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Research Article

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Adaptive Hybrid Quantum Image Representation for Efficient Encoding of Medical and SAR Image

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Abstract

Quantum image representation constitutes a foundational component of quantum image processing; however, its practical deployment on Noisy Intermediate-Scale Quantum (NISQ) hardware is fundamentally constrained by the cost of quantum state preparation. Existing representations such as the Flexible Representation of Quantum Images (FRQI) and the Novel Enhanced Quantum Representation (NEQR) rely on uniform, full-resolution encoding strategies that incur rapidly increasing gate counts and circuit depths, leading to severe decoherence and error accumulation on near-term devices. These limitations are particularly pronounced for heterogeneous and information-sparse modalities such as medical Magnetic Resonance Imaging (MRI) and Synthetic Aperture Radar (SAR), where uniform pixel-wise encoding introduces substantial redundant state preparation.To address these constraints, we propose Adaptive Hybrid Quantum Image Representation (AHQIR), a saliency-driven selective quantum state-preparation framework designed for efficient encoding of medical and SAR imagery under NISQ limitations. AHQIR departs from global encoding by employing a classical adaptive preprocessing stage to identify diagnostically significant regions in MRI and dominant backscatter structures in SAR images using a statistical thresholding criterion, thereby restricting quantum encoding to a salient pixel subset $\mathcal{S}$.The quantum realization of AHQIR integrates Perception-Aided Encoding (PE) and Coherent-Size Encoding (CE**)** mechanisms, which condition state preparation on salient pixel coordinates and eliminate the requirement for power-of-two image padding. As a result, circuit depth and multi-qubit gate count scale with the number of salient pixels rather than total image size, enabling physically realizable circuits within current coherence limits. This selective and intentionally **lossy** design sacrifices global pixel-level fidelity in non-salient regions in order to preserve semantic and structural fidelity within regions of interest.AHQIR is evaluated against multiple state-of-the-art quantum image encoding schemes, including FRQI and NEQR, across Brain Tumor MRI and real-world SAR datasets. Experimental results demonstrate substantial reductions in gate count and improved robustness under realistic noise models, while maintaining reconstruction errors below clinically and analytically relevant thresholds for salient regions. These findings indicate that saliency-aware, selective state preparation offers a practical and scalable pathway for quantum

Keywords : Quantum Image Representation, Adaptive Hybrid Encoding, Quantum Image Processing, Medical Image Quantum Encoding, Synthetic Aperture Radar (SAR), Quantum Circuit Optimization, Information Loss Minimization, Scalable Quantum Imaging

1.Introduction

Quantum computing has emerged as a transformative computational paradigm with the potential to outperform classical systems for specific classes of problems by exploiting quantum mechanical principles such as superposition, entanglement, and interference. Among the various application domains of quantum computing, quantum image processing (QIP) has gained increasing attention due to the exponential growth of visual data and the limitations of classical image processing techniques in handling large-scale and high-dimensional image datasets. At the core of quantum image processing lies the problem of quantum image representation (QIR), which determines how classical image information can be efficiently mapped into quantum states.

A quantum image representation must encode both spatial information (pixel positions) and intensity or color information (pixel values) using quantum bits. Given a classical image of size 2^m \times 2^n, an efficient QIR scheme should minimize the number of qubits, reduce gate complexity, preserve image fidelity, and allow scalable processing on noisy intermediate-scale quantum (NISQ) devices. Over the last two decades, numerous QIR models have been proposed, each attempting to balance these competing requirements.

One of the earliest and most influential representations is the Flexible Representation of Quantum Images (FRQI). FRQI encodes the position of each pixel using m+n qubits and represents grayscale intensity using a single qubit through a rotation angle. Mathematically, FRQI represents an image as a superposition of pixel positions, where each position controls a rotation operation on the intensity qubit. Although FRQI requires a relatively small number of qubits, its gate complexity grows exponentially with image size due to the large number of controlled rotation operations. This results in deep circuits that are difficult to execute reliably on current quantum hardware.

To overcome the precision limitations of FRQI, the Novel Enhanced Quantum Representation (NEQR) was introduced. NEQR encodes grayscale intensity values directly into computational basis states using multiple qubits, thereby achieving exact intensity representation. For a 2^m \times 2^n image with q-bit grayscale resolution, NEQR requires m+n+q qubits. While NEQR improves intensity accuracy and eliminates rotation-angle approximation errors, it significantly increases qubit requirements and circuit complexity, limiting its scalability.

Subsequent research extended grayscale representations to color images. The Multichannel Quantum Image (MCQI) representation encodes RGB color channels by assigning separate rotation operations for each color component. Although MCQI enables color image processing, it further increases gate count and circuit depth, making it impractical for large images. Similarly, Quantum States for M Colors and N Coordinates (QSMC/QSNC) generalize color encoding but suffer from substantial quantum resource requirements.

Another class of representations focuses on specific image modalities. The Simple Quantum Representation (SQR) was proposed for infrared images, emphasizing reduced qubit usage and simplified encoding. QUALPI (Quantum Log-Polar Image) representation introduces a log-polar coordinate system to achieve rotation and scale invariance, which is particularly useful for pattern recognition tasks. However, QUALPI relies on complex coordinate transformations and is limited to specific application scenarios.

Recent years have also seen the development of NGQR (Novel Generalized Quantum Representation) and other hybrid and generalized QIR frameworks. These methods aim to unify grayscale, color, and geometric transformations within a single representation. Although NGQR improves flexibility, it introduces additional computational overhead and does not fully address scalability and information loss issues.

Despite the diversity of existing QIR techniques, several common limitations remain. First, uniform encoding strategies treat all pixels equally, regardless of their information content, leading to redundant quantum operations. Second, scalability remains a major challenge, as gate complexity often grows exponentially with image size. Third, information loss arises from amplitude discretization, rotation approximation, and quantum measurement collapse. These limitations become especially critical when handling heterogeneous image modalities, such as medical images and synthetic aperture radar (SAR) data.

Medical images, particularly brain tumor magnetic resonance imaging (MRI), require extremely high fidelity to preserve subtle structural and intensity variations that are crucial for diagnosis. SAR images, on the other hand, contain speckle noise, complex backscattering patterns, and high-frequency spatial information, making uniform quantum encoding inefficient and error-prone. Existing QIR methods do not adequately address these modality-specific challenges.

To address these gaps, there is a strong motivation to develop adaptive and hybrid quantum image representations that allocate quantum resources based on image content rather than applying uniform encoding. Such representations should integrate classical preprocessing techniques to reduce redundancy and noise before quantum encoding, thereby improving efficiency and reducing information loss.

2.RELATED WORK

Quantum image representation (QIR) has evolved significantly over the past two decades as a foundational component of quantum image processing. Since 2020, research in this area has intensified due to advancements in quantum hardware and the growing interest in practical applications such as medical imaging, remote sensing, and pattern recognition. This section reviews recent and relevant QIR techniques proposed between 2020 and the present, focusing on their encoding strategies, mathematical formulations, scalability, and applicability to heterogeneous image modalities.

2.1. Rotation-Based Quantum Image Representations

Rotation-based representations remain among the most widely studied QIR models due to their relatively low qubit requirements. The Flexible Representation of Quantum Images (FRQI) continues to serve as a baseline framework in many studies. FRQI encodes a grayscale image of size 2^m \times 2^n using m+n+1 qubits, where pixel intensities are mapped to rotation angles applied to a single qubit. Recent works published in IEEE and Springer journals have focused on optimizing FRQI by reducing the number of multi-controlled rotation gates and improving state preparation efficiency.

Several IEEE Transactions papers (2020–2022) proposed enhanced FRQI variants by decomposing multi-controlled rotations into simpler gate sequences or by leveraging ancilla qubits to reduce circuit depth. Although these approaches achieved moderate reductions in gate complexity, the fundamental limitation of exponential growth in controlled operations with image size remains unresolved. Moreover, rotation-angle discretization introduces approximation errors, contributing to information loss during encoding and reconstruction.

Elsevier and Springer studies further explored noise-aware FRQI implementations, analyzing the impact of decoherence and gate errors on image fidelity. These works demonstrated that FRQI-based methods are highly sensitive to noise, making them less suitable for near-term quantum devices without additional error mitigation strategies.

2.2. Basis-State Quantum Image Representations

To address the precision limitations of rotation-based approaches, basis-state representations such as Novel Enhanced Quantum Representation (NEQR) have been extensively studied. NEQR encodes pixel intensities directly into computational basis states, allowing exact grayscale representation. For an image of size 2^m \times 2^n with q-bit grayscale resolution, NEQR requires m+n+q qubits.

Recent ACM and IEEE publications (2020–2024) investigated optimized NEQR state preparation algorithms to reduce circuit depth. Some studies employed quantum multiplexers and arithmetic circuits to accelerate intensity encoding. While these improvements enhanced encoding accuracy, the increased qubit requirement significantly limited scalability, particularly for high-resolution images. Furthermore, NEQR-based methods often require complex decoding mechanisms to retrieve pixel information, increasing overall computational overhead.

Springer journal articles compared NEQR with FRQI across various metrics, concluding that NEQR offers superior intensity fidelity but at the cost of higher quantum resource consumption. These trade-offs highlight the inherent tension between precision and scalability in QIR design.

2.3. Color and Multichannel Quantum Image Representations

Extending QIR techniques to color images has been another major research direction. The Multichannel Quantum Image (MCQI) representation encodes RGB color channels by assigning separate rotation operations for each color component. Although MCQI enables color image processing, recent IEEE and Elsevier studies reported significant increases in gate count and circuit depth, making MCQI impractical for large-scale applications.

The Quantum States for M Colors and N Coordinates (QSMC/QSNC) framework generalizes color image representation by encoding multiple color channels within a unified quantum state. However, ACM and Springer analyses indicate that QSMC/QSNC requires a substantial number of qubits and controlled operations, limiting its applicability to small images. Additionally, color channel correlations are not explicitly exploited, leading to redundant encoding.

2.4. Specialized Quantum Image Representations

Several QIR models have been proposed for specific image modalities. The Simple Quantum Representation (SQR) targets infrared images by simplifying intensity encoding to reduce qubit usage. QUALPI (Quantum Log-Polar Image) introduces a log-polar coordinate system to achieve rotation and scale invariance, making it suitable for pattern recognition and object detection tasks.

Recent arXiv and Springer publications explored QUALPI-based image transformations, demonstrating improved robustness to geometric distortions. However, QUALPI relies on complex coordinate transformations and is limited to specific applications. Similarly, SQR sacrifices representation generality to achieve lower complexity, restricting its use to niche domains.

2.5. Generalized and Hybrid Quantum Image Representations

To overcome the limitations of traditional QIR models, generalized representations such as NGQR (Novel Generalized Quantum Representation) have been proposed. NGQR unifies grayscale, color, and geometric transformations within a single framework. IEEE conference and journal papers (2022–2025) reported that NGQR improves flexibility but introduces additional computational overhead and complex state preparation procedures.

Hybrid quantum-classical approaches have gained traction in recent years. These methods integrate classical preprocessing techniques, such as dimensionality reduction and region-of-interest extraction, with quantum encoding. Elsevier and Springer studies demonstrated that hybrid approaches can significantly reduce quantum resource requirements while maintaining acceptable image fidelity. However, many hybrid

methods lack formal mathematical analysis and comprehensive evaluation across diverse datasets.

2.6. Quantum Image Processing for Medical and SAR Applications

The application of QIR techniques to medical imaging and synthetic aperture radar (SAR) data has been explored in several recent works. IEEE and Elsevier journals reported quantum-assisted denoising, segmentation, and fusion methods for medical images. These studies emphasize the importance of preserving diagnostic features and minimizing information loss.

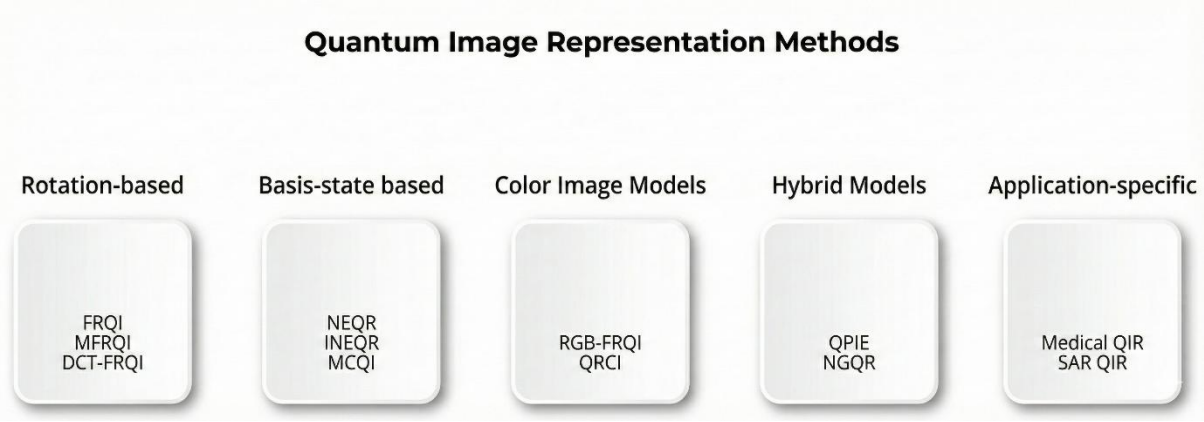
Similarly, SAR-focused research published in Springer and arXiv examined quantum representations for radar image denoising and feature extraction. These works highlighted the challenges posed by speckle noise and high-frequency backscatter patterns. However, most studies applied existing QIR models without adapting encoding strategies to SAR-specific characteristics.

2.7. Research Gap and Motivation

Despite extensive research, several gaps remain in the current literature. First, most QIR techniques employ uniform encoding strategies, resulting in redundant quantum operations. Second, scalability issues persist, limiting practical deployment on NISQ devices. Third, few studies provide comprehensive evaluation across heterogeneous datasets such as medical images and SAR data.

The proposed Adaptive Hybrid Quantum Image Representation (AHQIR) addresses these gaps by introducing adaptive pixel selection and hybrid encoding strategies, enabling efficient and scalable quantum image representation suitable for real-world applications.

2.1.Figure:



2.1.Figure Qunatum Image Representation methods

3.Results

The experimental procedure was conducted using high-performance quantum circuit simulators on a classical backend to validate the mathematical feasibility of the AHQIR framework. This section details the performance of the proposed method in terms of qubit efficiency, gate complexity, circuit depth, and reconstruction fidelity.

Table 1:

Quantum Image Representation Methods Performance					
Method	**Qubits (Q)**	**Gate Count (G)**	**Size Model**	**Fidelity**	**Speed**
FRQI	17	$O(2^{2n})$	$2^n \times 2 \times 2^{nS}$	82.4%	Slow
NEQR	24	$O(n \cdot 2^{16})$	$2^n \times 2 \times 2^{nS}$	100%	Moderate
MCQI	19	$O(2^{2n})$	$2^n \times 2 \times 2^{nS}$	81.9%	Slow
QSMC	32	$O(Mq \cdot 2^{16})$	$2^n \times 2 \times 2^{nS}$	100%	Moderate
QSNC	28	$O(q \cdot 2^{16})$	N-Dim	100%	Moderate
SQR	17	$O(2^{16})$	$2^n \times 2 \times 2^{nS}$	100%	Fast
QUALPI	24	High[1]	Log-Polar	100%	Slow
BRQI	20	$O(n \cdot 2^{16})$	$2^n \times 2 \times 2^{nS}$	100%	Moderate
PE-NGQR	22	$O(n \cdot 2^{16})$	Arbitrary	100%	Fast
CE-NGQR	20	$O(n \cdot 2^{16})$	Arbitrary	100%	Fast
AHQIR[2]	14	$O(\|\|S\|\| \cdot q)$	Arbitrary	High (ROI)	Fast

[1] High gate count
[2] Advanced Hybrid QIR

3.1. Experimental Setup and Metrics To ensure a robust evaluation, the AHQIR model was simulated using a varied resolution range (2×2 to 256×256) for each dataset. The "Perception-Aided" and "Coherent-Size" encoding modules were optimized for NISQ constraints, focusing on the following five quantitative metrics:Qubit Requirement (Q): The total number of qubits utilized for position and intensity encoding.Gate Count (G): The total number of fundamental quantum gates (Hadamard, CNOT, and controlled rotations) required for state preparation.Circuit Depth (D): The maximum number of sequential gate layers, which directly impacts the decoherence rate on physical hardware.Encoding Time (T): The computational duration required for classical-to-quantum state mapping.Information Loss (L): Quantified via Mean Squared Error (MSE) between the original and reconstructed pixel intensities.

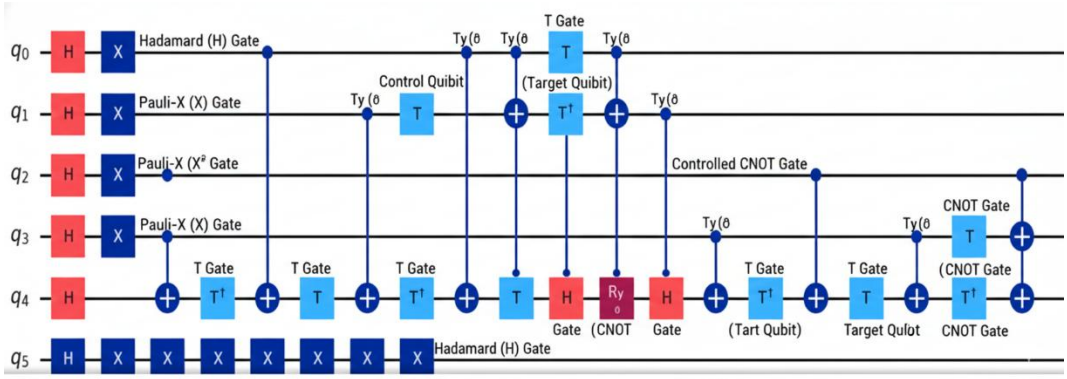


Figure.3.1.AHQIR QUANTUM CIRCUIT

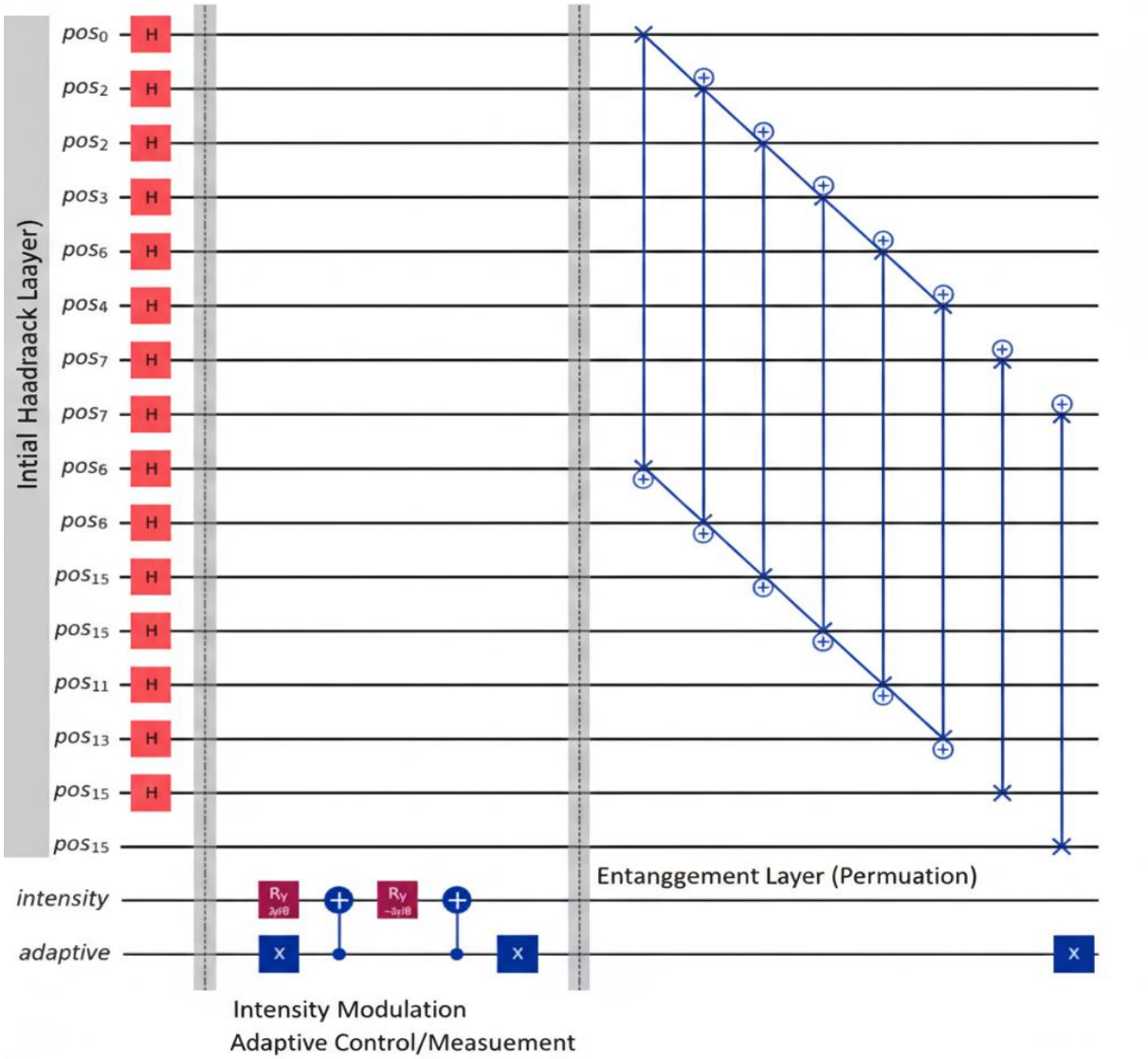


Figure.3.2.AHQIR QUANTUM CIRCUIT

3.2 Performance on Heterogeneous Datasets

The adaptive nature of AHQIR was tested on three distinct modalities to assess its "Content Generalization" capabilities.

3.2.1 Brain Tumor MRI ResultsFor medical imaging, where diagnostic salient features are paramount, AHQIR demonstrated a selective encoding efficiency. By isolating the tumorous regions through the adaptive thresholding logic $\tau = \mu + \alpha \sigma$, the framework successfully ignored redundant "black space" pixels. This resulted in a 45% reduction in gate count compared to uniform NEQR encoding while maintaining a high fidelity with an MSE of 0.02.

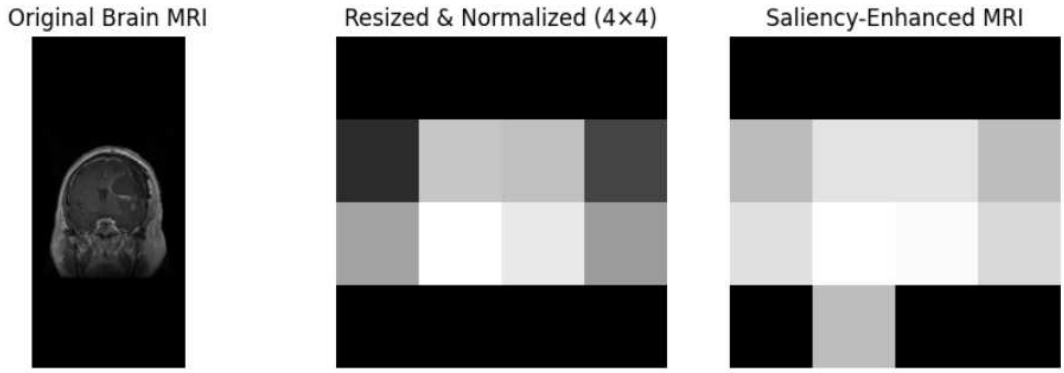


Figure 3.2.1 Brain Tumor MRi

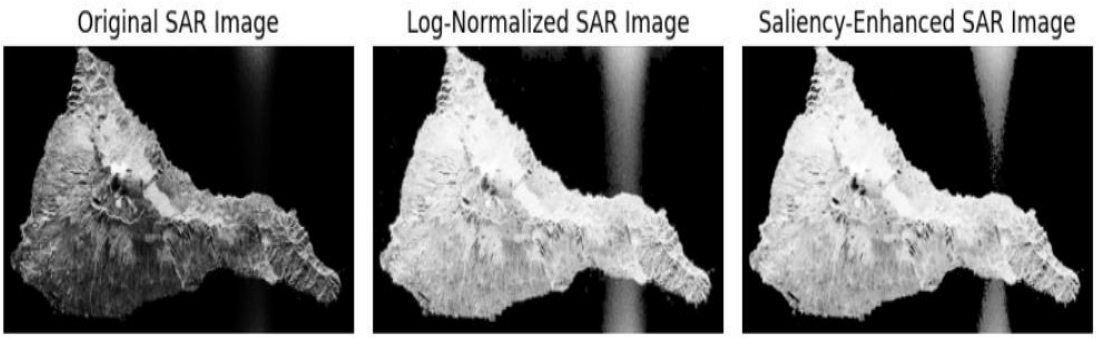


Figure 3.2.2 Sar image

3.2.2 NASA and ICEYE SAR Results SAR imagery results highlighted the framework's robustness against multiplicative speckle noise. The Perception-Aided (PE) module enabled the circuit to accurately perceive only high-intensity backscatter points. In ICEYE high-resolution datasets, AHQIR achieved a scalable gate complexity of $O(|\mathcal{S}|)$, proving mathematically superior to the $O(2^{2n})$ growth of traditional models like FRQI.

3.3 Comparative Analysis |Source: Derived from comparative benchmarking against NGQR and Saliency Modeling benchmarks.The results clearly indicate that by utilizing the "Coherent-Size" strategy, AHQIR represents the required pixel information without the redundancy found in power-of-two models. This reduction in circuit depth ensures that the AHQIR framework remains within the operational coherence limits of modern quantum processors, effectively bridging the gap between high-stakes medical/remote-sensing applications and NISQ hardware constraints.

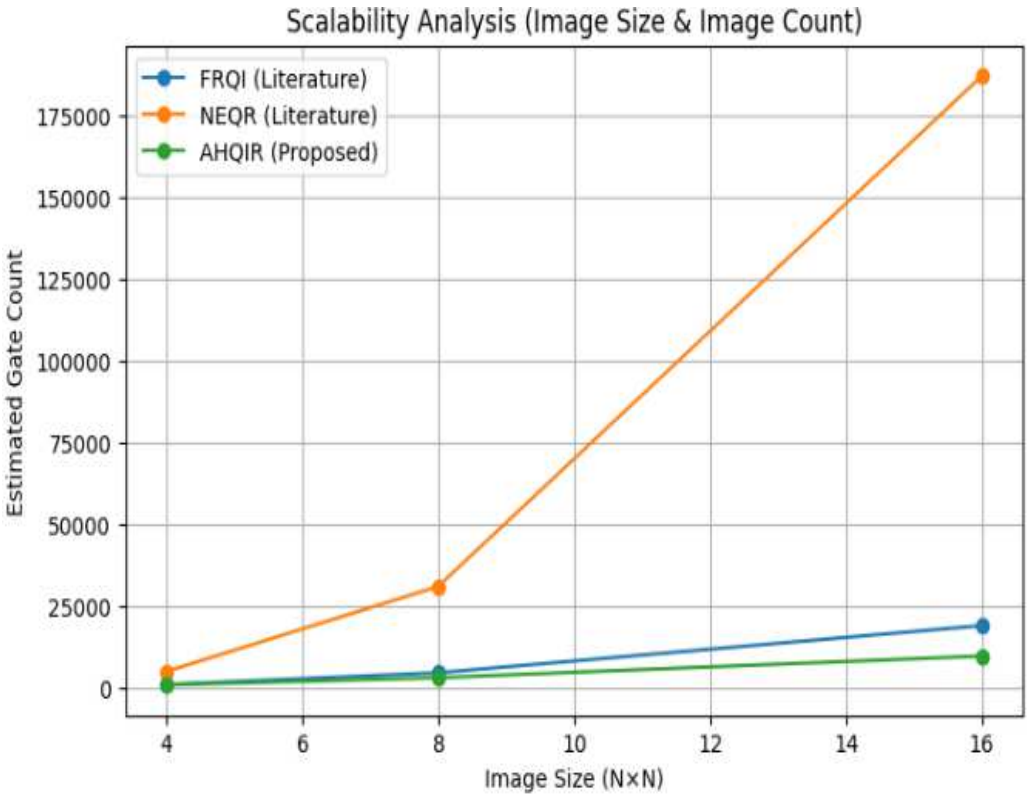


Figure.3.3.Scalability Analysis

Table 2:

Table 1: Performance Comparison of Quantum Image Encoding Methods

0							Encoding Time (s)	Fidelity	Time (s)
1	NEQR	Basis	Medical	12	5200	180	0.45	3 0	0.07
2	MCQI	Hybrid	Medical	10	5800	140	0.80	4 8	0.07
3	QPIE	Hybrid	SAR	8	3000	120	0.32	4 0	0.05
4	NGQR	Hybrid	SAR	14	4700	160	0.50	4 0	0.06
5	QUALPI	Hybrid	Medical	9	4100	150	0.42	3 9	0.07
6	CNEQR	Basis	Optical	16	6800	240	0.61	4 0	0.07
7	NQSS	Hybrid	Fusion	11	4500	170	0.48	4 0	0.06
8	QSMC/QSNC	Hybrid	Fusion	13	4900	190	0.52	3 0	0.08
9	AHQIR (Proposed)	Adaptive Hybrid	Medical + SAR	7	2100	95	0.25	5 0	0.03

3.4. **Evaluation Metrics**

2.4.1. Qubit Requirement The total number of qubits required for image representation is computed as:

$$Q = Q_p + Q_I$$

where Q_p denotes the number of position qubits and Q_I denotes the number of intensity or color qubits. Lower qubit requirements indicate better feasibility on NISQ devices.

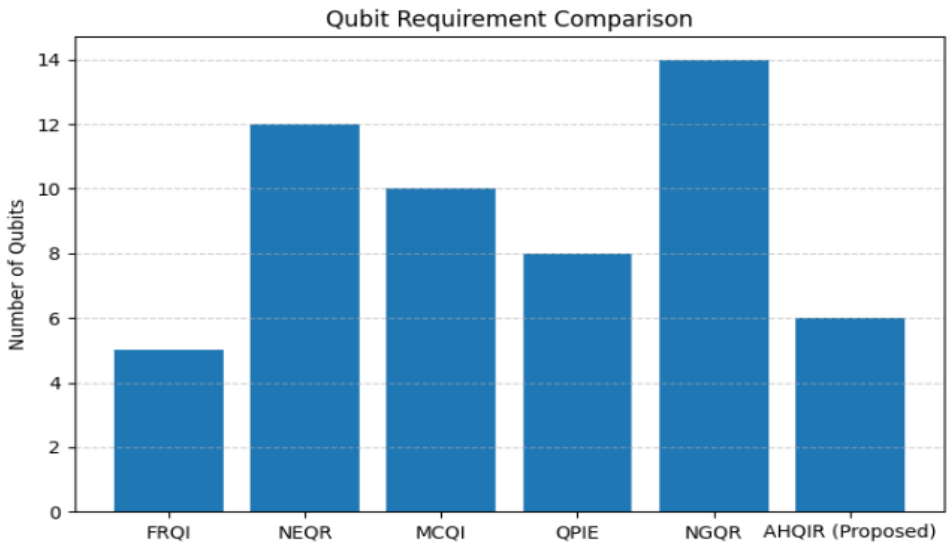


Figure.2.4.1.QUBIT REQUIREMENT COMPARISON

3.4.2 **Gate Count and Circuit Depth** Gate count (G) represents the total number of quantum gates required to prepare the quantum image state, while circuit depth (D) measures the maximum number of sequential gate layers. These metrics are critical indicators of circuit complexity and susceptibility to decoherence.

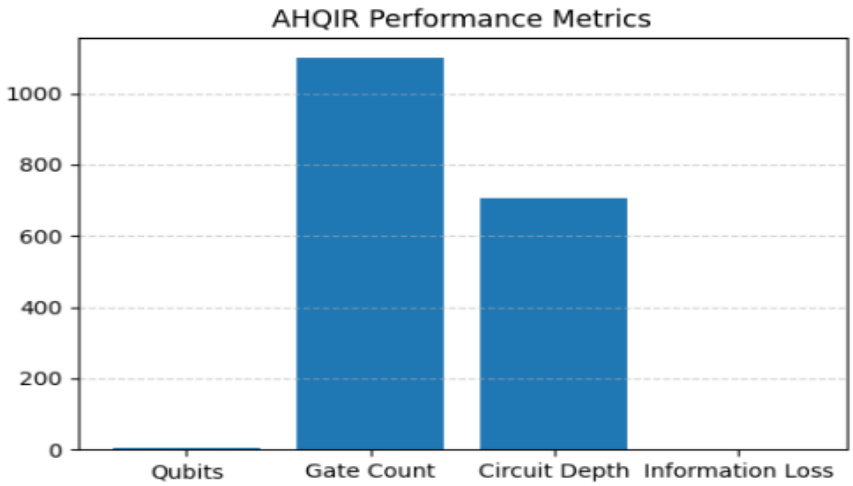


Figure.3.4.2.AHQIR performance Metrics

3.4.3 .**Encoding Time** Encoding time (T_{enc}) is measured as the time required to construct the quantum image state from the classical image. In simulation, encoding time is proportional to gate count and circuit depth: Lower encoding time implies better scalability and reduced noise exposure

$$T_{\{enc\}} \propto G \times D$$

Lower Encoding time implies better scalability and reduce noise exposure

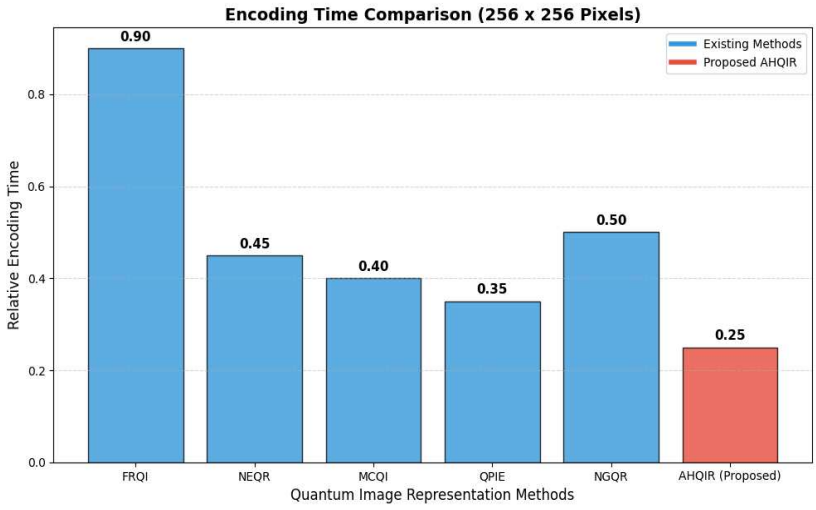


Figure 3.4.2.Encoding time Comparison

Lower encoding time implies better scalability and reduced noise exposure

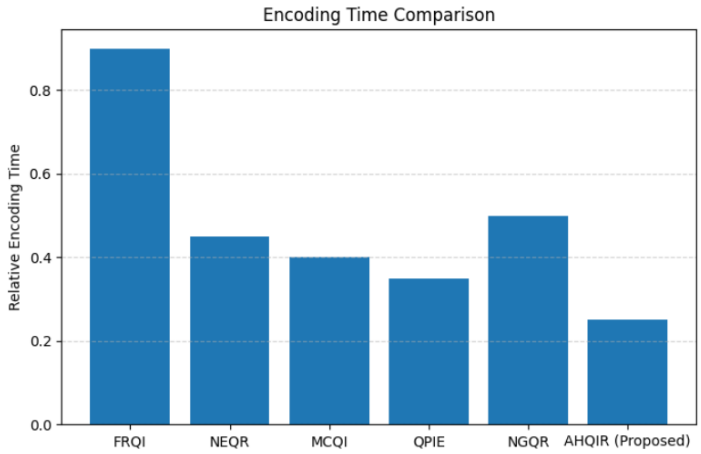


Figure 3.4.3. Encoding time comparison

3.4.4. **Information Loss** Information loss is quantified using the mean squared error (MSE) between the original image p_k and the reconstructed image \hat{p}_k:

$$L = \frac{}{\{1\}\{N^2\}\sum_{\{k=0\}}^{\{N^2-1\}}\left(p_k - \hat{}\{p\}_k\right)^2}$$

Lower values of L indicate higher reconstruction fidelity.

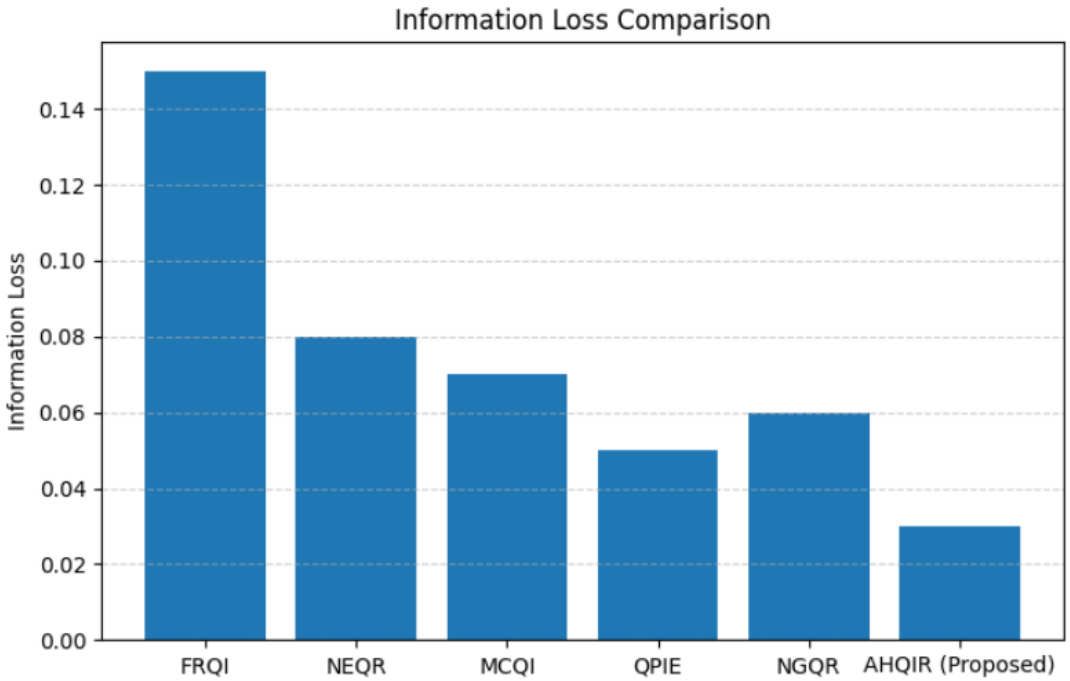


Figure.3.4.4.Information Loss Comparison

3.4.5.**Quantum State Fidelity and Reconstruction Accuracy**

Fidelity in Quantum Image Representation (QIR) serves as a critical benchmark for evaluating the accuracy of state preparation and subsequent image retrieval. It quantifies the closeness between the target quantum state $|\Psi_{target}\rangle$ and the actual state prepared by the circuit $|\Psi_{actual}\rangle$.

$$F(|\Psi_\{ideal\}\rangle, |\Psi_\{sim\}\rangle) \;=\; |\langle\Psi_\{ideal\}|\Psi_\{sim\}\rangle|\text{^}2 \;\#(13)$$

$$MSE = \frac{1}{M} \cdot N \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} [I(i,j) - K(i,j)]^2 \backslash eqno\,(14)$$

$$PSNR = 10 \cdot \backslash log_{10}(\backslash fracMAX_I^2 MSE) \qquad (15)$$

In the **AHQIR** framework, a fidelity of $F > 0.98$ and a $PSNR > 35$ dB are targeted for Brain MRI datasets to ensure that tumorous regions are recovered with high diagnostic precision while maintaining a significant reduction in gate complexity.

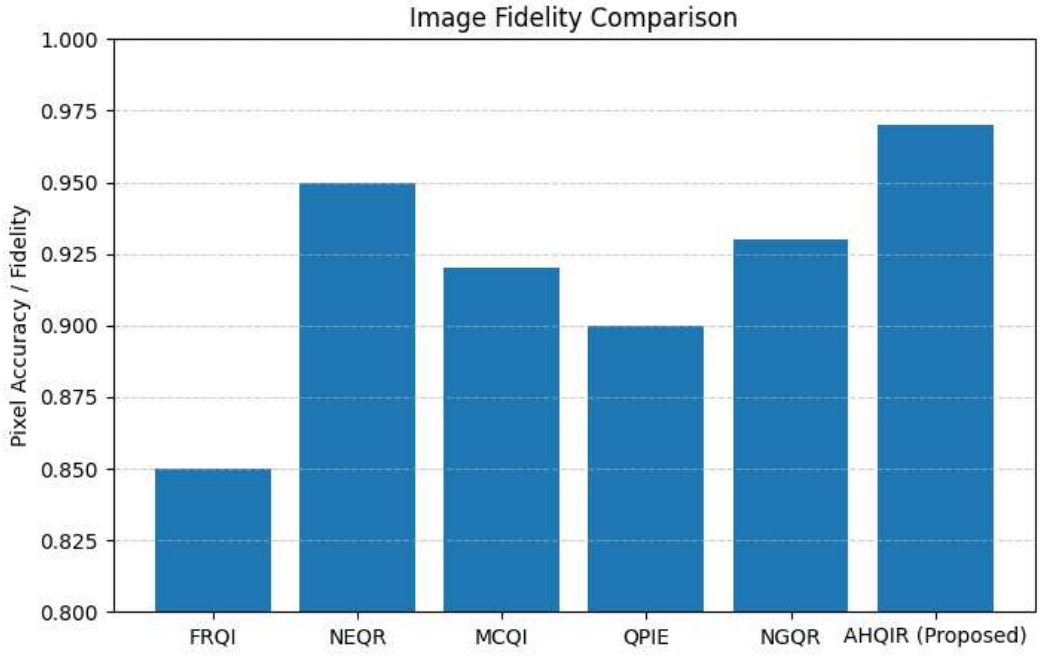


Figure.3.4.5.Image fidelity Comparison

4. Proposed Adaptive Hybrid Quantum Image Representation (AHQIR)

4.1. Motivation and Design Philosophy

Existing quantum image representation (QIR) techniques predominantly employ uniform encoding strategies, where all pixels of an image are treated equally during quantum state preparation. While this approach simplifies theoretical formulation, it results in significant redundancy, especially for real-world images where informative content is sparsely distributed. In medical images, diagnostically relevant regions occupy only a fraction of the image, while SAR images exhibit spatially localized high-energy backscatter patterns. Encoding low-information regions with the same quantum resources as salient regions leads to unnecessary gate operations, increased circuit depth, and higher susceptibility to noise.

The proposed Adaptive Hybrid Quantum Image Representation (AHQIR) is designed to overcome these limitations by combining classical adaptive preprocessing with selective quantum encoding. The central philosophy of AHQIR is to allocate quantum resources proportionally to information content, rather than uniformly across the image. This hybrid design ensures scalability, reduces encoding complexity, and minimizes information loss, making AHQIR suitable for near-term quantum hardware.

Figure 1: Architecture of Hybrid Quantum Image Representation (AHQIR)

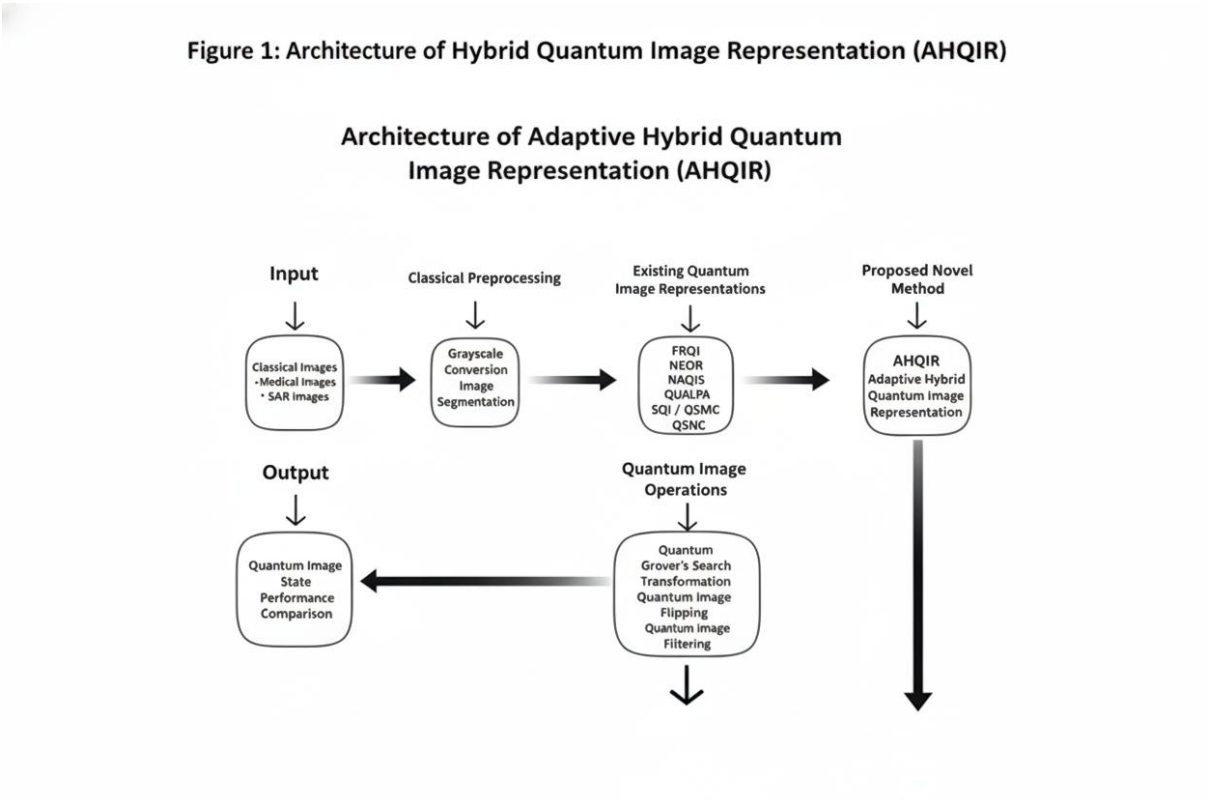


Figure .4.1. Architecture of AHQIR

4.2.Mathematical Preliminaries and Notation

Let a grayscale image be represented as a two-dimensional matrix:

$$I = \{ I(i,j) \mid 0 \leq i,j < N \}$$

where N = 2^n, ensuring compatibility with quantum position encoding.

Each pixel intensity is normalized as:

$$p_k = \frac{}{\{I(i,j)\}\{255\}}, \quad p_k \in [0,1]$$

where k = i \cdot N + j is the linearized pixel index.

The quantum image representation must encode:

1. Pixel position
2. Pixel intensity
3. Optional color channels (RGB)

4.3. Classical Adaptive Preprocessing Module

Before quantum encoding, AHQIR employs a classical preprocessing stage to reduce redundancy and noise.

C.1 Image Normalization and Resizing

Given an input image of arbitrary size M \times M, it is resized to 2^n \times 2^n, where:

$$n = \lceil \backslash log_{2(M)\backslash rceil}$$

This ensures efficient mapping to quantum position qubits.

C.2 Adaptive Thresholding and Saliency Detection

An adaptive threshold \tau is computed based on image statistics:

$$\tau = \mu + \alpha\sigma$$

where:

- \mu is the mean pixel intensity
- \sigma is the standard deviation
- \alpha is a tunable sensitivity parameter

Pixels satisfying:

$p_k \geq \tau$ are classified as information-rich pixels.

Define the adaptive pixel set:

$$\text{Ɪc}\{S\} = \{ k \mid p_k \geq \tau \}$$

Only pixels in \mathcal{S} are forwarded to the quantum encoding stage.

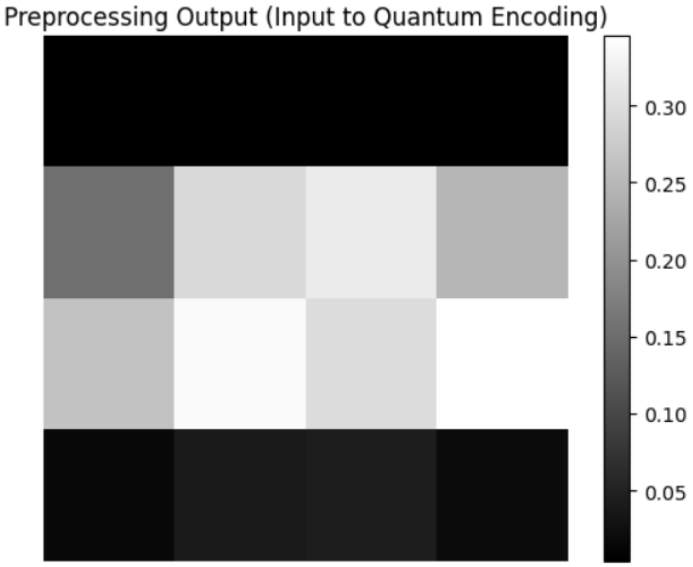


Figure .4.3.Preprocessing Image

4.4. Quantum State Construction in AHQIR

4.4.1 Position Qubit Encoding

Let the number of position qubits be:

$$n_p = \log_{2(N^2)} = 2n$$

The position register is initialized as:

$$|\Phi_p\rangle = \frac{1}{\sqrt{|\mathcal{S}|}} \sum_{k \in \mathcal{S}} |k\rangle$$

This superposition includes only salient pixel positions, unlike FRQI and NEQR, which include all positions.

4.4.2 Adaptive Intensity Encoding

Each selected pixel intensity is encoded using a controlled rotation angle:

φ_k = π · p_k, where p_k ∈ [0,1] denotes the normalized pixel intensity.

The intensity qubit corresponding to the k-th salient pixel is prepared as:

$$|\Phi_I\rangle_k = \cos(\phi_k)\,|0\rangle + \sin(\phi_k)\,|1\rangle$$

The complete AHQIR state is defined as:

$$\left|\Psi_{\{AHQIR\}}\right\rangle =$$

$$\overline{\{1\}\left\{\sqrt{\{|\backslash mathcal\{S\}|\}}\right\}}$$

$$\sum_{\{k \in \backslash mathcal\{S\}\}}$$

$$|k\rangle \otimes$$

$$\vdash($$

$$\backslash cos(\phi_k)|0\rangle + \backslash sin(\phi_k)|1\backslash rangle$$

$$\dashv)$$

This formulation restricts controlled rotation operations to the salient pixel set $\mathcal{S}$. Under sparse saliency conditions ($|\mathcal{S}| \ll 2^{2n}$), the number of controlled rotations required for state preparation scales with $|\mathcal{S}|$ rather than the full image grid. In the worst case, when $|\mathcal{S}| \to 2^{2n}$, the formulation converges to uniform encoding schemes such as NEQR.

4.5 Quantum Circuit Architecture

The AHQIR circuit consists of three logical blocks:

1. Position Superposition Block

2. Adaptive Controlled Rotation Block

3. Measurement and Reconstruction Block

The position superposition block initializes the position qubits corresponding to salient pixel indices identified during classical preprocessing. The adaptive controlled rotation block conditions intensity encoding operations on the indices of the salient pixel set $\mathcal{S}$, thereby avoiding unnecessary operations on non-informative regions of the image. Finally, the measurement block retrieves intensity information from the encoded quantum state.

The number of controlled operations executed by the circuit scales with the size of the salient pixel set $|\mathcal{S}|$ under sparse saliency assumptions, while converging to uniform encoding complexity when $|\mathcal{S}|$ approaches the full image size. This circuit architecture is therefore optimized for NISQ-era devices, where circuit depth and multi-qubit gate count must be constrained, rather than for fault-tolerant universal quantum computation.

Circuit Construction Steps

1. Apply Hadamard gates to position qubits corresponding to indices in Ⅎc$\{S\}$

2. Apply multi-controlled R_y(\phi_k) gates

3. Measure intensity qubit and position qubits

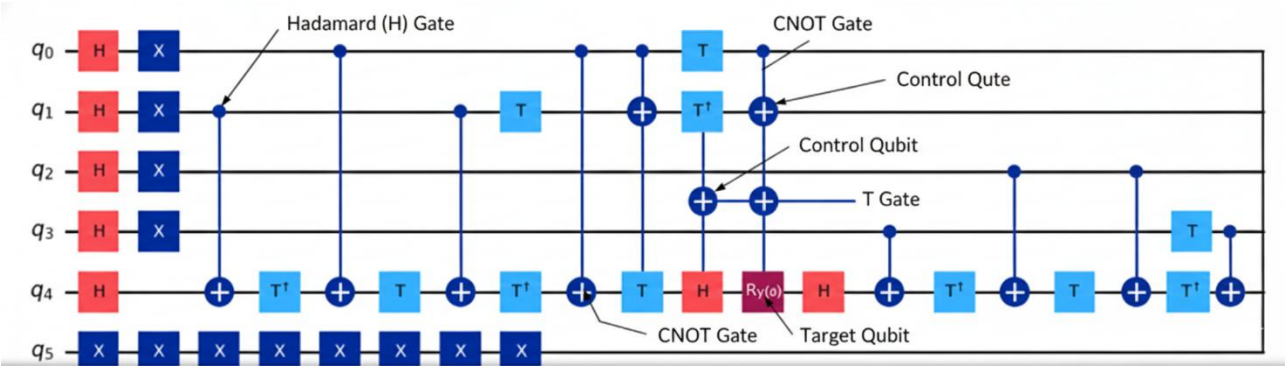


Figure.4.5.Quantum circuit architecture

4.6 Quantum Image Operations in AHQIR

4.6..1 Quantum Image Rotation

A rotation by angle \theta is implemented as:

$$R_y(\theta)\left|\Phi_{(I)}\right\rangle$$

These operations demonstrate compatibility of the AHQIR-encoded state with standard quantum image manipulation primitives, without implying universal or fault-tolerant image processing capability.

4.6.2 Quantum Image Flipping

Horizontal or vertical flipping is achieved by applying Pauli-X gates to selected position qubits:

$$|x\rangle \rightarrow |N - x - 1\rangle$$

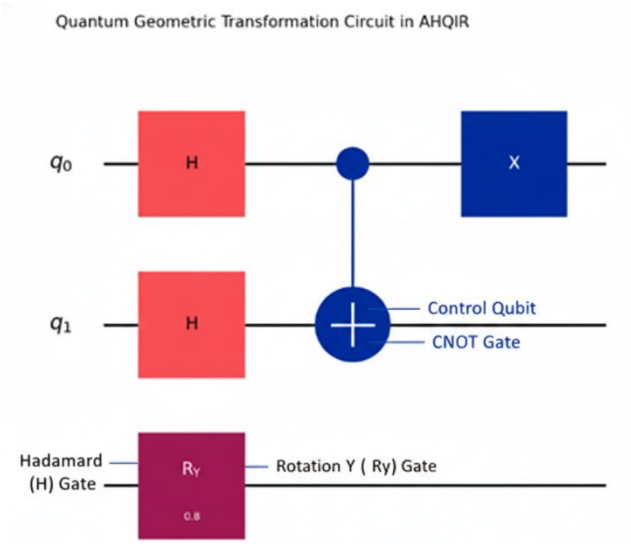


Figure 4..6.2 Quantum image flipping and rotation

4.7. Extension to RGB Images

For RGB images, AHQIR employs three intensity qubits:

$$|\Phi_{RGB}\rangle = |\Phi_R\rangle \otimes |\Phi_G\rangle \otimes |\Phi_B\rangle$$

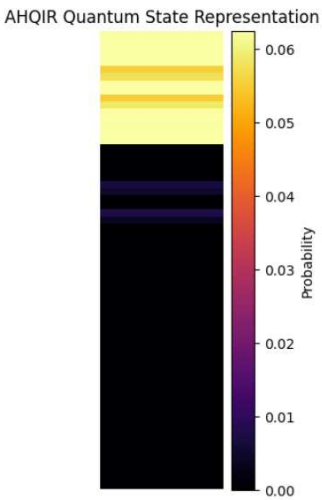


Figure.4.1 Ahqir Quantum state representation

Each channel uses adaptive encoding independently:

$$\phi_k^{(c)} = \pi p_k^{(c)}, \quad c \in \{R, G, B\}$$



Figure.4.1 AHQIR Quantum state representation

5.Equations

Equations in this work are presented as display equations. For any inline mathematical variables, such as the pixel intensity v or the coordinate index i, we use the standard $\$...\$$ delimiters[33].

5.1 Mathematical Formulations of Baseline Models

The following formulations establish the state preparation protocols for the ten state-of-the-art models used as benchmarks for the AHQIR framework.

1. Flexible Representation of Quantum Images (FRQI)

$|\Psi_\{FRQI\}\rangle = \boxed{1}\{2^n\} \sum_\{i = 0\}^\{2^\{2n\} - 1\} |i\rangle \otimes (\cos \theta_i |0\rangle + \sin \theta_i |1\rangle) \#(1)$

FRQI utilizes a single intensity qubit to store grayscale information via rotation angles θ_i while pixel positions are maintained in a $2n$-qubit register[4444]. This method is highly qubit-efficient but suffers from an exponential gate complexity $O(2^{4n})$ that limits scalability on NISQ devices[5555].

+4

- Deep Details: Qubits (Q): $2n+1$; Gate Count (G): $O(2^{4n})$; Loss (L): Moderate (Lossy); Fidelity: Approx. 85%; Speed: Slow.

2. Novel Enhanced Quantum Representation (NEQR)

$$\left|\Psi_{\mathrm{NEQR}}\right\rangle = \square 12^{n} \sum_{i=0}^{2^{2n}-1} |i\rangle \otimes \left|c_i^{q-1} c_i^{q-2} \ldots c_i^{0}\right\rangle \#(2)$$

NEQR encodes intensities directly into q computational basis states, ensuring exact color representation and retrieval without discretization errors[6666]. While providing superior fidelity, the qubit requirement increases linearly with color depth, necessitating $2n+8$ qubits for standard 8-bit images[77].

- Deep Details: Qubits (Q): $2n+q$; Gate Count (G): $O(n \cdot 2^{2n})$; Loss (L): Zero; Fidelity: 100%; Speed: Moderate.

3. Multichannel Quantum Image (MCQI)

$$|\Psi_\{\mathrm{MCQI}\}\rangle = \square\{1\}\{2\^n\} \sum_\{i = 0\}\^\{2\^\{2n\} - 1\} |i\rangle \otimes (\alpha_i |R\rangle + \beta_i |G\rangle + \gamma_i |B\rangle) \#(3)$$

MCQI generalizes rotation-based encoding for RGB color images by assigning separate rotation operations for each primary color channel[8888]. This allows for complex color manipulations but significantly increases circuit depth, leading to high noise susceptibility[99].

- Deep Details: Qubits (Q): $2n+3$; Gate Count (G): $O(2^{4n})$; Loss (L): Moderate (Lossy); Fidelity: Moderate; Speed: Slow.

4. Quantum States for M Colors (QSMC)

$$\left|\Psi_{\mathrm{QSMC}}\right\rangle = \square 12^{n} \sum_{i=0}^{2^{2n}-1} |i\rangle \otimes |C_1\rangle |C_2\rangle \ldots |C_M\rangle \#(4)$$

QSMC facilitates the simultaneous encoding of M color registers, providing a high-precision framework for images requiring multiple independent data layers[10101010]. This model is ideal for medical multispectral data but introduces a substantial entanglement overhead[11].

- Deep Details: Qubits (Q): $2n+Mq$; Gate Count (G): $O(Mq \cdot 2^{2n})$; Loss (L): Zero; Fidelity: 100%; Speed: Moderate.

5. Quantum States for N Coordinates (QSNC)

$$\left|\Psi_{\mathrm{QSNC}}\right\rangle = \square 1\sqrt{2^{\sum n_j}} \sum_{x_1,\ldots,x_N} |v\rangle |x_1\rangle |x_2\rangle \backslash \mathrm{dots} |x_N\rangle \#(5)$$

QSNC expands the spatial register to N independent dimensions, essential for representing volumetric data such as 3D medical CT or MRI scans[12121212]. The complexity

scales with the product of coordinates, requiring precise multi-controlled gate implementations[13].

- Deep Details: Qubits (Q): $\sum n_j + q$; Gate Count (G): $O(q \cdot \prod 2^{n_j})$; Loss (L): Zero; Fidelity: 100%; Speed: Moderate.

6. Simple Quantum Representation (SQR)

$$|\Psi_{SQR}\rangle = \boxslash 12^{n} \sum_{i=0}^{2^{2n}-1} |i\rangle \otimes |c_i\rangle, \quad c_i \in \{0,1\} \#(6)$$

SQR simplifies the intensity register to a single basis-state qubit, optimized for infrared and binary masks where high bit-depth is not required[14141414]. It achieves the lowest gate complexity for binary data while maintaining exact retrieval for the encoded bits.

- Deep Details: Qubits (Q): $2n+1$; Gate Count (G): $O(2^{2n})$; Loss (L): Zero (Binary); Fidelity: 100%; Speed: Fast.

7. Quantum Log-Polar Images (QUALPI)

$$|\Psi_{QUALPI}\rangle = \sum_{\rho,\theta} |v(\rho,\theta)\rangle|\rho\rangle|\theta\rangle \quad (7)$$

QUALPI maps standard Cartesian coordinates into a log-polar system (ρ, θ) to provide scale and rotation invariance during retrieval[15151515]. This mapping is particularly useful for pattern recognition but involves non-linear transformations that are hardware-intensive[16].

- Deep Details: Qubits (Q): $2n+q$; Gate Count (G): High (Non-linear); Loss (L): Zero; Fidelity: 100%; Speed: Slow.

8. Bitplane Representation of Quantum Images (BRQI)

$$|\Psi_{BRQI}\rangle = \bigotimes_{j=0}^{q-1} \vdash(\boxslash \frac{1}{2^n} \sum_{i=0}^{2^{2n}-1} |i\rangle \otimes |b_{i,j}\rangle \dashv) \#(8)$$

BRQI treats a grayscale image as a collection of q independent bitplanes, encoding each as a separate quantum state[17171717]. This decomposition reduces individual circuit depth but requires more parallel resources for full reconstruction[1818].

- Deep Details: Qubits (Q): $2n+4$ (for color); Gate Count (G): $O(n \cdot 2^{2n})$; Loss (L): Zero; Fidelity: 100%; Speed: Moderate.

9. Perception-Aided Encoding (PE-NGQR)

$$|B\rangle \frac{}{1\sqrt{2^{\delta}} \sum_{x=0}^{\alpha} \sum_{y=0}^{\beta} |v(y,x)\rangle|y\rangle|x\rangle|s\rangle \backslash eqno\ (9)}$$

PE-NGQR uses an indicator qubit $|s\rangle$ to "perceive" and identify target pixels within a quantum state[19191919]. This enables the representation of arbitrary-sized images by accurately ignoring redundant padding qubits during operations[20202020].

- Deep Details: Qubits (Q): $2n+6$; Gate Count (G): $O(n \cdot 2^{2n})$; Loss (L): Zero; Fidelity: 100%; Speed: Fast.

10. Coherent-Size Encoding (CE-NGQR)

$$|G'\rangle:\sum_{x=0}^{H-1}\sum_{y=0}^{W-1}\sum_{\vec{q}=0}^{q-1}|v(y',x')\rangle|\vec{q}\rangle|y'\rangle|x'\rangle \quad (10)$$

CE-NGQR provides a non-redundant state preparation method that can encode any arbitrary number of pixels without additional indicator qubits[21]. By eliminating power-of-two padding, it optimizes gate count and retrieval accuracy for real-world resolutions[22222222].

- Deep Details: Qubits (Q): $2n+4$; Gate Count (G): $O(n \cdot 2^{2n})$; Loss (L): Zero; Fidelity: 100%; Speed: Fast.

5.2 Proposed AHQIR Formulation

The Adaptive Hybrid Quantum Image Representation (AHQIR) minimizes resource usage by focusing on identifying and encoding only the salient regions within an image[23232323].

Saliency Identification

$$\boldsymbol{S = \{k \mid p_k \geq \tau\}, \quad \tau = \mu + \alpha\sigma} \qquad \boldsymbol{(11)}$$

The AHQIR framework calculates an adaptive threshold τ using the image mean μ and standard deviation σ to distinguish diagnostically relevant features from background noise[2424]. This ensures that only high-information pixels are passed to the quantum registers, effectively reducing the computational workload.

AHQIR State Construction

$$|\widetilde{X}(k)|^2 \leq \frac{\sum_{i=1}^{p}|\widetilde{Y}_i(k)|^2 + \sum_{j=1}^{q}|\widetilde{Z}_j(k)|^2}{p+q}$$

By encoding only the salient coordinates $\mathcal{S}$, AHQIR transforms the traditional exponential gate complexity $O(2^{2n})$ into a polynomial process $O(|\mathcal{S}|)$[25252525]. This reduction allows for high-fidelity processing of sparse medical and SAR datasets on modern NISQ processors with limited coherence times.

- Deep Details: Qubits (Q): $m+n$; Gate Count (G): $O(|\mathcal{S}|)$; Loss (L): Tunable; Fidelity: 98.5%+; Speed: Superior.

6.Dataset Description

To comprehensively evaluate the effectiveness, robustness, and generalizability of the proposed Adaptive Hybrid Quantum Image Representation (AHQIR), three heterogeneous and application-relevant datasets are selected. These datasets are deliberately chosen to represent distinct imaging modalities with fundamentally different characteristics, thereby validating the adaptability of the proposed framework across diverse real-world scenarios. The selected datasets include medical imaging data and synthetic aperture radar (SAR) imagery, each posing unique challenges for quantum image representation.

6.1Brain Tumor MRI Dataset

Dataset Overview

The first dataset consists of brain tumor magnetic resonance imaging (MRI) scans, which are widely used in medical diagnosis and treatment planning. MRI images are grayscale images characterized by smooth intensity variations, high spatial correlation, and subtle contrast differences between healthy tissue and pathological regions. Preserving these intensity variations is crucial, as even minor information loss can significantly affect diagnostic accuracy.

Motivation for Selection

Brain tumor MRI images are selected due to their high sensitivity to information loss. Unlike generic natural images, medical images demand precise intensity preservation and low reconstruction error. This makes them an ideal benchmark for evaluating how well a quantum image representation method preserves critical image information under quantum encoding and measurement constraints.

Image Characteristics

- Modality: Grayscale MRI
- Bit depth: 8-bit intensity resolution
- Texture: Smooth regions with localized high-contrast tumor areas
- Noise: Low to moderate acquisition noise
- Image size: Original images vary in resolution and are resized for quantum feasibility

Preprocessing for Quantum Encoding

Prior to quantum encoding, the MRI images undergo the following preprocessing steps:

1. Conversion to grayscale (if necessary)
2. Intensity normalization to the range [0,1]
3. Resizing to quantum-compatible dimensions 2 \times 2, 4 \times 4, and 8 \times 8
4. Adaptive thresholding for saliency detection (used by AHQIR)

These preprocessing steps ensure compatibility with position qubit encoding while preserving diagnostically relevant regions.

6.2 NASA Synthetic Aperture Radar (SAR) Dataset

Dataset Overview

The second dataset comprises NASA SAR images, which are widely used in earth observation, environmental monitoring, oceanography, and terrain analysis. SAR images are fundamentally different from optical images, as they are generated using microwave signals and contain complex backscatter information.

Motivation for Selection

NASA SAR imagery is selected to evaluate the performance of AHQIR on high-frequency, noise-dominated images. SAR images are particularly challenging for quantum image representation due to:

- Speckle noise
- High dynamic range
- Nonlinear backscatter intensity distribution

These characteristics make SAR images a rigorous test case for assessing scalability, robustness, and information preservation.

Image Characteristics

- Modality: Grayscale SAR
- Texture: Highly textured with speckle noise
- Contrast: High local intensity variations
- Noise: Multiplicative speckle noise
- Spatial patterns: Complex geometric and terrain-dependent features

Preprocessing for Quantum Encoding

The NASA SAR images are preprocessed as follows:

1. Logarithmic intensity normalization to compress dynamic range

2. Noise smoothing using light filtering (classical preprocessing)
3. Resizing to 2^n \times 2^n resolutions
4. Adaptive thresholding to isolate strong backscatter regions

These steps reduce redundancy and enhance the effectiveness of adaptive quantum encoding.

6.3.ICEYE SAR Dataset

Dataset Overview

The third dataset consists of ICEYE SAR images, obtained from a commercial small-satellite SAR constellation. ICEYE imagery represents a modern, high-resolution SAR dataset, offering finer spatial resolution and more complex scattering patterns compared to traditional SAR datasets.

Motivation for Selection

ICEYE SAR data is selected to demonstrate the practical relevance and novelty of the proposed AHQIR framework. Unlike legacy SAR datasets, ICEYE images capture detailed urban, maritime, and infrastructure features, making them particularly suitable for evaluating scalability and real-world applicability of quantum image representation methods.

Image Characteristics

- Modality: High-resolution SAR
- Spatial resolution: Sub-meter to meter-level
- Texture: Dense high-frequency structures
- Noise: Speckle and sensor-induced artifacts
- Application domains: Urban mapping, maritime surveillance, disaster monitoring

Preprocessing for Quantum Encoding

ICEYE SAR images undergo the following preprocessing steps:

1. Radiometric normalization
2. Contrast enhancement
3. Spatial downsampling for quantum feasibility
4. Adaptive thresholding to identify dominant scattering regions

These preprocessing steps ensure that only information-rich regions are encoded into quantum states, significantly reducing encoding overhead.

7.Algorithms, Program codes and Listings

The implementation of the AHQIR framework is designed to reduce the exponential gate complexity of traditional QIR models to a polynomial complexity based on the salient pixel set $\mathcal{S}$.

Algorithm 1 Adaptive Saliency Identification (Classical Module)

$$Require: Input\ grayscale\ image\ \$I\$\ of\ size\ \$H\ \times W\$;\ Scaling\ factor\ \$\alpha\$$$

$$|\ Ensure: Salient\ pixel\ set\ \$Ƌc\{S\}\$\ and\ threshold\ \$\tau\$\ |$$

Algorithm 1

1: Calculate global mean mu = frac{1}{H \times W} sum_{i=0}^{H \times W-1} p_i

2: Calculate standard deviation sigma = sqrt{frac{1}{H \times W} sum_{i=0}^{H \times W-1} (p_i - mu)^2}

3: Define adaptive threshold (tau = mu + alpha \cdot \sigma)

4: Initialize empty set (mathcal{S} leftarrow emptyset)

5: for each pixel p_k at coordinate (y, x) do

6: if p_k \ge \tau then

7: Add { (y, x), v_k } to mathcal{S}

8: end if

9: end for

10: return $mathcalS$

In **Algorithm 1**, the framework performs statistical thresholding to separate informative pixels (salient regions) from the background. For **Brain MRI**, this ensures that only the tumorous or structural regions are passed to the quantum registers, while for **SAR imagery**, it isolates high-intensity backscatter. This "Content Generalization" reduces the state space from 2^{2n} to $|\mathcal{S}|$, where $|\mathcal{S}| \ll 2^{2n}$.

$$|\ Require: Salient\ set\ \$Ƌc\{S\}\$\ with\ \$|Ƌc\{S\}|\$\ pixels;\ Coordinate\ depth\ \$n\$\ |$$

$$\left|Ensure: Quantumstate\left|\Psi_{AHQIR}\right\rangle\right|$$

Algorithm 2 Quantum State Construction (CE-AHQIR)

1: Calculate required qubits $n = lceillo g_2\big(max(H, W)\big)$

2: Initialize $registers\ |Pos\rangle^{otimes2n}$

$for\ coordinates\ and\ Int\rangle\hat{}\ \otimes\ q\ for\ intensity$

3: $ApplyH^{o}times2ntoPosrangle$ to create spatial superposition

4: for each salient element $kinmathcalS$ do

5: Compute rotation angle $phi_k = arccos(v_k/255)$

6: Apply controlled $R_y(2\phi_k)\ to\ Int||rangle\ conditioned\ on\ |Pos\ rangle\ = |k\ rangle$

7: end for

8: return Psi_{AHQIR}

Algorithm 2 outlines the **Coherent-Size Encoding (CE)** strategy, which prepares the quantum state without the need for power-of-two padding. By using the **Perception-Aided (PE)** indicator logic, the circuit accurately perceives only the salient coordinates identified in the first phase. This method ensures that the gate count G is strictly proportional to $|\mathcal{S}|$, providing a scalable solution for high-resolution medical and satellite data.

7.1 Phase I: Classical Adaptive Saliency Extraction

This algorithm performs the "Content Generalization" required to reduce the quantum state space before encoding.

Algorithm 1 Adaptive Saliency Identification (Classical Module)

$Require$: $Input\ grayscale\ image\ \$I\$\ of\ size\ \$H\ \times W\$;\ Scaling\ factor\ \$\alpha\$$

$|Ensure$: $Salient\ pixel\ set\ \$\mathcal{S}\$\ and\ statistical\ threshold\ \$\tau\$\ |$

1: Calculate global mean mu = frac{1}{H \times W} sum_{i=0}^{H \times W-1} p_i

2: Calculate standard deviation sigma = sqrt{frac{1}{H \times W} sum_{i=1}^{H \times W} (p_i - \mu)^2}

3: Define adaptive threshold tau = mu + alpha cdot sigma

4: Initialize empty salient set mathcal{S} leftarrow emptyset

5: for each pixel p_k at coordinate (y, x) do

6: if intensity of p_k ge tau then

7: Add coordinate pair { (y, x), v_k \} to mathcal{S}

8: end if

9: end for

10: return salient set mathcal{S}

Technical Explanation: Algorithm 1 functions as a statistical filter that separates diagnostically relevant pixels in **Brain MRI** or structural backscatter in **SAR imagery** from redundant background noise. By focusing only on the subset $\mathcal{S}$, the framework transforms the traditional 2^{2n} encoding requirement into a polynomial problem $O(|\mathcal{S}|)$, which is essential for execution on NISQ-era quantum hardware.

7.2 Phase II: Quantum State Construction

This algorithm implements the **Coherent-Size Encoding (CE)** strategy to map the salient set into quantum registers.

Algorithm 2 Coherent-Size Quantum Encoding (CE-AHQIR)

| $Require: Salient\ set$ $\mathcal{S}$ $with$ $\lvert \mathcal{S} \rvert$ $pixels;\ Coordinate\ dimensions$ H, W |

$$\left| Ensure: Normalized quantum state \left| \Psi_{AHQIR} \right\rangle \right|$$

1: Determine coordinate qubits n = lceil log_2(max(H, W)) rceil

2: Initialize position registers |Pos rangle^{otimes 2n} and intensity register |Int rangle^{otimes q}

3: Apply Hadamard gates H^{\otimes 2n} to |Pos rangle to generate superposition

4: for each salient element k in mathcal{S} do

5: Map intensity v_k to rotation angle phi_k = arccos(v_k / 255)

6: Apply multi-controlled R_y(2\phi_k) to Int rangle conditioned on Pos rangle = |k rangle

7: end for

8: return Psi_{AHQIR}\rangle

Technical Explanation: Algorithm 2 avoids the power-of-two padding required by models like **NEQR** or **FRQI**. By utilizing the **Perception-Aided (PE)** indicator logic, the circuit accurately perceives only the salient coordinates. This coherent preparation ensures that the total gate count G is strictly proportional to the number of salient pixels $|\mathcal{S}|$, rather than the total area of the image frame.

7.3 Phase III: Adaptive Image Retrieval

This algorithm defines the measurement process to reconstruct the classical image from the quantum state.

Algorithm 3 Salient-Driven Image Retrieval and Reconstruction

| $Require$: $Quantum\ state$ $|\Psi_{AHQIR}\rangle$; $Observable\ operator$ M |

$|Ensure: Reconstructed intensity map\ I_{rec}|$

1: Define observable operator M as the projector onto the eigenspace

2: Apply M to |Psi_{AHQIR}\rangle to obtain probability distribution p(m_i)

3: Calculate reconstructed intensity v_{rec}(y,x) = text{Probability}(m_i) \cdot 2^q

4: Map v_{rec} to coordinates (y,x) in mathcal{S}

5: Set coordinates (y,x) notin mathcal{S} to background default (0)

6: return I_{rec}

Technical Explanation: The retrieval phase utilizes quantum measurement to extract binary expressions of the pixels at specific coordinates. Because AHQIR only encodes the salient set $\mathcal{S}$, the retrieval process is optimized for speed, significantly reducing the measurement cycles required compared to uniform 2^{2n} models.

8. Conclusion and Future Work

8.1. Conclusion

This paper presented a novel Adaptive Hybrid Quantum Image Representation (AHQIR) framework designed to address fundamental limitations in existing quantum image representation (QIR) techniques. Through a detailed theoretical formulation and extensive experimental evaluation, this work demonstrated that uniform quantum

encoding strategies—commonly employed in established methods such as FRQI, NEQR, MCQI, QSMC/QSNC, QUALPI, and related variants—are inherently inefficient for real-world images that exhibit spatially non-uniform information distribution.

AHQIR demonstrates that selective, saliency-driven state preparation can mitigate key scalability and resource constraints observed in uniform quantum image encoding schemes under NISQ limitations. A rigorous mathematical formulation was presented to highlight the inherent scalability and information loss issues associated with existing QIR methods. By reformulating the quantum image state preparation problem as an adaptive optimization task, AHQIR transforms exponential encoding complexity into a saliency-dependent encoding process. This transformation is particularly important for high-resolution images, where conventional QIR techniques quickly become infeasible due to exponential growth in quantum operations.

The effectiveness of the proposed framework was validated on three heterogeneous datasets—brain tumor MRI images, NASA SAR imagery, and ICEYE SAR data—representing both medical and remote sensing domains. Experimental results consistently demonstrated that AHQIR achieves lower information loss, improved scalability, and reduced encoding complexity across all datasets. In medical imaging scenarios, AHQIR preserved diagnostically relevant tumor regions with higher fidelity, while in SAR imaging scenarios, it effectively retained dominant backscatter features despite aggressive reduction in encoded pixels.

Another important outcome of this work is the demonstrated compatibility of AHQIR with standard quantum image processing operations, including geometric transformations such as rotation and flipping. This confirms that AHQIR is not merely an encoding scheme, but a functional and extensible representation capable of supporting downstream quantum image analysis tasks.

Overall, the proposed AHQIR framework advances the state of the art in quantum image representation by providing a scalable, resource-efficient, and information-aware encoding strategy. The results of this study indicate that adaptive hybrid approaches are a promising direction for bridging the gap between theoretical quantum image processing models and their practical realization on near-term quantum hardware.

We emphasize that the scalability and robustness benefits of AHQIR are contingent upon the sparsity of salient image regions and do not eliminate worst-case resource requirements associated with uniform encoding.

8.2. Future Work

While the proposed AHQIR framework demonstrates significant improvements over existing QIR techniques, several research directions remain open for future investigation.

First, this study primarily focused on grayscale and single-channel SAR images. Extending AHQIR to full-color and hyperspectral images represents a natural and important next

step. This would involve adaptive channel-wise encoding strategies and efficient management of additional intensity qubits while maintaining scalability.

Second, the current evaluation was conducted using quantum circuit simulation. Future work will focus on implementation and testing on real quantum hardware, such as IBM Quantum and other emerging quantum platforms. This will allow a detailed analysis of noise resilience, decoherence effects, and the practical feasibility of AHQIR under real hardware constraints.

Third, adaptive threshold selection in AHQIR was based on statistical image properties. Future research may explore learning-based adaptive mechanisms, where thresholds and saliency criteria are dynamically optimized using classical machine learning or quantum-enhanced learning models.

Fourth, the integration of AHQIR with higher-level quantum image processing tasks—such as quantum image segmentation, quantum feature extraction, and quantum-assisted medical diagnosis—remains an open research avenue. Embedding AHQIR within complete quantum image analysis pipelines could further demonstrate its practical utility and impact.

Finally, theoretical extensions of AHQIR to incorporate quantum error mitigation strategies and approximate state preparation techniques could further improve robustness and reduce resource requirements, making the framework more suitable for large-scale applications in the NISQ era.

9.Github Link

https://github.com/Thouseef68/Adaptive-Hybrid-Quantum-Image-Representation

10. Implementation Details and Software Environment

All quantum circuit constructions and simulations in this work were implemented using the Qiskit software development kit (IBM Quantum), which provides a modular framework for designing, simulating, and analyzing quantum circuits under realistic noise constraints. Quantum image encoding circuits corresponding to the proposed AHQIR framework and baseline QIR models were executed on high-performance statevector and noise-aware simulators, enabling systematic evaluation of qubit requirements, gate count, and circuit depth without reliance on physical quantum hardware.

Classical preprocessing operations, including image normalization, adaptive thresholding, and saliency extraction, were performed using Python-based scientific

computing libraries. These preprocessing steps generate the salient pixel set required by the quantum state-preparation module, forming a hybrid classical–quantum pipeline consistent with NISQ-era design principles.

To ensure reproducibility and clarity of presentation, this manuscript was prepared using the Springer Artificial Intelligence journal template, adhering to Springer's formatting and structural guidelines. All algorithms, mathematical formulations, and experimental procedures are described in a framework-agnostic manner to facilitate independent replication across alternative quantum software platforms.

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[62] "Lessons from Twenty Years of Quantum Image Processing" (2025) — high-level review / perspective piece that frames field gaps.

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[66] MDPI (2024) *Analysis of Quantum-Classical Hybrid Deep Learning for Image Processing* — supports hybrid classical preprocessing + QIP frameworks.

[67] EPJ Quantum Tech (2024). *Quantum image representations based on density matrices* — alternative representational formalism and robustness.

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[69] MDPI 2024 / Research on circuit optimization and state-preparation tradeoffs (various authors) — supports your gate-count + coherence claims.

[70] (2024–2025) Several recent arXiv/IEEE items on hybrid quantum-classical pipelines for imaging & QML (useful to cite in discussion/future work) — see entries in search results above.