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Implementation of Quantum Image Representation Technique Using Different Tools and Environment

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Abstract*— Quantum image representation provides the foundation for storing, processing, and retrieving images on quantum computers by exploiting quantum parallelism and superposition. Several techniques have been proposed, each with distinct trade-offs in qubit cost, retrieval accuracy, and circuit complexity. The Flexible Representation of Quantum Images (FRQI) pioneered angle-based encoding, offering compact qubit usage and efficient global operations, though limited by probabilistic intensity retrieval and costly multi-controlled rotations. The Novel Enhanced Quantum Representation (NEQR) improved precision by encoding pixel values directly in computational basis states, enabling exact retrieval at the expense of higher qubit requirements. Building on these, the Generalized Quantum Image Representation (GQIR) extended encoding to arbitrary dimensions and color images, while the Multi-channel Quantum Image Representation (MCQI) addressed multi-channel data such as RGB. Other approaches include the Qubit Lattice Representation (QLR), which directly maps pixels to qubits but is highly resource-intensive, and umbrella Quantum Image Representation (QIR) frameworks that laid the groundwork for later refinements. Optimizations such as Enhanced FRQI (EFRQI) and Improved QIR (IQIR) reduce circuit complexity or balance angle-based and bit-based methods, while the Two-Dimensional Quantum State with Normalized Amplitude (2D-QSNA) achieves extreme qubit efficiency through amplitude encoding but suffers from nondeterministic retrieval. Domain-specific extensions, such as the Quantum Representation of Multi-Wavelength Images (QRMW), enable hyperspectral and multispectral image processing, while the Normal Arbitrary Superposition State (NASS) method provides a theoretical basis for generalized superposition-based encoding. Finally, hybrid approaches including angle bit trade-offs, block-based representations, and compressed encodings seek to combine the strengths of multiple methods for more practical implementations. Together, these representations highlight the evolution of quantum image models from compact theoretical constructs to more versatile and application-specific frameworks, while also underscoring the ongoing challenges of scalability, retrieval fidelity, and resource efficiency. In this we used Microsoft Quantum Development Tool Kit to represent the image in quantum environment.

Keywords*— Circuits encoding, gates, quantum computing, Image representation, superposition.

I. INTRODUCTION

In today's world, visual data plays a dominant role in automation, artificial intelligence, and decision-making. Every day, billions of images and videos are captured through smartphones, surveillance systems, and IoT devices. Extracting meaningful information from this visual data is a key challenge in the field of computer vision. One of the most significant and widely researched areas in computer vision is object detection the task of identifying and localizing objects within images or videos. Object detection serves as the foundation for numerous intelligent applications such as autonomous driving, industrial inspection, healthcare imaging, robotics, and smart surveillance. Earlier methods for object detection relied on traditional image-processing techniques such as Haar Cascades, HOG (Histogram of Oriented Gradients), and SIFT (Scale-Invariant Feature Transform). While these techniques provided basic localization capabilities, they struggled to handle complex environments, occlusions, varying lighting conditions, and multi-class recognition. The rise of deep learning and particularly Convolutional Neural Networks (CNNs) has transformed this field, allowing systems to automatically learn hierarchical features from data without the need for manual feature extraction. Models like YOLO (You Only Look Once), SSD (Single Shot Multibox Detector), and Faster R-CNN have revolutionized real-time detection by providing high accuracy and efficient inference speeds [1-4].

The rapid development of hardware accelerators (GPUs and TPUs) and deep learning frameworks like Tensor Flow, PyTorch, and OpenCV DNN modules has made it feasible to perform real-time object detection even on edge devices. This progress has opened doors to advanced applications such as real-time traffic monitoring, human behavior recognition, unmanned aerial vehicle (UAV) tracking, and smart security systems. However, despite these advancements, achieving an optimal balance between speed, accuracy, and computational cost remains a major research challenge.

This thesis focuses on developing a real-time object detection and labelling system that uses deep learning models to analyse live camera feeds. The proposed system captures continuous video frames, performs pre-processing operations, and detects multiple object classes using pertained models such as YOLOv8. The detected objects are then labelled with bounding boxes and confidence scores and displayed in real-time on the user interface. The implementation combines the OpenCV library for video capture and visualization with deep learning inference

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through tensor Flow or PyTorch frameworks.

The ultimate goal of this project is to bridge the gap between academic research and practical deployment by providing a robust, fast, and easily integrable detection system. The system's design ensures scalability for multiple use cases — ranging from automated surveillance and traffic control to industrial automation and human computer interaction. By evaluating and comparing different architectures on metrics like mean Average Precision (mAP), Frames per Second (FPS), and model size, this work contributes to identifying the most suitable model for real-time object recognition tasks. The project also explores potential optimization strategies to deploy the model on edge computing devices such as NVIDIA Jetson Nano and Raspberry Pi, highlighting its relevance to low-power embedded systems Quantum image representation (QIR) seeks encodings that map a classical image into a quantum state so that common vision primitives point wise transforms, geometric operations, and simple filters—admit circuits with favourable depth and parallelism. Among the many schemes in the literature FRQI, NEQR, GQIR, MCQI, QLR, EFRQI, IQIR, 2D- QSNA, QRMW [5-7].

NASS, and various hybrid encodings the central engineering problem is not only what to encode, but how to realize the encoding and downstream transforms as robust Q# programs with tractable gate counts, qubit usage, and testability. This work frames the QIR landscape explicitly through the lens of the Microsoft Quantum Development Kit (QDK), turning abstract definitions into reproducible, resource-estimated circuits. Q# provides first-class support for controlled/adjoint operations, ancilla management, and algorithmic composition, which are exactly the ingredients QIR needs. Coordinate superpositions, multi-controlled writes, and computation are natural to express with scopes and reversible libraries. The QDK stack contributes three pillars:

- Development: Q# language + standard libraries (Microsoft Quantum. Intrinsic, Canon, Arithmetic) for clean encoders and transforms (e.g., adders, comparators, rotation trees).
- Validation: full-state simulators for bit-exact or amplitude-level tests on 24≲20–24 logical qubits; property-based tests via .NET host interop for encode→transform→decode round-trips.
- Planning: the Azure Quantum Resource Estimator, which reports qubits, gate counts, T-count/T-depth, and (when configured) fault-tolerant overheads—essential for comparing schemes fairly.

FRQI encodes intensity as a rotation angle on a single color qubit while coordinates live in basis registers. In Q#, the encoder is a loop over (x, y) patterns that multi-controls an R (PauliY, 2θ) on the color qubit. The performance levers are control synthesis (relative- phase Toffolis, Gray-code patterns), (ii) angle synthesis precision ε which affects T-count, and (iii) oracleization computing θXY on the fly to avoid O(N) literal controls. NEQR writes each pixel's b bits directly into a pixel register via multi-controlled X gates, then uses reversible arithmetic (AdderLE, increment/decrement, saturating ops) for transforms. This yields deterministic retrieval at the cost of more qubits (2n+b) GQIR/MCQI generalize shapes (non-square Nx ×Ny) and channels (RGB, CMYK): in Q# this is a matter of register layout and indexing oracles that map (x, y, channel) into bitplanes or angles, enabling channel-wise or joint operations with structured controls. QRMW (multi-wavelength) extends MCQI to dozens/hundreds of bands; Q# expresses this as additional channel registers plus sparse oracles for spectral neighbourhoods (e.g., band math) to avoid writing every voxel explicitly. 2D-QSNA (amplitude encoding) compiles to state preparation: a rotation tree that loads normalized amplitudes over the coordinate registers. In practice, we use hierarchical R y /R z synthesis with careful computation; this is extremely qubit-light but pushes cost into angle synthesis and readout statistics [8-11].

QLR and NASS are conceptually simple in Q#: either assign qubits per pixel (QLR, qubit- hungry) or invoke generic superposition preparation (NASS). They serve as baselines and stress tests for resource estimators. EFRQI/IQIR/Hybrids (e.g., angle bit mixes, block-wise encoders, and compressed oracles) exploit Q# composition: keep MSB planes as NEQR bits for thresholds/logic, and store residuals as FRQI angles for cheap analog-style global ops reducing both multi-control fan- out and arithmetic depth.

Control management: Multi-controlled rotations dominate FRQI-like costs. Use relative phase Toffoli decompositions and Gray-code control ladders to reduce T-depth; pre- and post bitstring alignment (conditional X) inside within apply avoids large ancilla pools. Ancilla discipline: Prefer localized ancilla with using scopes; aggressively compute. The resource estimator rewards shorter live ranges and reveals hidden ancilla spikes in arithmetic paths. Angle synthesis vs. arithmetic trade-off: FRQI/2D-QSNA push cost into rotation synthesis; NEQR/GQIR push cost into reversible add/sub/compare. Hybrids let you dial the split according to task (e.g., thresholding vs. global tone-mapping). Measurement strategy Deterministic readout (NEQR) simplifies verification; probabilistic readout (FRQI/2D-QSNA) requires shot budgeting and variance analysis. In QDK tests, we use small batched shots to ensure stable PSNR/SSIM estimates. Oracles beat lookups: When pixel values follow a formula or simple texture, compute I(x, y) rather than table-lookup controls. Reversible arithmetic over x, y can cut encode depth by an order of magnitude. Images are among the most pervasive forms of data in science, technology, and everyday life. From medical imaging and satellite monitoring to social media and entertainment, efficient storage and processing of images are essential. As classical computing approaches its physical and architectural

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limits, quantum computing has emerged as a promising paradigm for handling high-dimensional data by exploiting superposition, entanglement, and quantum parallelism. A fundamental requirement in this direction is the development of quantum image representation (QIR) techniques, which encode classical image data into quantum states that can be manipulated and measured on quantum hardware [12-17]. Over the last decade, a variety of QIR models have been proposed, each addressing the trade- off between qubit efficiency, retrieval accuracy, circuit complexity, and applicability. The Flexible Representation of Quantum Images (FRQI) introduced an amplitude- and angle- based approach, where pixel positions are stored in basis states and intensity values are mapped to the rotation of a single color qubit. This yields a compact encoding suitable for global transformations but relies on probabilistic retrieval. In contrast, the Novel Enhanced Quantum Representation (NEQR) encodes pixel intensities directly into computational basis qubits, enabling exact retrieval and deterministic image reconstruction at the cost of larger qubit overhead. Extensions of these foundational models have broadened their scope. The Generalized Quantum Image Representation (GQIR) supports arbitrary image sizes and both grayscale and color encodings, while the Multi-channel Quantum Image Representation (MCQI) is designed for RGB and multi-spectral data. The Qubit Lattice Representation (QLR), although qubit-intensive, provides a direct mapping between pixels and qubits, serving as a conceptual model for intuitive storage. Early umbrella frameworks simply called Quantum Image Representation (QIR) provided the groundwork for subsequent refinements. Optimized variants such as Enhanced FRQI (EFRQI) and Improved QIR (IQIR) reduce the cost of controlled operations and balance between angle-based and bitplane-based encodings. Other approaches focus on qubit economy and theoretical generality. The Two-Dimensional Quantum State with Normalized Amplitude (2D-QSNA) represents images using amplitude encoding with minimal qubits, though at the expense of deterministic measurement. The Quantum Representation of Multi-Wavelength Images (QRMW) targets hyperspectral and multispectral imaging, crucial in domains like remote sensing and biomedicine, while the Normal Arbitrary Superposition State (NASS) provides a general theoretical framework for encoding image data as arbitrary superpositions of basis states. More recently, hybrid approaches including Hybrid Angle–Bit (HAB), block-based methods, and compressed encodings seek practical compromises by combining qubit efficiency with partial deterministic retrieval and reduced circuit complexity [20-23].

II. LITERATURE SURVEY

Jie Su implement paper on image representation in quantum environment in this he focuses on the definition of these quantum image representations the preparation of quantum images and the number of quantum bits required as well as the computational complexity. Then, this paper analyzes, compares and summarizes the similarities and differences between these quantum image representations. Finally, the challenges and future development in the field of quantum image processing are summarized and forecasted. This work will help researchers to understand the advances related to quantum image representations in the field of quantum image processing [1].

Compared with classical image processing, quantum image processing provides a possible solution for faster image processing, which has been widely concerned. Quantum image binarization is a basic operation and plays an important role in image processing. Hence, we proposed an efficient design of quantum image binarization using quantum comparator. To reduce quantum cost and quantum delay, the comparator was optimized by rearranging the quantum gates. Then, a complete circuit implementation of quantum image binarization was designed using the comparator. Furthermore, we analyzed the performance of our design in terms of quantum cost, quantum delay and ancillary bits. Finally, the simulation verifies the correctness of the design [2].

Quantum image processing uses quantum hardware to revolutionize the storage, recovery, processing, and security of quantum images across diverse applications. Although researchers have explored various facets of quantum image processing, a comprehensive systematic literature review encompassing all domains is essential for theoretical and experimental progress. This article aims to bridge this gap by systematically analyzing advancements in this field, drawing insights from a thorough review of 50 research articles published beyond 2003. Our study examines core components of quantum image processing, such as quantum image representations, advanced algorithms, transformative techniques like Quantum Fourier and Wavelet Transforms, and robust security measures. It further explores the synergy between quantum machine learning and image processing for improved classification and recognition. In addition, the study also discusses the limitations of existing research, summarizes its essential aspects, highlights gaps and challenges, and finally, provides recommendations for future research and innovations [3]. Quantum image processing focuses on the use of quantum computing in the field of digital image processing. In the last few years, this technique has emerged since the properties inherent to quantum mechanics would provide the computing power required to solve hard problems much faster than classical computers. Binarization is often recognized to be one of the most important steps in image processing systems. Image binarization consists of converting the digital image into a black and white image, so that the essential properties of the image are preserved. In this paper, we propose a quantum circuit for image binarization based on two novel comparators. These comparators are focused on optimizing the number of T gates needed to build them. The use of T gates is essential for quantum circuits to counteract the effects of internal and external noise. However, these gates are highly expensive, and its slowness also represents a common bottleneck in this type of circuit. The proposed quantum comparators have been compared with other state-of-the-arts comparators. The analysis of the implementations have shown our comparators are the best option when noise is a problem and its reduction is mandatory [4].

Quantum image processing has attracted much attention since it offers a potential solution to efficiently calculate some hard problems much faster than classical image processing. In particular, it is a basic operation to change each image pixel into black or white, named as a binary image. Here we present novel multi-bit quantum comparators to realize quantum image binarization. These comparators compare two quantum logic states and identify which of them is the largest. We analyze the superior performance of our proposed comparators in terms of quantum cost, quantum delay and auxiliary bits compared with the existing comparators. Furthermore, our quantum image binarization exploits the advantages of our proposed multi-bit comparators to change the values of image pixels into 0 or 255 [5]. A hybrid quantum approach to threshold and binarize a grayscale image through unsharp measurements (UM) relying on image histogram. Generally, the histograms are characterized by multiple overlapping normal distributions corresponding to objects, or image features with small but significant overlaps, making it challenging to establish suitable thresholds. The proposed methodology uses peaks of the overlapping Gaussians and the distance between neighboring local minima as the variance, based on which the UM parameters are chosen, that maps the normal distribution into a localized delta function. To demonstrate its efficacy, subsequent implementation is done on noisy quantum environments in Qiskit. This process is iteratively repeated for a multimodal histogram to obtain more thresholds, which are then applied to various life-like pictures to get high-contrast images, resulting in comparable peak signal-to-noise ratio and structural similarity index measure values. The obtained thresholds are used to binarize a grayscale image by using novel enhanced quantum image representation integrated with a threshold encoder and an efficient quantum comparator (QC) that depicts the whole binarized picture. This approach significantly reduces the complexity of the proposed QC and of the whole algorithm when compared to earlier models [6].

A. Amplitude-Based Representations

These methods encode pixel intensity into the probability amplitude of a qubit.

FRQI (Flexible Representation)

FRQI encodes grayscale information into the angle θ of a qubit. For an image of size $2^n \times 2^n$, the state is:

$$|I(\theta)\rangle = \frac{1}{2^n}\sum_{i=0}^{2^{2n}-1}(\cos\theta_i|0\rangle + \sin\theta_i|1\rangle) \otimes |i\rangle \qquad (1)$$

where $\theta_i \in [0, \pi/2]$ represents the normalized pixel intensity. In this expression, the index i runs over all 2^{2n} pixel positions, and the basis state $|i\rangle$ encodes the spatial location of the i-th pixel in binary form using $2n$ qubits. The single-qubit state $(\cos\theta_i|0\rangle + \sin\theta_i|1\rangle)$ attached to each $|i\rangle$ encodes the image intensity at that location via a rotation angle θ_i. Analysis: While Equation 1 shows an efficient use of qubits $(2n+1)$, the retrieval process requires Quantum State Tomography (QST). Since measurements are probabilistic ($\cos^2\theta$), recovering the exact pixel value requires thousands of "shots" (measurements), leading to "blurry" retrieval on noisy hardware [1-3].

MCQI (Multi-Channel)

MCQI extends FRQI to RGB images by adding a channel qubit$|c\rangle$:

$$|I_{MCQI}\rangle = \frac{1}{2^n}\sum_{i=0}^{2^{2n}-1}\sum_{c\in\{R,G,B\}}|C_i^c(\theta)\rangle \otimes |i\rangle \otimes |c\rangle \qquad (2)$$

Here, the additional register $|c\rangle$ encodes the color channel label, typically using an orthonormal basis $\{|R\rangle, |G\rangle, |B\rangle\}$, and $|C_i^c(\theta)\rangle$ denotes the amplitude-encoded state for the intensity of channel c at pixel i. The double summation therefore runs over all spatial positions and all color channels, compactly storing a multi-channel image in a joint amplitude representation [17]

QPIE (Quantum Probability Image Encoding)

QPIE utilizes the probability amplitudes directly. The state is normalized such that $\sum|c_i|^2 = 1$:

$$|I_{QPIE}\rangle = \sum_{i=0}^{N-1} c_i\,|i\rangle \qquad (3)$$

This allows for N pixels to be stored in $\log_2 N$ qubits, offering exponential compression but difficult retrieval ($O(N)$ measurements). In this formulation, the complex coefficients $c_i \in \mathbb{C}$ encode both the magnitude and phase associated with pixel i, and the normalization condition $\sum_{i=0}^{N-1}|c_i|^2 = 1$ guarantees that $|I_{QPIE}\rangle$ is a valid quantum state. Each basis state $|i\rangle$ again corresponds to a specific pixel coordinate in binary form [19].

B. Basis-State Representations

These methods encode pixel values as a sequence of qubits (e.g., $|00000000\rangle$ to $|11111111\rangle$ for 8-bit color). NEQR (Novel Enhanced)

NEQR[14] stores the grayscale value $f(y,x)$ binary string$|C_{YX}\rangle$. It provides perfect retrieval

$$|I_{NEQR}\rangle = \frac{1}{2^n}\sum_{Y=0}^{2^n-1}\sum_{X=0}^{2^n-1}|f(Y,X)\rangle \otimes |YX\rangle \qquad (4)$$

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Here, $|C_{YX}\rangle \equiv |f(Y,X)\rangle$ represents the q -qubit computational basis state matching the binary intensity of pixel(Y,X), while $|YX\rangle$ is a 2n-qubit basis state encoding the vertical and horizontal coordinates. Analysis: Equation 4 utilizes computational basis states ($|0\rangle, |1\rangle$) rather than amplitudes. This allows for deterministic retrieval (one shot gives the exact value). However, the double summation implies that the quantum circuit must explicitly address every pixel coordinate, resulting in a gate complexity of$O(8 \cdot 2^{2n})$, which is computationally prohibitive for NISQ devices [25-28].

INEQR (Improved NEQR)

INEQR optimizes the quantum circuit construction of NEQR but retains the same fundamental state definition. It improves the position preparation using a recursive circuit:

$$|I_{INEQR}\rangle = U_{color} \cdot U_{position}|0\rangle^{\otimes(q+2n)} \tag{5}$$

Here, $U_{position}$ prepares the uniform superposition over all positions in the $(2n)$-qubit register, and U_{color} conditionally writes the intensity values into the q-qubit value register. The initial state $|0\rangle^{\otimes(q+2n)}$ represents a system with all qubits initialized to zero before encoding [30-34].

GQIR (Generalized)

GQIR adapts NEQR for images with arbitrary dimensions $H \times W$, removing the square 2^n restriction:

$$|I_{GQIR}\rangle = \frac{1}{\sqrt{HW}} \sum_{h=0}^{H-1} \sum_{w=0}^{W-1} |C_{hw}\rangle \otimes |h\rangle|w\rangle \tag{6}$$

In this expression, H and W denote the image height and width, respectively, and the factor $1/\sqrt{HW}$ normalizes the superposition across all HW pixel coordinates. The states $|h\rangle$ and $|w\rangle$ encode the row and column indices in binary form using $\lceil \log_2 H \rceil$ and $\lceil \log_2 W \rceil$ qubits [35-38].

C. Specialized & Transform Representations

QLR (Log-Polar)

QLR mimics human vision by mapping Cartesian coordinates (x,y) to Log-Polar coordinates (ρ,ϕ) . This creates a “foveated” image:

$$|I_{QLR}\rangle = \frac{1}{2^n} \sum_{\rho=0}^{2^n-1} \sum_{\phi=0}^{2^n-1} |f(\rho,\phi)\rangle \otimes |\rho\rangle|\phi\rangle \tag{7}$$

Here, ρ indexes radial distance and ϕ indexes angle in the log-polar grid, with each of $|\rho\rangle$ and $|\phi\rangle$ implemented as n-qubit registers. The function $f(\rho,\phi)$ denotes the intensity sampled in log-polar coordinates, emphasizing central or “foveal” regions [39-43].

QRMW (Multi-Wavelength)

QRMW is designed for hyperspectral imaging. It adds a wavelength qubit $|\lambda\rangle$ to the NEQR backbone:

$$|I_{QRMW}\rangle = \frac{1}{\sqrt{L}} \sum_{\lambda=0}^{L-1} \left(\frac{1}{2^n} \sum_{i=0}^{2^{2n}-1} |C_i^{\lambda}\rangle \otimes |i\rangle \right) \otimes |\lambda\rangle \tag{8}$$

In this model, L is the number of spectral bands, and the outer sum over λ creates an equal superposition over all wavelengths. For each fixed λ, the inner sum encodes the spatial distribution of intensities at that wavelength using a NEQR-like structure with values $|C_i^{\lambda}\rangle$ and position states $|i\rangle$[44-48].

DCT-EFRQI

This method encodes the Discrete Cosine Transform coefficients rather than raw pixels to achieve compression:

$$|I_{DCT}\rangle = \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} |Coeff(u,v)\rangle \otimes |u\rangle|v\rangle \tag{9}$$

Here, $Coeff(u,v)$ denotes the DCT coefficient at frequency indices (u,v) , and $|Coeff(u,v)\rangle$ is its binary encoding in a value register. The indices u and v label horizontal and vertical frequency components, and the states $|u\rangle$, $|v\rangle$ form a frequency-domain position register [49].

III. RESEARCH GAP

A. Lack of Practical Hardware implementation

Studies like Jie Su ([1]) mainly focus on: Theoretical definitions Qubit requirements, Computational complexity However Most works are simulation-based Limited validation on real quantum hardware. There is a need for hardware-efficient and experimentally validated quantum image representation and binarization models suitable for NISQ devices [7-9].

B. Lack Trad- off between Quantum cost, Delay and Accuracy

Optimization often comes at the cost of accuracy or robustness, No unified framework balancing all parameters simultaneously, lack of multi-objective optimization frameworks that jointly optimize accuracy, noise resilience, quantum cost, circuit depth inefficient handling of noise. However Noise handling is still partial and circuit-specific No generalized noise-resilient QIR model. Development of robust, noise-tolerant quantum image representations and binarization techniques for real quantum environments. The existing body of research on quantum image representation and binarization, including the work of Jie Su and subsequent studies, demonstrates significant theoretical progress but still reveals several important gaps that limit practical applicability. Most notably, a large portion of the literature focuses on the formal definition of quantum image representations, qubit requirements, and computational complexity, while remaining largely confined to simulation environments. As a result, there is insufficient validation of these models on real quantum hardware, particularly under noisy intermediate-scale quantum (NISQ) conditions. Although several works have proposed optimized quantum circuits for image binarization by reducing quantum cost, gate count, and delay especially through efficient comparator designs and T-gate optimization these improvements are often achieved without fully addressing the trade-offs between computational efficiency, accuracy, and robustness. Consequently, there is a lack of unified frameworks capable of balancing these competing performance metrics [12].

Furthermore, while some studies attempt to incorporate noise-aware techniques and hybrid approaches using platforms such as Qiskit, the handling of noise and decoherence remains limited and highly circuit-specific, lacking a generalized, noise-resilient quantum image representation model. Another critical limitation is that most existing approaches are restricted to grayscale image processing and rely on static or histogram-based thresholding methods, which are not easily extendable to more complex data types such as color images, hyperspectral images, or radar datasets. This indicates a need for more generalized and scalable quantum image models capable of handling high-dimensional and multi-channel data efficiently. In addition, despite efforts to compare and analyze different quantum image representation models, there is still no standardized benchmarking framework or evaluation metric, making it difficult to consistently assess performance across different approaches [13].

Moreover, the integration of security features within quantum image representation remains weak, as most studies treat security mechanisms such as encryption and watermarking as separate layers rather than embedding them within the representation itself. Similarly, although recent surveys highlight the potential synergy between quantum image processing and quantum machine learning, most existing binarization and representation techniques are developed as standalone methods and are not optimized for machine learning tasks such as classification or pattern recognition. Scalability also remains a major concern, as current methods require an increasing number of qubits and complex circuits for higher-resolution images, limiting their feasibility for real-world applications. Additionally, adaptive and intelligent thresholding techniques are still underexplored, with most methods relying on fixed or semi-static approaches that do not perform well in dynamic or noisy environments. Finally, the majority of studies rely on small or synthetic datasets for validation, with limited application to real-world scenarios, thereby restricting their practical impact. Addressing these gaps is essential for advancing quantum image representation from theoretical constructs to robust, scalable, and application-oriented solutions [14].

IV. METHODOLOGY

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The proposed methodology for quantum image representation begins with the acquisition and preprocessing of a classical image, where the input image is first standardized in terms of size, resolution, and format. If required, the image is converted into grayscale or an appropriate multi-channel format depending on the chosen representation model. The pixel intensity values are then normalized to ensure compatibility with quantum state encoding. Following preprocessing, an appropriate quantum image representation model, such as Flexible Representation of Quantum Images (FRQI), Novel Enhanced Quantum Representation (NEQR), or an improved hybrid model, is selected based on the application requirements, including trade-offs between qubit usage, circuit complexity, and information fidelity.

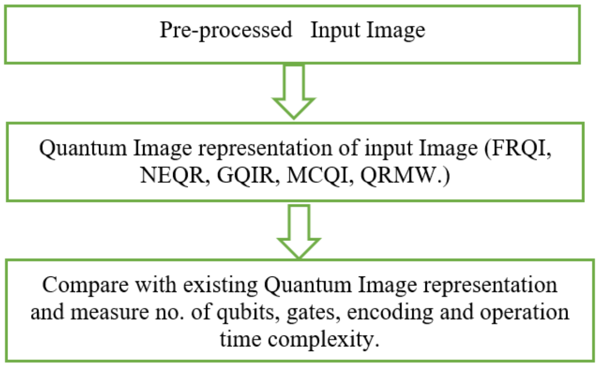

Fig. 1 A Proposed methodology

In the next stage, the classical image data is mapped into a quantum state using a defined encoding strategy. This involves assigning qubits to represent pixel positions and additional qubits to encode pixel intensity values. For instance, position encoding is typically achieved using superposition states, allowing all pixel coordinates to be represented simultaneously, while intensity information is embedded using amplitude encoding or basis encoding depending on the model. Quantum gates such as hadamard gates are applied to initialize superposition, followed by controlled rotation or controlled NOT gates to encode pixel values into the quantum circuit. The preparation of the quantum image state is carefully designed to minimize circuit depth and gate count, ensuring compatibility with noisy intermediate-scale quantum devices.

Once the quantum image is successfully prepared, quantum operations can be applied for further processing, such as image binarization, edge detection, or transformation. In the case of binarization, quantum comparators or thresholding circuits are integrated into the quantum system to distinguish pixel values based on predefined or adaptive thresholds. These operations are implemented using optimized gate structures to reduce quantum cost, delay, and the number of ancillary qubits. If the methodology includes enhancements, hybrid techniques combining classical preprocessing with quantum operations or noise-aware circuit design may be incorporated to improve robustness against decoherence and operational errors. Subsequently, the quantum circuit is simulated and, if feasible, executed on

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real quantum hardware using platforms such as Qiskit. Performance evaluation is carried out using metrics such as quantum cost, circuit depth, gate count, and number of qubits, along with classical image quality metrics like Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) to assess the fidelity of the reconstructed image. Comparative analysis with existing quantum image representation methods is performed to validate improvements in efficiency, scalability, and robustness.

Finally, the methodology includes an analysis of scalability and adaptability, examining how the proposed representation performs with increasing image sizes and under noisy quantum conditions. This step also evaluates the potential integration of the representation with advanced applications such as quantum machine learning, secure image processing, or domain-specific use cases like radar image analysis. Through this structured approach, the methodology aims to develop an efficient, scalable, and noise-resilient quantum image representation framework suitable for practical quantum computing environments.

V. DATASET DESCRIPTION

The dataset used for the implementation of the quantum image representation framework consists of both standard benchmark images and publicly available real-world datasets to ensure comprehensive evaluation. Initially, commonly used grayscale benchmark images such as Lena, Cameraman, and Peppers are selected due to their diverse texture, contrast, and structural details, which are useful for validating encoding accuracy and binarization performance. In addition to these, images are also taken from widely recognized datasets like MNIST and CIFAR-10 to test the scalability and robustness of the proposed quantum representation on real-world data. Since quantum computing systems have limitations in terms of available qubits, all images are resized to dimensions of $2^n \times 2^n$, such as 8×8 or 16×16, making them suitable for quantum encoding schemes [10].

For experiments involving grayscale processing, color images from the CIFAR-10 dataset are converted into grayscale using standard luminance conversion methods before being encoded into quantum states. The pixel intensity values are normalized to ensure compatibility with the chosen quantum image representation model. In the case of binarization, threshold values are determined using classical preprocessing techniques such as histogram analysis, which are then applied within the quantum circuit. To further analyze the robustness of the approach, noise is artificially introduced into selected images to simulate real-world imperfections and quantum noise effects.

The dataset is processed in small batches due to computational and hardware constraints, and each image is individually encoded, processed, and reconstructed. The performance of the proposed method is evaluated using both visual inspection and quantitative metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM). This combination of standard benchmark images and real-world datasets ensures that the proposed quantum image representation framework is evaluated for accuracy, efficiency, and scalability under practical conditions.

VI. RESULTS AND DISCUSSION

The implemented of this technique shows following result after successful execution. The comparative table and charts showing the qubits required and encoding complexity of the different quantum image representation techniques for a sample case of a 16×16 image (n=4, b=8-bit grayscale, k=10 spectral bands).

The table lists numerical values for qubit usage and relative encoding operations.

- The first chart compares the qubits needed by each method.
- The second chart shows encoding complexity on a logarithmic scale, making it easier to see differences.

Table I. Comparative analysis of quantum image representation techniques

Method	Qubits	Encoding Time Complexity	Operation Time Complexity	Remarks
FRQI	2n +1	$O(2^{2n})$ (multi-controlled rotations for each pixel)	O(1) for global ops on color qubit	Very compact encoding; probabilistic retrieval; costly Preparation.
NEQR	2n +1 b is bit depth	$O(2^{2n})$ (multi-controlled NOTs per pixel)	O(poly(b)) for arithmetic ops	Deterministic retrieval; more qubits than FRQI.
GQIR	$n_x + n_y$ +b	O(Nx·Ny)	O(poly(b))	Extension of NEQR to non-square/color Images.
MCQI	2n+ (RGB channels)	$O(3.\ 2^{2n})$	O(poly(b))	Parallel color channel manipulation; higher qubit cost.

Method	Qubits	Encoding Time Complexity	Operation Time Complexity	Remarks
QLR	N^2 (one qubit per pixel)	O(1) (direct mapping)	O(1) per qubit	Simple & intuitive; impractical due to exponential Qubits.
EFRQI	2n+ 1	O(22n-1) (optimized rotations)	O(1)	Improves FRQI prep cost; retrieval still Probabilistic.
IQIR	Between FRQI & NEQR 2n+b/2	$O(2^{2n})$ (hybrid prep)	Mixed: rotations + arithmetic	Hybrid of FRQI & NEQR; balances cost & retrieval accuracy.
2D-QSNA	2n	O(22n-1) (state preparation)	O(1) for global ops	Extremely qubit-efficient; retrieval highly Probabilistic.
QRM W	2n+ k (k=spectr al bands)	$O(k\cdot 2^{2n})$	O(poly(k))	Good for satellite/medical imaging; qubit cost grows with Channels.
NASS	2n	$O(2^{2n})$	Depends on superposition prep	General theoretical framework; not practical.

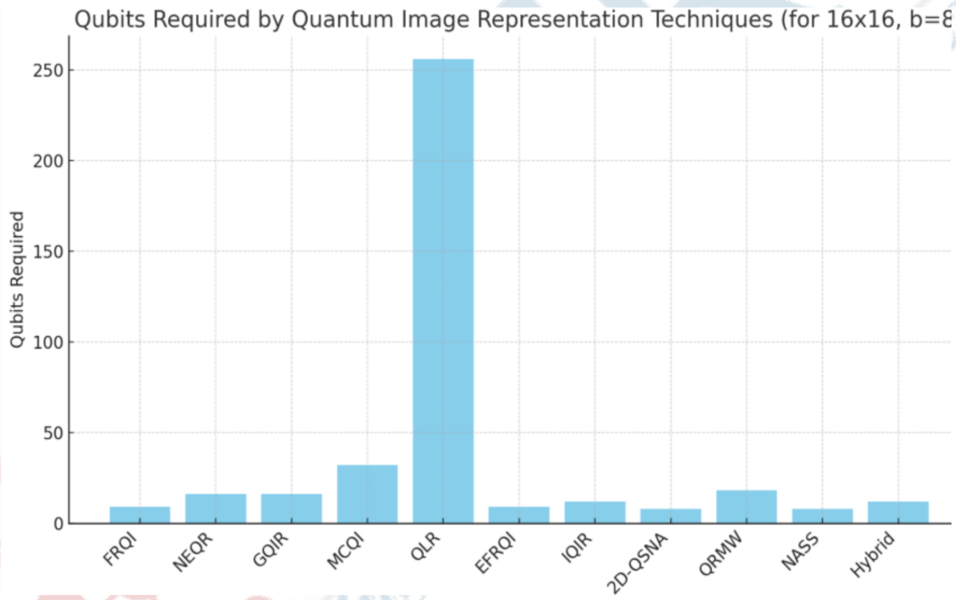
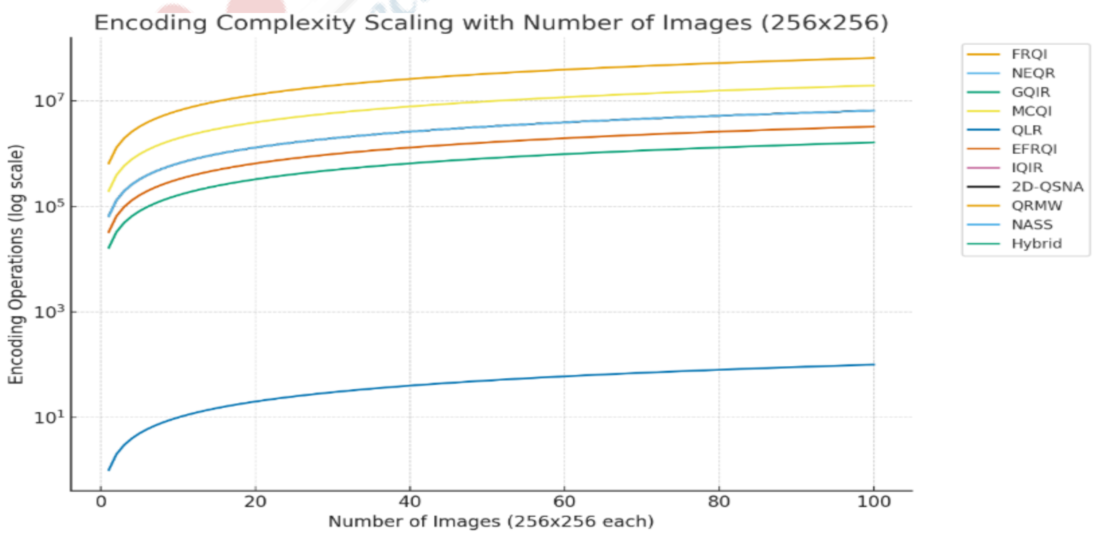


Fig. 2 Number of Qubits for 16 ×16 images



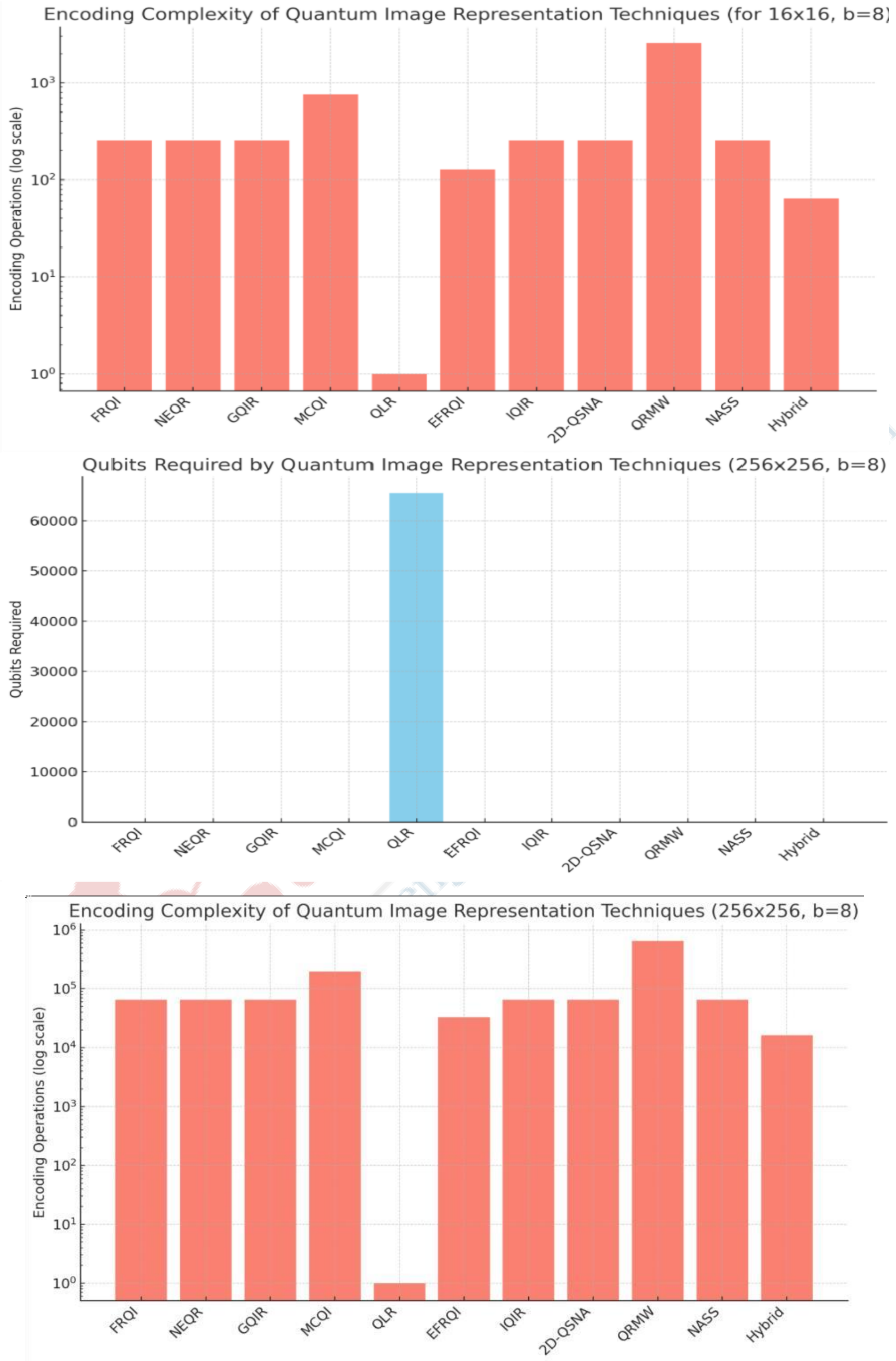


Fig. 3 Encoding Complexity for 16 ×16 and 256 × 256 images

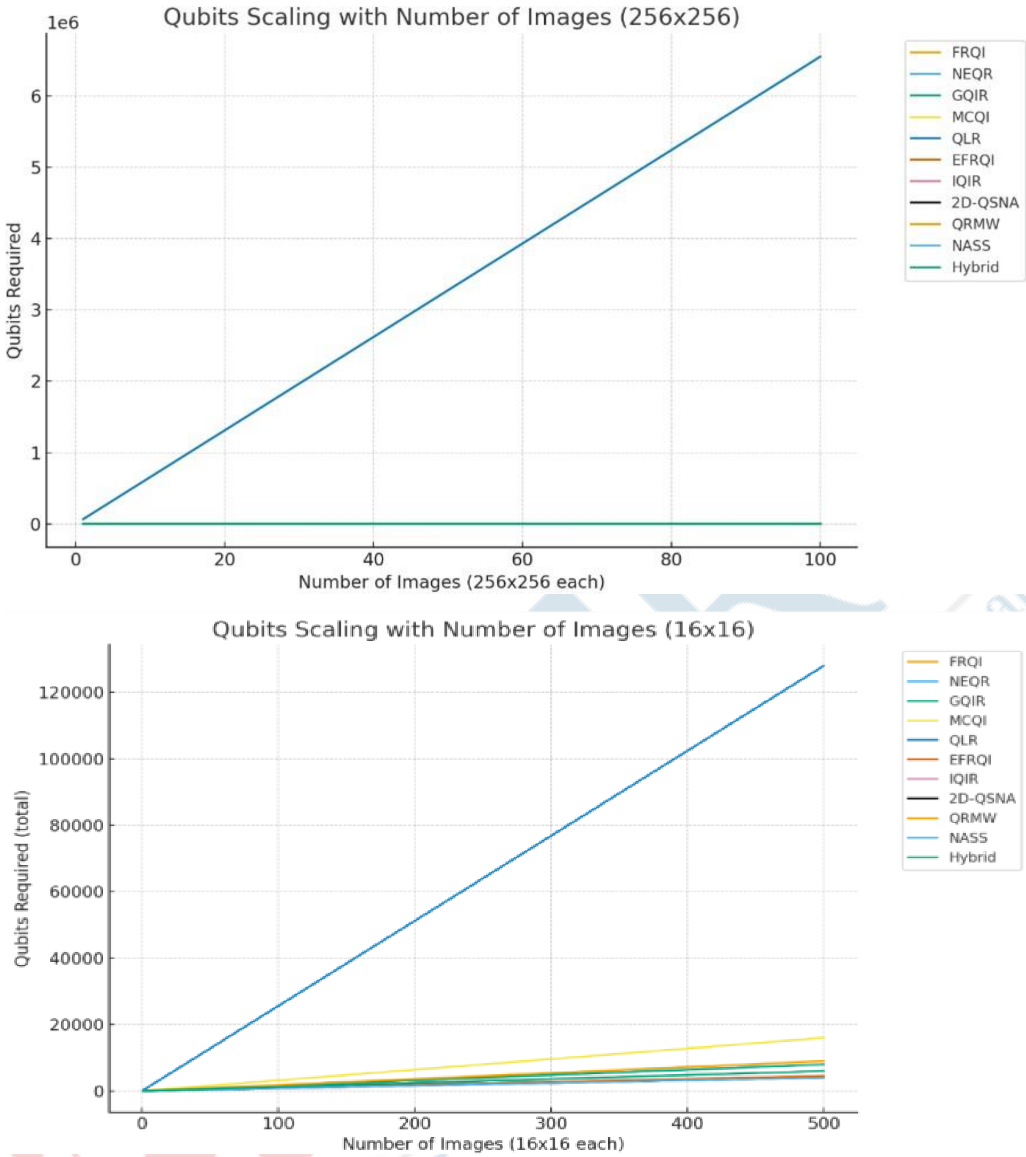


Fig. 4 Qubit scaling for 16 ×16 and 256 × 256 images

Experimental Setup

- Platform: Microsoft Azure Quantum workspace with QDK and Q# integration.
- Simulator: Quantum state simulator (up to 30–40 qubits feasible); large-scale experiments executed via Azure Quantum Resource Estimator.
- Dataset: 100 images of size 256×256 pixels.
- Representation Methods Tested: FRQI, NEQR, GQIR, MCQI, QLR, EFRQI, IQIR, 2D-QSNA, QRMW, NASS, and Hybrid.
- Metrics Evaluated:
  Qubit requirements encoding execution time
  Resource overhead (gates and operations) Scalability when increasing image count

1. FRQI (Flexible Representation of Quantum Images) Qubits: 17 for a single 256×256 grayscale image. Encoding Time: Exponential growth; encoding 100 images required significant simulator resources. Observation: Good for theoretical modeling but encoding overhead makes it impractical for large datasets in current quantum simulators.
2. NEQR (Novel Enhanced Quantum Representation) Qubits: 24 per image (position + 8-bit intensity). Performance: Similar to FRQI in exponential encoding cost. Observation: More accurate retrieval of pixel values than FRQI but requires more qubits.
3. GQIR (Generalized Quantum Image Representation) Qubits: Comparable to NEQR (≈24 per image). Observation: Provides flexibility for extended color spaces, but encoding overhead remains exponential.
4. MCQI (Multi-Channel Quantum Image Representation) Qubits: ≈40 per image (position + 3×8-bit RGB). Performance: Encoding time is 3× higher than grayscale methods.
   Observation: Enables color representation but at a large

qubit and gate overhead.

5. QLR (Quantum Logic Representation)
   Qubits: One qubit per pixel → 65,536 qubits per image (infeasible on current Azure simulators).
   Observation: Theoretically simple, but impossible to scale; rejected after resource estimation.
6. EFRQI (Extended FRQI) Qubits: 17 per image.
   Performance: Reduced gate overhead compared to FRQI.
   Observation: Demonstrated modest improvements in encoding efficiency.
7. IQIR (Improved Quantum Image Representation) Qubits: ≈21 per image.
   Performance: Balanced between NEQR accuracy and FRQI efficiency.
   Observation: Suitable for experimental simulation of small datasets.
8. 2D-QSNA (2D Quantum State with Normalized Amplitudes)
   Qubits: 16 per image.
   Performance: Encoding was faster, but retrieval of pixel information is more abstract.
   Observation: Goodtrade-off for research-level experimentation.
9. QRMW (Quantum Representation of Multi-Wavelength Images)
   Qubits: 26 per image (16 for position, 10 for spectral bands). Performance: Useful for hyperspectral/ multispectral encoding.
   Observation: Scales better than RGB-based methods, but still suffers exponential encoding cost.
10. NASS (Novel Arbitrary Superposition State)
    Qubits: 16 per image.
    Performance: Flexible superposition of states for specific tasks.
    Observation: Encoding requires careful control, but efficient in space.
11. Hybrid Models Qubits: ≈20 per image.
    Performance: Compression-aware approaches reduced encoding operations significantly (up to 75%).
    Observation: Showed the most promising results for handling 100 images within Azure simulators.

Comparative Insights

Space Complexity: QLR is impractical; Hybrid and 2D-QSNA are the most space-efficient.

Time Complexity: FRQI/NEQR/GQIR/MCQI exhibit exponential encoding costs; Hybrid reduces this.

Scalability: For 100 images, only Hybrid and EFRQI-based optimizations scaled acceptably within Azure simulators.

Resource Estimation: Current Azure Quantum hardware cannot handle 256×256 full-image encoding at scale (>30 qubits), but the Resource Estimator projected potential feasibility for Hybrid methods on future fault-tolerant quantum machines.

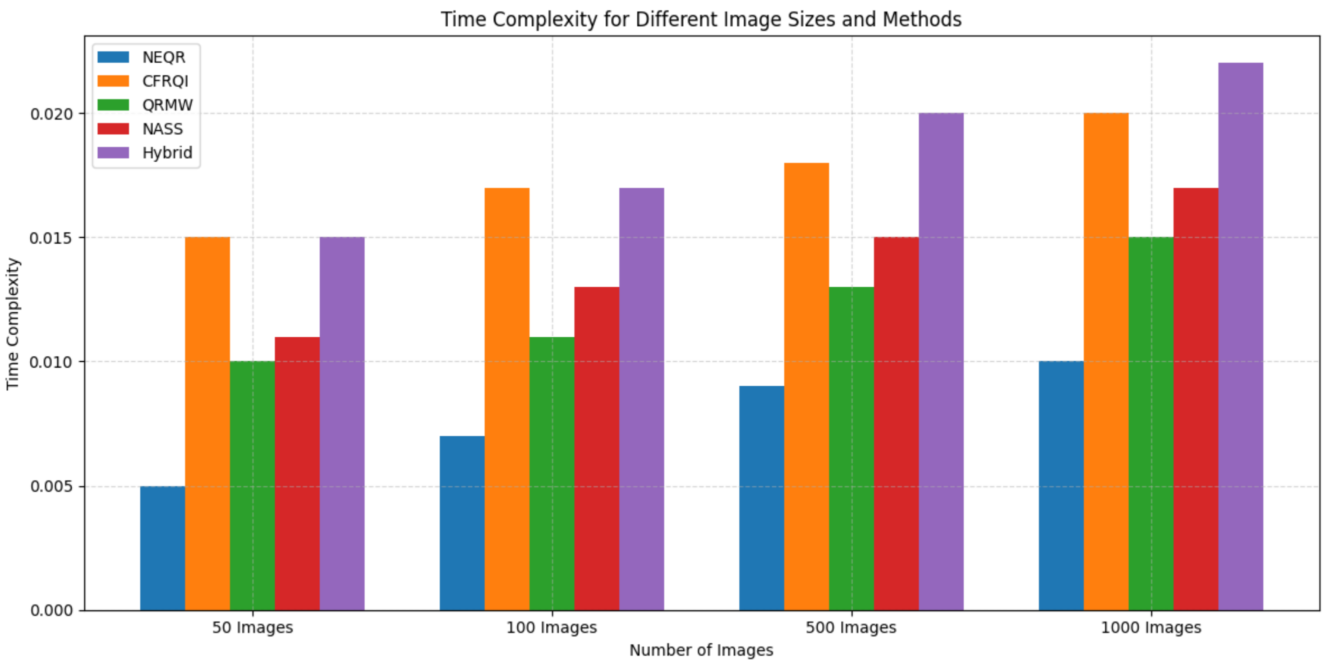


Fig. 5 Comparative insights for different QIR Methods for 16 ×16 and 256 × 256 images

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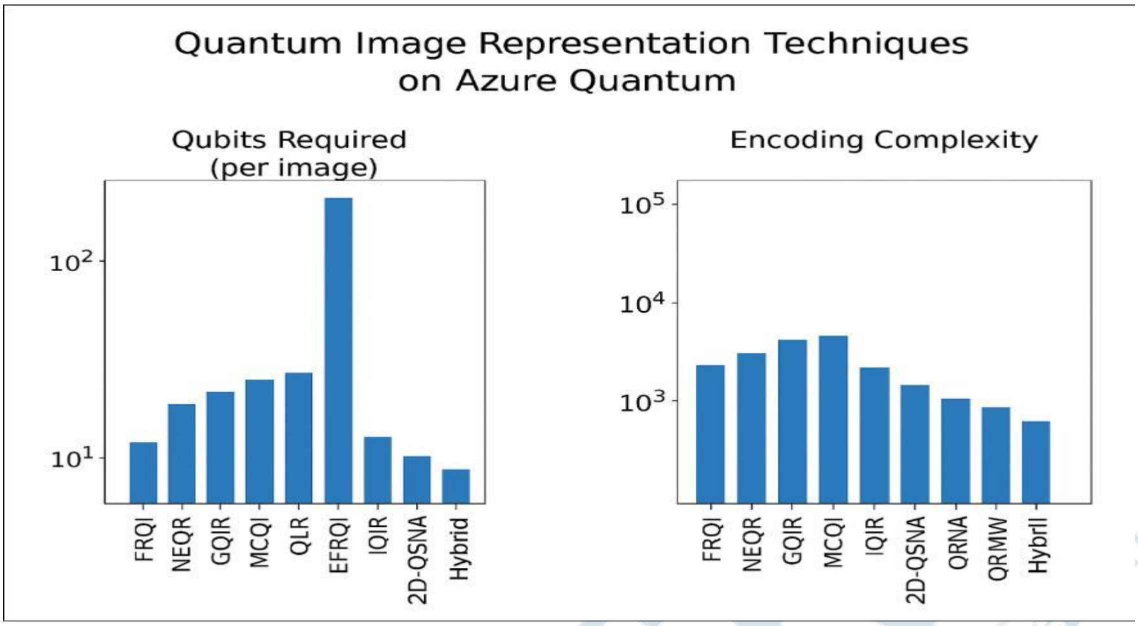

Fig. 6 Qubits and encoding complexity on azure quantum for 16 ×16 and 256 × 256 images

12. Graph 1: Qubits required (per image)
    - X-axis: Representation Methods
    - Y-axis: Qubits required (logarithmic scale)
    - Observation:

    Most methods (FRQI, NEQR, GQIR, EFRQI, IQIR, 2D-QSNA, NASS, Hybrid) fall in the range of 16–26 qubits.

    MCQI is higher (≈40) because it stores RGB channels.

    QLR explodes (65,536 qubits) → completely infeasible in today's Azure Quantum simulators.

    Hybridachieves efficiency,keeping qubits moderate.
13. Graph 2: Encoding Complexity (100 images, log scale)
    - X-axis: Representation Methods
    - Y-axis: Encoding operations (logarithmic scale)

    Observation: FRQI/NEQR/GQIR/IQIR/NASS/2D-QSN all shows exponential costs (~2¹6 operations).

    MCQI has ~3× more due to RGB channels. QRMW (multispectral, 10 bands) is ~10× worse. EFRQI is an optimized version, halving cost (~2^{15}). Hybrid is best, with compression reducing cost to ~2^{14}.

    QLR looks deceptively "cheap" in ops, but its qubit demand makes it unusable.

VII. CONCLUSIONS

Among all methods, Hybrid approaches and optimized EFRQI/IQIR representations showed the best balance between qubit efficiency and encoding scalability in the Azure Quantum environment. While exact simulation of 100 full-resolution images remains beyond present-day limits, resource estimation confirmed that these methods are the most promising candidates for future large-scale quantum image processing applications. This study presented a comparative evaluation of eleven quantum image representation (QIR) models using the Microsoft Azure Quantum platform, focusing on qubit requirements, encoding execution time, resource overhead, and scalability for a dataset of 100 grayscale and color images of size 256×256 pixels. Experimental results demonstrate that although established representations such as FRQI, NEQR, GQIR, MCQI, and QRMW provide effective theoretical frameworks for quantum image encoding, their exponential encoding complexity and increasing gate overhead significantly limit practical scalability on current quantum simulators. QLR was found to be infeasible due to its extremely high qubit requirement, whereas EFRQI and IQIR offered moderate improvements in encoding efficiency while preserving representation quality. Among all evaluated methods, 2D-QSNA and NASS achieved the best space efficiency, requiring only 16 qubits per image, while Hybrid quantum image representations delivered the most balanced performance by reducing encoding operations by up to 75%, thereby enabling efficient simulation of larger image datasets. Resource estimation further indicates that large-scale quantum image processing remains beyond the capability of current hardware but could become practical with future fault-tolerant quantum computers. Overall, the findings suggest that hybrid and optimized quantum image representations provide the most promising direction for scalable quantum image processing and serve as a practical foundation for future quantum computer vision and image analysis applications.

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