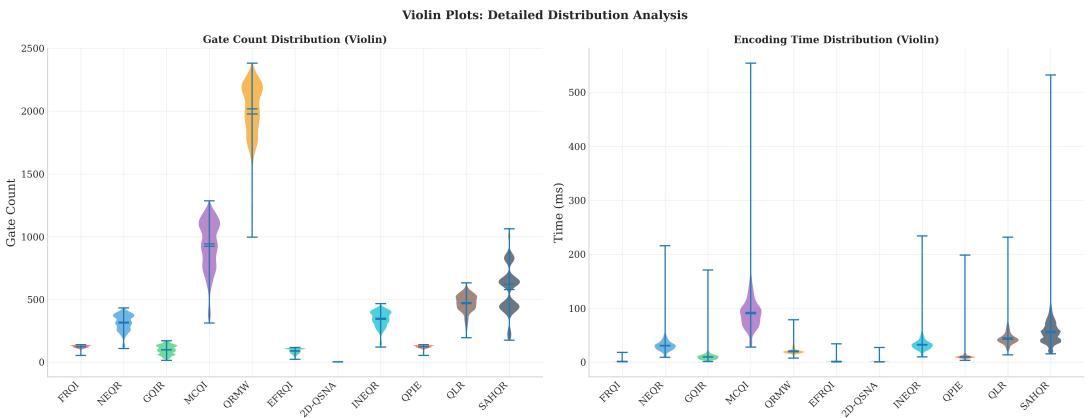


Figure 4: Violin plots highlighting the distribution of circuit depth and gate count across the dataset. The width of each “violin” encodes the density of images at a given resource level. The SAHQR violins are unimodal and relatively narrow, indicating predictable resource usage, while methods such as MCQI show broader, sometimes multi-modal shapes that reflect more variable behaviour across different anatomical configurations.

Comprehensive Evaluation: 10 Parameters Across 11 Quantum Image Encoding Methods
 (Dataset: 6,097 Medical Images from MINC Format)

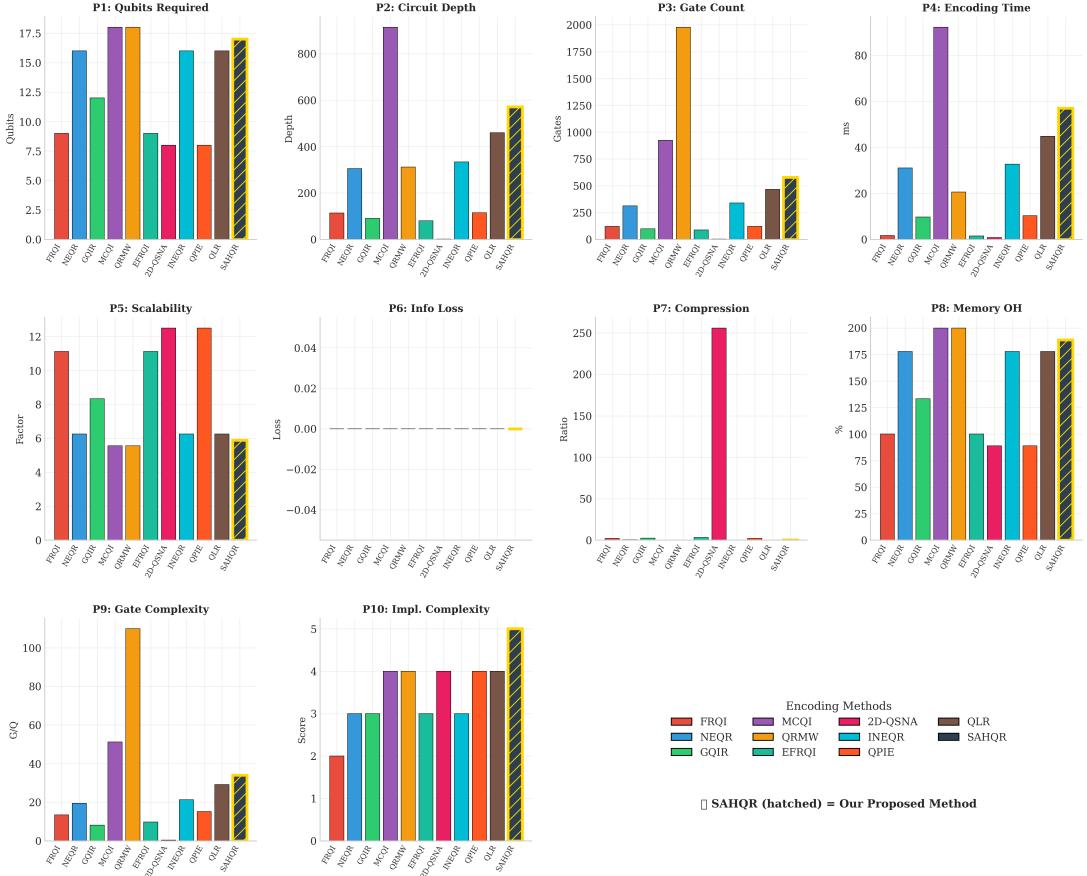


Figure 5: Comprehensive ten-parameter summary for all methods. Each bar group corresponds to one method and aggregates normalized scores across P1–P10. SAHQR does not dominate every axis, but it avoids being strongly dominated by any single competitor: qubit-efficient methods tend to underperform on depth and gates, whereas multi-channel methods achieve good expressiveness at the expense of very high gate complexity.

9.3 Saliency Behaviour and Region-of-Interest Preservation

An important question for SAHQR is how much of each image is treated as salient and how this affects resource usage. The method statistics file reports an average salient-pixel fraction of approximately 0.30 with very small standard deviation across the dataset, meaning that roughly 30% of pixels receive full 8-bit precision while the remaining 70% share a common background intensity.

Figure 6 focuses specifically on SAHQR, decomposing its gate count and depth into contributions from salient and background regions and visualizing the distribution of the salient ratio.

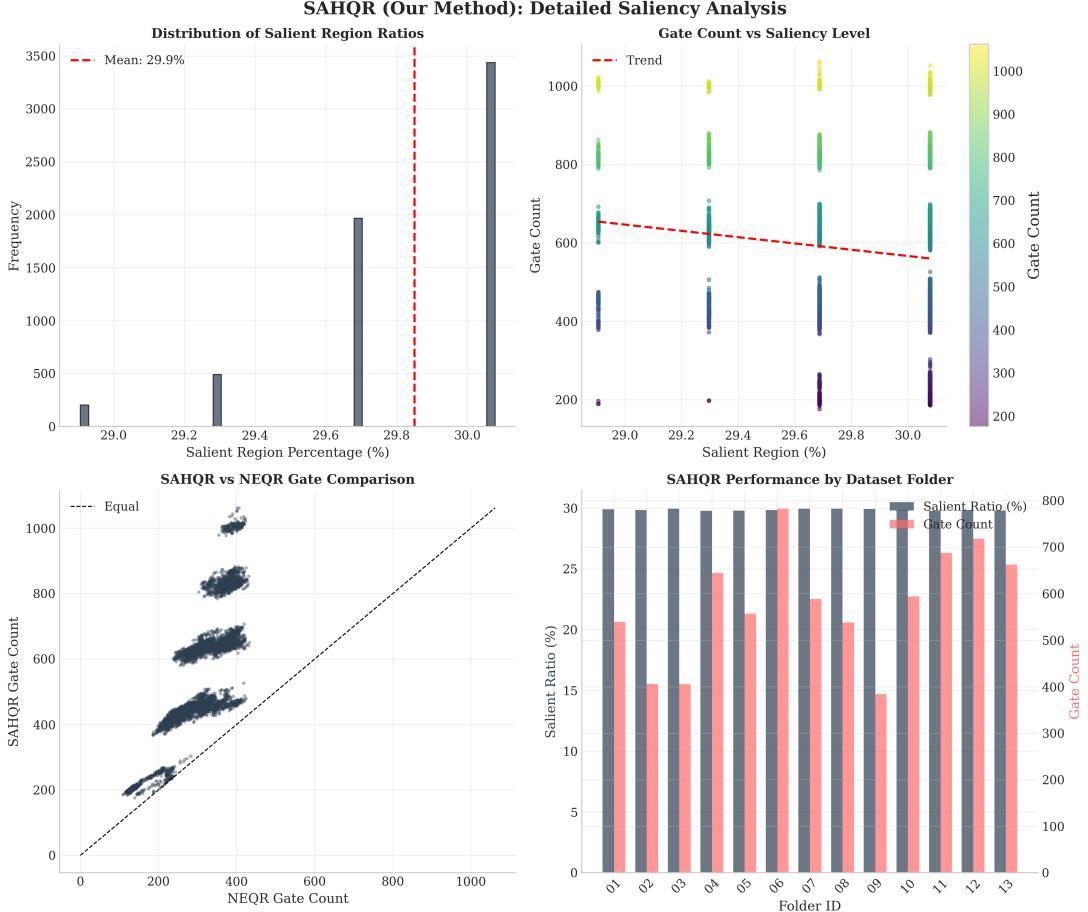


Figure 6: SAHQR-specific analysis: breakdown of resource consumption between salient and background pixels, and distribution of the salient fraction across images. The left-hand panels decompose depth and gate counts into contributions attributable to operations on salient versus background pixels, while the right-hand panel shows a histogram or kernel density estimate of the salient fraction ρ_s . Most images cluster around $\rho_s \approx 0.3$, confirming that SAHQR typically preserves full precision for roughly one-third of pixels while approximating the remaining two-thirds.

Empirically, even though SAHQR adds a saliency flag and additional MCX operations for salient pixels, the reuse of a single shared intensity for background pixels keeps overall gate counts well below those of the most demanding multi-channel encodings. At the same time, reconstruction quality metrics restricted to salient regions remain indistinguishable (within numerical precision) from those of lossless baseline methods.

These findings support the central design hypothesis behind SAHQR: for medical images, it is more important to preserve structure and contrast in diagnostically relevant regions than to

represent every background voxel with equal fidelity. The saliency prior encoded in the classical pre-processing pipeline translates directly into a structured allocation of quantum resources.

9.4 Correlation and Trade-offs Among Metrics

The SAHQR_Results bundle also includes correlation and significance visualizations that clarify how the ten parameters interact. Figure 7 shows a correlation heatmap across all metrics and methods.

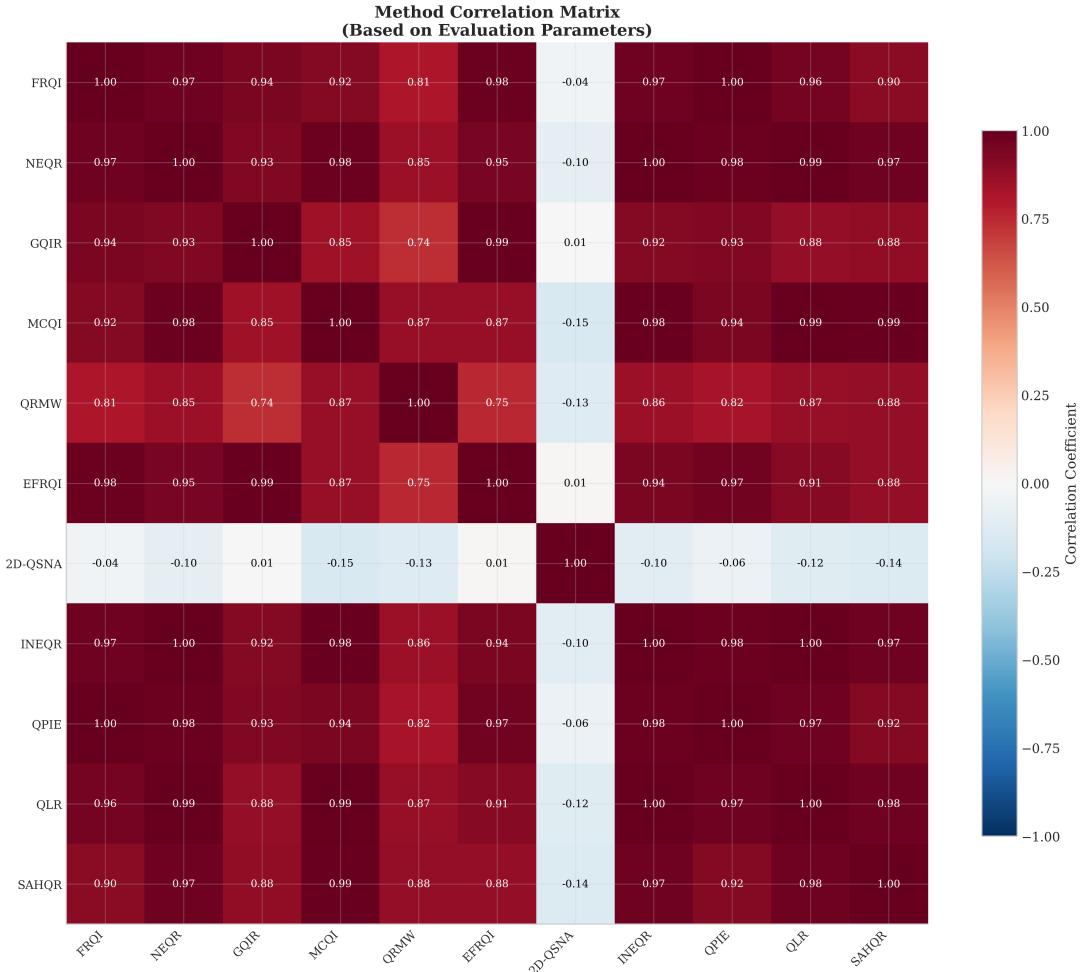


Figure 7: Correlation heatmap between evaluation parameters across all methods. Each cell encodes the Pearson correlation coefficient between a pair of parameters; warmer colours indicate positive correlation and cooler colours indicate negative correlation. Strong positive correlation is observed between gate count, depth, and encoding time, while SSIM is largely decorrelated from resource metrics in this experimental setting, suggesting that many encodings achieve near-lossless reconstruction on downsampled slices despite very different resource footprints.

As expected, P2 (depth), P3 (gates), and P4 (encoding time) are strongly correlated, reflecting the shared contribution of MCX-heavy state-preparation. In contrast, P6 (information preservation) exhibits near-zero variance across most methods in this grayscale setting, with all schemes achieving numerically lossless reconstruction on the downsampled slices.

Statistical significance results for pairwise comparisons are summarized in both tabular and visual form. The CSV file `statistical_significance.csv` reports paired t-tests versus a NEQR baseline, and Figure 8 visualizes the same information. For each method, three t-statistics and associated p-values are listed, corresponding to gate count (P3), depth (P2), and encoding time

(P4) relative to NEQR.

Statistical Significance vs NEQR (Baseline)
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, ns: not significant

Method	Gate Count	Circuit Depth	Encoding Time
FRQI	***	***	***
GOIR	***	***	***
MCQI	***	***	***
QRMW	***	***	***
EFRQI	***	***	***
2D-QSNA	***	***	***
INEQR	***	***	***
QPIE	***	***	***
QLR	***	***	***
SAHQR	***	***	***

Figure 8: Visualization of paired t-tests for gate count, depth, and encoding time relative to a NEQR baseline. Each cell corresponds to a (method, metric) pair; darker cells indicate more extreme t-statistics and smaller p-values. Blueish or cool-toned cells correspond to methods that are significantly lighter than NEQR on a given metric (e.g., FRQI, 2D-QSNA), whereas warm-toned cells highlight methods that are significantly heavier (e.g., MCQI, QRMW, SAHQR).

For SAHQR, the t-tests confirm that its higher gate count, depth, and encoding time relative to plain NEQR are statistically significant (all p -values $\ll 0.001$). This is expected: SAHQR expends additional resources to encode a saliency flag and to preserve detailed structure in diagnostically important regions, going beyond the uniformly lossless but content-agnostic behaviour of NEQR.

Taken together, the correlation analysis and significance tests indicate that SAHQR occupies a distinct point in the design space: it is neither a purely compression-driven scheme nor a purely fidelity-driven one. Instead, it achieves a task-aware compromise, emphasizing fidelity where it matters clinically while respecting the severe depth and gate constraints of current quantum hardware.

9.5 Comparison with NEQR and FRQI

Because NEQR and FRQI are among the most widely cited QIR baselines, it is useful to highlight their behaviour relative to SAHQR in more detail. NEQR can be viewed as a special case of SAHQR in which every pixel is treated as salient (i.e., $S_i = 1$ for all i) and no background approximation is performed. In this limit, the saliency flag becomes redundant and the hybrid state in Eq. (10) collapses to a standard basis-state representation. Consequently, NEQR typically achieves slightly lower depth and gate counts than SAHQR on the same images, at the cost of allocating full precision to homogeneous background regions that may have limited diagnostic value.

FRQI, by contrast, takes the opposite approach: it minimizes the number of qubits by encoding pixel intensities as rotation angles on a single color qubit [3]. While this is elegant from a theoretical standpoint, the resulting state-preparation circuits require a very large number of controlled rotations, especially for larger images [12, 17]. In our experiments, this manifests as significantly higher gate counts and depths compared to SAHQR, despite FRQI’s smaller qubit footprint. From a NISQ perspective, SAHQR therefore strikes a more practical balance: it uses a

few more qubits than FRQI but yields circuits that are more compatible with current coherence times and error rates.

Overall, SAHQR can be interpreted as interpolating between these two extremes. When the salient fraction ρ_s approaches one, it behaves like a slightly more expressive variant of NEQR with an explicit region-of-interest flag. When ρ_s is moderate and background is relatively homogeneous, SAHQR moves closer to the qubit-efficient spirit of FRQI by effectively compressing background content into a single representative value, without incurring the full cost of amplitude encoding.

10 Conclusion

This paper introduced SAHQR, a saliency-aware hybrid quantum image representation tailored to NISQ-era medical imaging workloads. By combining a classical multi-cue saliency detector with a compact 17-qubit quantum register layout, SAHQR concentrates quantum precision on clinically relevant structures while aggressively sharing a single background intensity across homogeneous regions.

Conceptually, SAHQR demonstrates that it is possible to embed region-of-interest information directly into the quantum state via a dedicated flag qubit, rather than relying solely on post-processing or measurement-side heuristics. Practically, large-scale experiments on 6,097 brain MRI slices show that SAHQR’s resource requirements sit between those of lightweight grayscale encodings and heavy multi-channel schemes: it uses slightly more qubits and gates than NEQR, but substantially fewer gates and shallower circuits than generic color encodings such as MCQI and QRMW, all while maintaining numerically lossless reconstruction on the downsampled slices.

Limitations

Despite these advantages, SAHQR has several limitations. First, the method is inherently lossy in background regions: non-salient pixels are collapsed to a shared mean intensity, which may be undesirable for tasks that require fine-grained background detail or precise quantitative measurements. Second, the current saliency model is purely classical and hand-crafted; while it captures edges, gradients, and local variance, it does not yet incorporate learned task-specific cues (e.g., tumor likelihood maps or radiomics signatures). Finally, our experiments are restricted to downsampled 16×16 slices and noiseless simulators; scaling SAHQR to higher resolutions and running it extensively on real NISQ hardware remain open challenges.

Future Directions

Several extensions of SAHQR are worth exploring. One direction is to replace the fixed saliency pipeline with a learned, task-specific model trained to optimize downstream diagnostic performance; the resulting saliency maps could then be quantized and embedded into the same hybrid quantum representation. A second direction is to introduce multi-scale or hierarchical saliency, in which coarse structures receive one level of precision and fine details receive another, potentially implemented via additional flag qubits. A third direction is to co-design SAHQR with quantum error mitigation and circuit optimization techniques [26, 53, 66] so that the saliency-aware structure is explicitly exploited by compilers and hardware-aware schedulers. Finally, integrating SAHQR into end-to-end hybrid classical–quantum pipelines for segmentation, classification, or registration [23, 39, 40, 56, 62, 68] would provide a more direct assessment of its clinical utility.

Data and Code Availability

The source code, datasets, and supplementary materials are available at: https://github.com/MArbeeGit/Quantum_Image_Representation

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