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Quantum Computing in Image Processing: A Review of Applications, Models, and Prospects

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learning-based methods have also been explored for tasks such as super-resolution and denoising. However, these techniques are often computationally intensive and may not generalize well across different image types and acquisition conditions.

Image Compression aims to reduce the size of image files while preserving as much visual fidelity as possible. Classical methods include transform-based techniques such as the Discrete Cosine Transform (DCT) used in JPEG and wavelet-based compression (e.g., JPEG2000). These methods are essential for efficient storage and transmission of image data. However, achieving high compression ratios often comes at the cost of perceptual quality, and current algorithms are approaching their theoretical performance limits.

Image Restoration involves recovering a degraded or corrupted image to its original quality. This may include removing blur, correcting distortions, or filling in missing regions (inpainting). Traditional restoration methods rely on optimization-based techniques, such as total variation minimization or inverse filtering, while newer approaches use deep learning-based generative models. Despite advances, challenges persist in balancing restoration accuracy with computational efficiency.

Situational Awareness Applications is about helping a system *see*, *understand*, and *respond* to what is happening around it using visual data. Instead of treating images as just collections of pixels, the goal is to extract meaningful information that explains the current situation and supports intelligent decision-making [1].

1.2 Lacunae in Existing Methods

While classical image processing techniques have achieved substantial progress, they also suffer from several limitations:

- Computational Bottlenecks: Many image processing tasks, especially those involving high-dimensional data (e.g., 4K video, 3D images), demand significant memory and processing time.
- Scalability Issues: Traditional algorithms may not scale efficiently with increasing data size or resolution.
- Limited Learning Efficiency: Machine learning models often require vast datasets and extensive training times to reach optimal performance.
- Security Vulnerabilities: Image encryption and watermarking techniques in classical systems are potentially vulnerable to attacks given sufficient computational power.
- Lossy Compression Trade-offs: In many cases, achieving high compression results in perceptual degradation, especially in medical or surveillance imaging where detail is crucial.

These shortcomings indicate a need for alternative computing paradigms that can overcome current computational and algorithmic limitations.

1.3 Quantum Computing and Its Promise in Image Processing

Quantum computing offers a radically different approach to computation, leveraging principles from quantum mechanics such as superposition, entanglement, and quantum parallelism. Unlike classical bits, which represent either 0 or 1, quantum bits (qubits) can represent both simultaneously, enabling massive parallelism. This allows quantum algorithms to solve certain problems exponentially faster than classical ones.

In the context of image processing, quantum computing holds the potential to revolutionize the four key areas namely, Image Classification, Image Enhancement, Image Compression and Image Restoration.

1.4 Objective of This Survey

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state of quantum computing as applied to image processing. This includes an exploration of quantum image representations, quantum-enhanced algorithms for classification, enhancement, compression, and restoration, and a discussion of the simulation frameworks and hardware constraints currently faced. The review also highlights the major challenges and potential future directions in this emerging interdisciplinary field. Graphical summary of the quantum image processing pipeline discussed in this survey, highlighting the interaction between image processing tasks, quantum image representations, hybrid quantum–classical models, benchmarking datasets, security considerations, and real-world applications within current hardware limitations.

1.5 Structure of the Paper

The rest of this paper is organized as follows:

Section 2 provides a background on quantum computing principles and explains key concepts relevant to image processing. Section 3 discusses various quantum image representation models, including FRQI, NEQR, and others. Section 4 elaborates on quantum image processing techniques categorized under classification, enhancement, compression, and restoration. Section 5 reviews available tools, simulators, and programming environments for quantum image processing research. Section 6 presents the current limitations and challenges associated with quantum image processing. Section 7 outlines future research directions and potential advancements in the field. Section 8 deals with the application spotlights in Quantum Image Processing. Section 9 talks about the Benchmarks and Datasets for Quantum Image Processing. Section 10 gives the Hybrid Quantum-Classical Models in Image Processing. Section 11 reviews the Quantum Security in Image Processing. Section 12 concludes the paper with a summary of findings and the long-term outlook.

2. Background on Quantum Computing for Image Processing

Quantum computing is an emerging paradigm that leverages the principles of quantum mechanics to perform computations that would be intractable for classical systems. At its core, it offers fundamentally new ways to represent and process data using qubits, quantum gates, and quantum circuits, all of which are essential in developing quantum image processing algorithms.

2.1 Fundamental Concepts of Quantum Computing

A qubit (quantum bit) is the quantum analog of a classical bit. It exists in a linear superposition of states $|0\rangle$ and $|1\rangle$, represented mathematically as:

$$|\varphi\rangle = \alpha|0\rangle + \beta|1\rangle, \ where\ \alpha, \beta \in C, |\alpha|^2 + |\beta|^2 = 1 \qquad \text{Equation 1}$$

Unlike classical bits that are strictly binary, qubits allow parallelism in computation due to their probabilistic nature. This enables simultaneous evaluation of multiple inputs, which is key to quantum speedup. Quantum gates such as Hadamard (H), Pauli-X, Y, Z, and controlled gates (CNOT, Toffoli, etc.) manipulate qubits within quantum circuits, altering their states and creating entanglement between them. Entanglement—a uniquely quantum phenomenon—enables qubits to share correlations that classical systems cannot emulate.

Quantum measurement collapses the superposition to a definitive state, making the design of quantum algorithms a careful balancing act between computation and observation. These concepts underpin several quantum algorithms—most notably, Shor's algorithm for factoring [2], Grover's search algorithm [3], and more recently, quantum machine learning models such as Variational Quantum Classifiers (VQCs) and Quantum Kernel Estimators [4].

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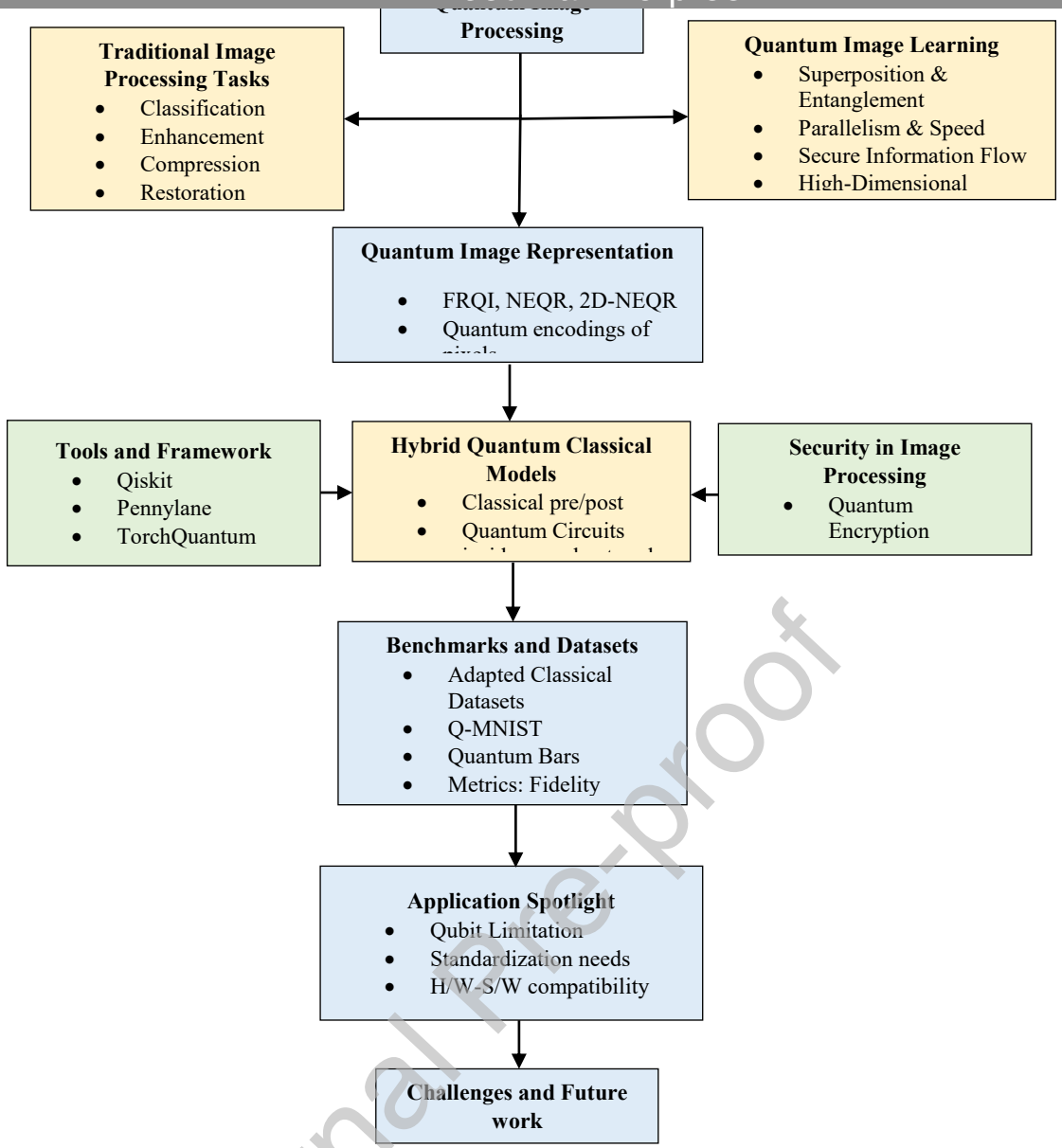

Figure 1: Graphical summary of the quantum image processing pipeline

2.2 Quantum Image Representations

To apply quantum computing to image processing, images must first be encoded into quantum states. Several models have been proposed, each balancing encoding complexity and image reconstruction fidelity.

Before quantum algorithms can operate on image data, it must be encoded into quantum states. Several encoding models have emerged, such as the Flexible Representation of Quantum Images (FRQI), Novel Enhanced Quantum Representation (NEQR), and recent tensor-network approaches. These models differ in how they map pixel positions and intensities into qubit states—either through amplitude encoding, basis state mapping, or probabilistic distributions. A detailed comparison of these models, their qubit requirements, and mathematical formulations is provided in Section 3. Furthermore, quantum tensor networks and quantum generative models are emerging as new tools for compressing and learning image representations efficiently [7, 8].

2.3 Quantum Algorithms for Image Processing

Once images are encoded, quantum computing enables efficient implementations of traditional image processing tasks:

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filtering and compression, QFT achieves exponential speedup over classical FFT.

- Grover's Algorithm: Useful in image search and retrieval by accelerating database queries with quadratic speedup.
- Variational Quantum Algorithms (VQAs): These hybrid classical-quantum algorithms are used in image classification, segmentation, and restoration [9].
- Quantum PCA: Enables extraction of dominant image features by estimating the principal components of a quantum state representing the image [10].

These algorithms are supported by simulation frameworks such as Qiskit, PennyLane, and Cirq, which allow for experimentation on classical systems with up to ~20 qubits.

2.4 Recent Developments and Hardware Prospects

Recent advancements in quantum hardware, such as IBM's Quantum System One and Google's Sycamore, offer hope for scalable quantum image processing in the near future. Though still limited by noise and decoherence, quantum volume and error correction techniques are improving rapidly. Quantum advantage in specific domains like image recognition or denoising is now a credible research objective.

As of 2024, simulation-based studies using hybrid quantum-classical methods have shown promising results in image classification on datasets like MNIST, Fashion-MNIST, and chest X-ray images [11, 12].

The authors [13] provide an extensive survey of classical image compression algorithms, including transform-based (DCT, DWT), predictive, and neural-network-based techniques. The authors systematically categorize methods based on entropy, complexity, and distortion metrics. It critically evaluates their limitations in terms of scalability, performance on high-resolution data, and energy efficiency. This work motivates the need for alternative paradigms such as quantum compression to overcome classical bottlenecks.

3. Quantum Image Representation Models

For quantum computing to be effective in image processing, digital images must first be encoded into quantum states. This process is referred to as quantum image representation, and it determines how efficiently an image can be manipulated, transformed, or analyzed using quantum operations.

Over the years, researchers have proposed several models, each with its own trade-offs in terms of qubit requirement, processing complexity, and image fidelity. The most prominent models are:

- FRQI (Flexible Representation of Quantum Images)
- NEQR (Novel Enhanced Quantum Representation)
- MCQI (Multi-Channel Quantum Image representation)
- QPIE (Quantum Probability Image Encoding)
- Recent tensor network-based encodings

3.1 Flexible Representation of Quantum Images (FRQI)

FRQI is one of the earliest and most widely studied quantum image representation models. It was introduced to encode grayscale images in a quantum state using position qubits and a single intensity qubit.

The general state of a FRQI-encoded image with 2^n pixels is given by:

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

Here

- $|i\rangle$ is the computational basis state representing pixel position
- θ_i is a rotation angle corresponding to the normalized grayscale value at pixel *i*
- The state $(cos(\theta_i)|0\rangle + \sin(\theta_i|1\rangle)$ encodes the pixel intensity

The main features are it is compact and efficient. It needs $n + 1$ qubits for a 2^n -pixel image. It allows quantum parallelism for operations like rotation, inversion, and filtering. The main limitation is pixel intensity is encoded in amplitude, which is not directly measurable. Therefore, image reconstruction requires indirect techniques or multiple observations [14].

3.2 Novel Enhanced Quantum Representation (NEQR)

The NEQR model improves upon FRQI by encoding grayscale pixel values directly in basis states rather than through rotation angles.

The NEQR state is expressed as:

$$|I\rangle = \frac{1}{2^n}\sum_{i=0}^{2^n-1} |f(i)\rangle \otimes |i\rangle \quad \text{Equation 3}$$

- $|i\rangle$ denotes the position of the pixel
- $|f(i)\rangle$ is the binary representation of the grayscale value (e.g., for a 8-bit image, 8-qubits are needed.

The main features are that it allows direct access to pixel values via measurement. It also offers higher fidelity image reconstruction. Hence it is efficient for grayscale images with precise intensity values. The main limitation is that it requires more qubits than FRQI (position qubits + intensity qubits). Hence it is less suited for transformations that rely on amplitude manipulation [15].

3.3 Multi-Channel Quantum Image Representation (MCQI)

MCQI extends FRQI to handle color images by representing RGB channels as entangled quantum states.

Each pixel has three components (R, G, B), encoded into rotation angles $\theta r, \theta g, \theta b$ The full state is expressed as:

$$|I\rangle = \frac{1}{2^n}\sum_{i=0}^{2^n-1} \left(cos(\theta_{r,i})|0\rangle + sin(\theta_{r,i})|1\rangle\right) \otimes \left(cos(\theta_{b,i})|0\rangle + \sin(\theta_{b,i}|1\rangle\right) \otimes \left(cos(\theta_{g,i})|0\rangle + \sin(\theta_{g,i}|1\rangle\right)\Big) \quad \text{Equation 4}$$

It is suitable for full-color (RGB) image encoding. It is also capable of color-based transformations on quantum devices [16].

3.4 Quantum Probability Image Encoding (QPIE)

QPIE is a probabilistic model aimed at efficient image encoding under noisy or uncertain environments. It uses quantum probability distributions to represent pixel intensities [17].

Rather than fixed angles or bit strings, QPIE associates a quantum probability amplitude to each pixel's intensity based on measurement likelihood as shown in Equation 5.

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$$|I\rangle = \sum_i a_i |i\rangle \text{ with } |a_i|^2 = P(i)$$ Equation 5

Where $P(i)$ is the probability distribution associated with pixel brightness.

3.5 Tensor Network-Based Representations

Quantum tensor networks offer a highly efficient way to encode image patches or local regions using quantum circuits with entanglement constraints. These models have been used in image compression and generative tasks. [4, 7]. It offers reduced qubit count through compressed entangled representations. Hence it is suitable for hybrid classical–quantum pipelines (e.g., VQAs + CNNs).

3.6 Comparison of Models

Table 1 gives a brief comparison of the of the above models with respect to the Pixel Encoding, Qubit Efficiency, the support for color Image Processing and the access to Pixel values.

Table 1: Comparison of the various Quantum Models.

Model	**Pixel Encoding**	**Qubit Efficiency**	**Supports Color?**	**Access to Pixel Values**
FRQI	Amplitude	High	No	Indirect
NEQR	Basis state	Medium	No	Direct
MCQI	Amplitude	Low	Yes	Indirect
QPIE	Probabilistic	Medium	No	Statistical
Tensor Networks	Compressed basis	High	Partial	Partial

The authors [18] introduce a novel quantum image representation grounded in the duality quantum computing model. Unlike FRQI and NEQR, the proposed model enables parallel processing and multi-dimensional image encoding using fewer quantum operations. It supports grayscale image representation with basic quantum arithmetic. This model broadens the theoretical foundations for efficient quantum image storage and transformation.

The authors [19] propose a quantum image compression method based on bitplane decomposition. By encoding each bitplane of a grayscale image separately into a quantum state, it achieves significant storage efficiency and modularity. The method is compatible with NEQR and FRQI encodings and demonstrates compression with minimal information loss. It is particularly useful in designing quantum autoencoder systems.

In summary, Quantum image representation models form the foundation of quantum image processing by defining how pixel position and intensity information are encoded into quantum states. The Flexible Representation of Quantum Images (FRQI) encodes grayscale intensity into probability amplitudes, offering high qubit efficiency but suffering from sensitivity to noise and lossy reconstruction. In contrast, the Novel Enhanced Quantum Representation (NEQR) stores pixel intensities in basis states, enabling exact grayscale recovery at the cost of increased qubit requirements and circuit complexity. Models such as Quantum Probability Image Encoding (QPIE) and Quantum Square Neighbourhood Amplitude (QSNA) aim to balance encoding precision and resource efficiency, particularly for irregular or non-square images. Overall, no single representation is universally optimal; FRQI favours compactness, NEQR prioritizes fidelity, and newer models attempt to mitigate scalability and noise limitations under NISQ constraints.

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Quantum computing enables novel approaches to classical image processing tasks through quantum-enhanced algorithms and hybrid architectures. Leveraging entanglement, superposition, and quantum parallelism, these techniques offer potential advantages in terms of speed, scalability, and feature encoding for high-dimensional visual data. This section explores quantum applications in four critical image processing areas.

4.1 Quantum Image Classification

Quantum classifiers seek to assign labels to images by exploiting high-dimensional Hilbert spaces and kernel-based separation between classes. These classifiers operate either as fully quantum or as hybrid quantum-classical systems.

VQCs utilize parameterized quantum circuits and cost function optimization to distinguish image classes. They are often used on encoded images from datasets such as MNIST or CIFAR-10. A typical VQC pipeline includes:

1. Encoding classical image features into quantum states.
2. Applying parameterized unitary operations (rotations and entanglement gates).
3. Measuring output qubits and comparing with labels via a classical optimizer.

Recent studies have demonstrated successful classification using 4–8 qubits with accuracies comparable to classical neural networks under noise-free conditions [20].

The authors [21] propose a novel quantum algorithm for edge detection that relies on Hadamard and CNOT gate operations. It operates directly on quantum image encodings like NEQR, identifying gradient regions through entangled quantum states. Simulation results on small binary images demonstrate effectiveness comparable to classical Sobel operators. The method is a step toward real-time quantum Image Processing applications.

The authors [22] discuss recent advances in quantum convolutional neural networks (QCNNs) and their applications in image classification. It outlines architecture types, learning mechanisms, and encoding strategies tailored for quantum circuits. The paper also compares classical CNNs and QCNNs in terms of expressivity, resource requirements, and noise resilience. It serves as a foundation for developing quantum-enhanced vision systems.

4.2 Quantum Image Enhancement:

Quantum-based transformations such as the Quantum Fourier Transform (QFT) or quantum filters can be applied to enhance image quality using fewer resources. Entanglement allows for more global and context-aware filtering mechanisms.

One promising direction involves quantum implementations of classical filtering algorithms. For example, guided image filtering — a widely used edge-preserving smoothing technique in classical image processing — has been adapted to the quantum setting using the Novel Enhanced Quantum Representation (NEQR) model. In this quantum implementation, the image is encoded into qubit registers via NEQR, and the guided filtering operations are executed using quantum circuits that apply weighted averaging and guidance functions in superposition. Experimental results indicate improved computational complexity and competitive quality in preserving edges while reducing noise when compared to classical guided filters, with exponential reduction in time complexity for certain subroutines due to quantum parallelism [23]

Another advanced enhancement technique focuses on quantum-assisted super-resolution, which aims to reconstruct higher-resolution images from lower-resolution inputs. A recent hybrid quantum-classical approach called Quantum Image Enhancement Transformer for Single Image Super-Resolution (QUIET-SR) integrates quantum attention mechanisms within a classical transformer architecture. In this model, quantum variational circuits are utilized to

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restoration. Evaluations on benchmarks such as MNIST and MedMNIST show that QUIET-SR achieves PSNR and SSIM scores comparable to state-of-the-art classical methods while requiring relatively fewer trainable parameters and qubits — highlighting the capability of quantum-enhanced architectures to balance quality and resource efficiency in enhancement tasks [24]

4.3 Quantum Image Compression

Quantum image representations such as FRQI (Flexible Representation of Quantum Images) or NEQR (Novel Enhanced Quantum Representation) allow image data to be encoded compactly in quantum states. These can lead to highly efficient image compression schemes, outperforming traditional methods in terms of data throughput.

Early quantum compression techniques rely on compact quantum image representations such as the Flexible Representation of Quantum Images (FRQI) and the Novel Enhanced Quantum Representation (NEQR). In FRQI, pixel position and grayscale intensity are jointly encoded using superposition, enabling the entire image to be represented by a single quantum state. Compression is achieved implicitly, as a $2^n \; x \; 2^n$ image can be encoded using $2n + 1$ qubits, independent of the number of pixels. This represents a significant theoretical reduction in storage compared to classical representations, particularly for large images [14].

However, comparative evaluations show that FRQI-based compression is lossy and sensitive to noise, as small perturbations in amplitude encoding can significantly affect reconstructed pixel values. NEQR improves upon this by storing pixel intensities in basis states rather than amplitudes, enabling exact grayscale representation and more stable reconstruction at the cost of increased qubit requirements. As a result, FRQI favors compression efficiency, while NEQR prioritizes reconstruction fidelity, highlighting an inherent trade-off between compactness and robustness [15].

Another important trend involves quantum implementations of classical transforms, such as the Quantum Fourier Transform (QFT) and Quantum Singular Value Decomposition (QSVD). These methods mirror classical transform coding (e.g., DCT-based JPEG compression) by concentrating image energy into a small number of coefficients. In QSVD-based compression, an image encoded in a quantum state is decomposed into singular values, and only the dominant components are retained, enabling effective dimensionality reduction [25].

4.4 Quantum Image Restoration:

Techniques such as quantum deblurring and quantum denoising are being explored, where quantum circuits are used to simulate inverse problems more efficiently than classical iterative solvers.

One of the earliest and most influential approaches to quantum image restoration is based on quantum linear system solvers, most notably the Harrow–Hassidim–Lloyd (HHL) algorithm. Many image restoration problems, including deblurring and denoising, can be formulated as linear inverse problems [8]. Comparative analyses, however, reveal that while HHL-based restoration is theoretically appealing, its practical utility is limited by strict requirements on matrix sparsity, condition number, and efficient quantum state preparation. As a result, these methods remain primarily proof-of-concept demonstrations, applicable to small images or simplified degradation models.

More recent work has shifted toward hybrid quantum–classical variational algorithms for image restoration. In these approaches, degraded images are encoded into quantum states, and parameterized quantum circuits (PQCs) are trained—often using classical optimizers—to minimize a reconstruction loss. This paradigm is particularly suited to denoising and inpainting tasks, where the restoration problem can be framed as learning a mapping from corrupted to

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achieve competitive reconstruction quality relative to shallow classical neural networks, especially for small grayscale images, while using fewer trainable parameters [26]. However, restoration performance degrades as circuit depth increases due to noise accumulation, reinforcing the trend toward shallow, noise-aware architectures.

Another emerging direction involves quantum implementations of wavelet and frequency-domain transforms, which are widely used in classical restoration for noise suppression and multiresolution analysis. Quantum wavelet transforms (QWTs) enable decomposition of images into multiple frequency bands in superposition, allowing selective suppression of high-frequency noise components. Compared to classical wavelet denoising, quantum versions offer theoretical advantages in transform efficiency but face practical challenges related to circuit complexity and error sensitivity [27].

In summary, Quantum techniques for image processing exploit quantum superposition, entanglement, and parallelism to encode and manipulate image information more compactly than classical methods. Core approaches include quantum image representation models (e.g., FRQI, NEQR) that define how pixel intensities and positions are stored in quantum states, and quantum transforms such as the Quantum Fourier and Wavelet Transforms for frequency-domain analysis. Hybrid quantum–classical learning models, including variational circuits and quantum autoencoders, are increasingly used for tasks such as classification, enhancement, compression, and restoration under NISQ constraints. These techniques show theoretical computational advantages and novel representational capabilities, though practical performance is currently limited by noise, qubit scalability, and data loading overhead.

5. Tools, Frameworks, and Simulators for Quantum Image Processing

The practical exploration of quantum image processing relies on a diverse set of software frameworks and hardware-compatible simulators. As quantum hardware remains limited in scale and noisy, most research and prototyping is conducted on quantum simulators and hybrid classical–quantum systems. This section presents key platforms, their features, and their relevance to image processing tasks.

5.1 Qiskit (IBM Quantum)

Qiskit is an open-source quantum computing framework developed by IBM. It provides tools for building quantum circuits, simulating quantum algorithms, and running them on real IBM quantum processors via the cloud [28].

Key Features:

- Qiskit Terra: Circuit construction and manipulation.
- Qiskit Aer: High-performance simulators.
- Qiskit Machine Learning: Includes quantum neural networks and VQC models.
- Supports FRQI and NEQR encoding using standard gates.
- Direct access to IBM Q hardware (5–127 qubit devices).

5.2 PennyLane (Xanadu)

PennyLane is a Python-based library for hybrid quantum-classical machine learning. It integrates seamlessly with PyTorch and TensorFlow, allowing researchers to build quantum neural networks for image classification and denoising [4].

Key Features:

- Supports backpropagation on quantum circuits.
- Native support for VQC, quantum autoencoders, and quantum convolutional layers.

5.3 Cirq (Google Quantum AI)
Cirq is a Python library for designing, simulating, and running quantum circuits, especially optimized for Google's Sycamore processor.

Key Features:

- Fine-grained control over low-level gate definitions.
- Designed for hardware-level experiments.
- Compatible with TensorFlow Quantum for hybrid modeling.

Cirq is particularly useful for developing quantum kernels and feature maps in classification tasks [29].

5.4 Ocean SDK (D-Wave Systems)
D-Wave's Ocean SDK supports quantum annealing—an approach suitable for energy-based optimization problems like image restoration or segmentation using Ising models [30].

Key Features:

- Solves discrete optimization problems via quantum annealers.
- Useful for tasks like image denoising, segmentation, and edge detection modeled as QUBOs.
- Access to D-Wave hardware (Advantage systems) through Leap cloud platform.

5.5 TensorFlow Quantum
TensorFlow Quantum (TFQ) integrates quantum computing into TensorFlow pipelines, allowing researchers to train quantum-enhanced deep learning models for image tasks [31].

Key Features:

- Bridges classical deep learning with quantum circuits.
- Useful for quantum convolutional neural networks (QCNNs).
- Can train models for denoising, super-resolution, and classification on quantum simulators.

5.6 QuTiP (Quantum Toolbox in Python)
QuTiP is a research-oriented library for simulating open quantum systems, including quantum optics and noise models. It is especially relevant for exploring image degradation and restoration under decoherence [32].
Key Features:

- Solves Lindblad master equations and models noise channels.
- Useful for modeling quantum image degradation, photon loss, and error mitigation.

The authors [33] introduce Qibo, a Python-based framework for quantum circuit simulation and execution on multiple backends including CPUs, GPUs, and quantum accelerators. Unlike Qiskit and PennyLane, Qibo emphasizes modularity and high-performance execution for variational algorithms. It supports hybrid workflows and is suitable for quantum image processing simulations. Its design is particularly useful in benchmarking quantum image encodings.

5.7 Comparison of Frameworks
A brief comparison of the Frameworks is given in Table 2. The comparison is done with respect to the Hardware Support, Language and the special features.

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Tool/Framework	Best Use Case	Hardware Support	Language	Special Features
Qiskit	General quantum image tasks	IBM Q, simulators	Python	FRQI, NEQR, QML libraries
PennyLane	Hybrid quantum-classical models	Xanadu, IBM, IonQ	Python	Auto differentiation, VQC
Cirq	Low-level quantum model design	Google Sycamore	Python	Quantum kernels, TFQ integration
Ocean SDK	Optimization (Ising/QUBO) models	D-Wave QPU	Python	Image segmentation, restoration
TensorFlow Quantum	Quantum deep learning	Simulators, Google	Python	CNNs, VQCs, end-to-end image pipelines
QuTiP	Quantum noise modeling	Simulators	Python	Decoherence, open system simulation

In summary, Quantum image processing frameworks such as Qiskit, Cirq, and PennyLane differ primarily in abstraction level and application focus: Qiskit offers comprehensive tools for quantum circuits, simulators, and hardware execution; Cirq emphasizes low-level, hardware-specific circuit control; and PennyLane enables seamless hybrid quantum–classical image processing workflows through automatic differentiation. Comparative studies show that PennyLane is particularly suited for variational image models, while Qiskit and Cirq provide greater flexibility for custom quantum image representations and algorithmic experimentation.

6. Challenges and Open Problems in Quantum Image Processing

Quantum image processing (QIP) holds the promise of transforming visual computing through exponential state-space representation, enhanced parallelism, and hybrid learning paradigms. However, practical implementation faces several technological, theoretical, and algorithmic bottlenecks. This section outlines the key challenges and open research problems that must be addressed before QIP can be reliably applied to real-world tasks.

6.1 Hardware Limitations

Despite advances in quantum hardware, current quantum processors suffer from constraints such as:

- **Limited number of qubits**: Most quantum processors available today support only 5–100 qubits, insufficient for high-resolution image processing.
- **Noise and decoherence**: Noisy Intermediate-Scale Quantum (NISQ) devices lose coherence within microseconds, disrupting image computations.
- **Qubit connectivity**: Real quantum devices impose hardware-specific topologies, limiting the range of quantum operations without additional SWAP gates (which increase error).

Example: IBM's 127-qubit "Eagle" processor can simulate only small image patches under error-free assumptions [20].

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Quantum image representations, though compact in theory, face practical encoding challenges. These limitations hinder the deployment of quantum methods for real-time imaging or video streams [14, 15].

- Cost of state preparation: Preparing quantum states like FRQI or NEQR for large images may require deep circuits or large ancillary systems, increasing error risk.
- Amplitude encoding difficulty: In FRQI, intensities are encoded in amplitude, which is hard to extract through direct measurement.
- Color image limitations: Extending quantum representations to RGB or hyperspectral images remains inefficient due to scaling in qubit requirements.

Open Problem: Developing low-depth, hardware-efficient image state preparation circuits for real-time encoding remains an unsolved issue.

6.3 Scalability of Algorithms

Most quantum algorithms for image processing have been validated only on toy datasets such as MNIST or 2×2 grayscale images [20].

- Quantum machine learning models struggle to scale to high-dimensional image spaces.
- Hybrid quantum-classical models require careful data orchestration between CPU and QPU, often leading to latency bottlenecks.

6.4 Algorithmic Stability and Robustness

Quantum algorithms are inherently stochastic due to probabilistic measurements. This introduces variability in outcomes, making them sensitive to:

- Gate noise
- Initialization errors
- Circuit depth
- Sampling strategies

These factors contribute to instability, requiring large numbers of repeated executions to estimate accurate results [5].

6.5 Lack of Standardized Quantum Image Datasets

Unlike classical computer vision, QIP lacks benchmark datasets for evaluating and comparing models. Although some efforts attempt to encode MNIST into quantum states, there is no widely accepted quantum-native dataset.

This makes it difficult to standardize experimental setups or assess generalizability across platforms [31].

6.6 Hybrid Quantum-Classical Integration Issues

Hybrid quantum–classical architectures have emerged as the most practical approach for quantum image processing in the NISQ era. While their advantages in reducing qubit requirements and enabling near-term experimentation are well recognized, a deeper evaluation reveals several non-trivial limitations that impact their scalability and real-world applicability.

1. Data Transmission Latency and Classical–Quantum Interface Overhead

One of the primary challenges in hybrid architectures lies in the frequent exchange of data between classical processors and quantum backends. Image features extracted by classical neural networks must be encoded into quantum states, processed by quantum circuits, and then measured and transferred back to the classical domain. This iterative process introduces significant latency, particularly when cloud-based quantum hardware is used, [4].

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segmentation or restoration—the communication overhead can dominate overall execution time. Even in simulator-based environments, the repeated classical–quantum synchronization limits throughput. As a result, hybrid models may offer theoretical advantages but remain slower than fully classical models for large-scale or real-time imaging tasks.

2. Noise Sensitivity and Error Accumulation

Noise remains a fundamental limitation in current quantum hardware, and hybrid architectures are not immune to its effects. Quantum circuits used in hybrid pipelines are particularly sensitive to gate errors, decoherence, and readout noise, all of which can distort intermediate feature representations. The authors [34], provide an *extensive noise robustness evaluation* of hybrid HQNN models across phase flip, bit flip, amplitude damping, and depolarizing channels, demonstrating that noise characteristics significantly affect classification performance and model stability.

In image processing applications, even small perturbations in quantum measurements can propagate through the classical post-processing stages, leading to visible artifacts or degraded reconstruction quality. While error mitigation techniques—such as measurement error correction and noise-aware training—have shown promise, they increase computational complexity and further amplify latency. The authors [35] analyze trainability and convergence of hybrid variational quantum circuits, showing that large gate noise and deep circuits lead to poor performance bounds and difficulties in classical optimization loops integrated with quantum circuits. The authors [36], present hybrid quantum–classical convolutional neural networks, demonstrating both potential performance benefits and practical limitations due to *trainable parameter constraints and model sensitivity to depth and noise*.

3. Limited Scalability to High-Resolution Images

Despite their reduced qubit requirements, hybrid architectures still struggle to scale beyond low-resolution or highly compressed image representations. Encoding large image patches or high-dimensional feature vectors into quantum states remains resource-intensive. As a result, most existing hybrid implementations operate on aggressively downsampled images, limiting their practical applicability in domains such as medical imaging or remote sensing.

4. Balanced Perspective on Advantages

Despite these limitations, hybrid architectures remain indispensable in the current phase of quantum computing. They:

- Enable experimental validation of quantum advantage in controlled settings
- Allow seamless integration with mature classical deep learning pipelines
- Serve as testbeds for developing quantum-aware training strategies

Importantly, many of the identified limitations are expected to diminish as quantum hardware, error mitigation techniques, and quantum networking infrastructures improve. The authors [36], explore the design space of hybrid quantum–classical neural networks, reinforcing that optimization challenges and architectural choices affect convergence, expressiveness, and noise susceptibility.

6.7 Immaturity of Software Tools for Image Processing

Quantum software libraries such as Qiskit, PennyLane, Cirq, and TFQ are robust for quantum computing but lack built-in support for image primitives like filters, layers, and transforms.

Developers must manually implement quantum analogs of classical techniques such as convolution, pooling, or histogram equalization, which adds to development complexity [28].

6.8 Ethical and Interpretability Concerns

emerge:

- Lack of interpretability in quantum decision-making.
- Uncertainty in outputs, due to probabilistic operations.
- Data privacy concerns when images are processed on remote quantum servers.

These concerns are compounded by a lack of regulatory standards for quantum technologies used in critical fields like medical diagnostics or security imaging.
Open Problem: There is an urgent need to develop quantum explainability frameworks, similar to classical XAI (explainable AI) systems, but suited to quantum phenomena.
Preskill's (2018) seminal paper [37] introduces the concept of the Noisy Intermediate-Scale Quantum (NISQ) era, characterizing the constraints and capabilities of near-term quantum devices. The work emphasizes hybrid quantum-classical strategies and variational algorithms as a path forward under noise and qubit limitations. This framework is highly relevant for implementing quantum image processing on currently available hardware. It sets the stage for realistic expectations in QIP research.

6.9 Summary of Key Open-Problems
Table 3 gives a brief overview of the Open Research problems in the Quantum Image Processing domain.

Table 3: Open Research Challenges

Domain	**Open Research Challenge**
Hardware	Scalable, error-resilient architectures for >128-qubit processing
Encoding/Representation	Efficient, noise-tolerant quantum image encoding of color/3D data
Algorithm Design	Robust learning under noise, deep QNNs with stable gradients
Benchmarking	Lack of quantum-native image datasets for fair model comparison
Hybrid Systems	Minimizing latency and inefficiency in classical-quantum pipelines
Tooling & Libraries	Native image-layer APIs for quantum development platforms
Ethics & Security	Privacy, interpretability, and fairness in QIP for medical/security

In summary, Quantum image processing faces significant challenges due to limited qubit counts, hardware noise, and decoherence, which restrict image resolution and circuit depth on current NISQ devices. Additional obstacles include inefficient data encoding and loading overhead, unstable training convergence in hybrid models, and the lack of standardized benchmarks for fair performance comparison with classical methods.

7. Future Directions

As quantum hardware, algorithms, and theoretical foundations continue to evolve, the field of Quantum Image Processing (QIP) is poised to benefit from several transformative advancements. These future directions are driven by the convergence of quantum computing with fields such as artificial intelligence, signal processing, cryptography, and biomedical engineering. This section outlines key areas where quantum methods are expected to play a foundational role in the next generation of image processing systems.

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A major focus for the future will be the development of encoding schemes that support high-resolution, color, and 3D images using fewer qubits and shallower circuits. New techniques are being explored:

- Hybrid classical-quantum encoding, where coarse features are encoded classically, and finer features quantumly.
- Tensor-network-based encodings, which leverage quantum entanglement to represent large-scale images efficiently [7].

7.2 Quantum Deep Learning for Vision Tasks

As quantum neural networks (QNNs) become more expressive, they may be applied to complex computer vision tasks:

- Quantum object detection and segmentation using entangled feature maps.
- Quantum Generative Adversarial Networks (QGANs) for image synthesis.
- Quantum Image Processing Transformers (QIPT), inspired by transformer models in deep learning.

Theoretical work on QNNs already shows promise for exponential advantage in specific learning tasks [20].

7.3 Quantum Medical Image Analysis

Quantum computing may soon revolutionize medical image processing due to its ability to manage high-dimensional data and solve inverse problems efficiently:

- Quantum-enhanced tomography and MRI reconstruction using quantum compressed sensing.
- Early diagnosis support using quantum classifiers trained on CT or histopathology images.
- Privacy-preserving diagnostics, where patient data is processed entirely within quantum encryption schemes.

Efforts are already underway to test QML algorithms on small chest X-ray datasets using real quantum hardware [38].

7.4 Quantum Edge Computing for Real-Time Vision

Future quantum sensors and edge devices could perform image processing in situ using embedded quantum chips. Applications include:

- Quantum-enhanced cameras that perform edge detection or noise filtering at the hardware level.
- Quantum radar and surveillance systems for night-vision or high-noise environments.
- Quantum photonic processors for drone and autonomous vehicle vision.

This vision aligns with ongoing work on photonic qubit processors and integrated quantum chips.

7.5 Quantum Federated Learning and Security

In sensitive domains like healthcare and defense, quantum approaches can offer:

- Federated QML frameworks where multiple institutions share quantum models without exchanging raw image data.
- Quantum homomorphic encryption, allowing encrypted image processing without decryption.
- Quantum watermarking and authentication techniques to protect digital image assets.

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interdisciplinary research area.

7.6 Standardization, Toolkits, and Education
To ensure robust adoption of QIP:

- Development of quantum image processing toolkits with APIs for tasks like segmentation, classification, or filtering.
- Inclusion of QIP modules in STEM and engineering curricula.
- Open-source simulators for quantum image datasets, including encoded MNIST, CIFAR-10, or biomedical images.

Frameworks like PennyLane, Qiskit, and TensorFlow Quantum are expected to introduce more native support for image data and visual debugging tools [4,7].

7.7 Quantum Explainability and Interpretability
As quantum models are deployed in high-stakes applications, ensuring their transparency will be essential. Future work may focus on:

- Quantum explainable AI (QXAI) to trace qubit-level decisions.
- Visual debugging tools for QML circuits.
- Certified quantum behavior, using quantum proof-of-verification techniques.

Establishing interpretable quantum Image Processing models will be critical for trust and regulation.
The foundational paper [39], presents quantum algorithms for both supervised and unsupervised learning tasks, including clustering, regression, and classification. The authors demonstrate that quantum states can encode large datasets and manipulate them efficiently using linear algebra subroutines. The proposed framework lays the groundwork for quantum-enhanced learning, applicable to image classification and segmentation. It bridges quantum computing with modern data science problems.
In summary, Future research in quantum image processing is expected to focus on noise-aware and hardware-efficient hybrid architectures, with measurable gains in convergence stability and reconstruction quality under NISQ constraints. Advancing efficient data encoding schemes, standardized benchmarks, and task-specific quantum advantage validation will be critical to transitioning from proof-of-concept studies to practical image processing applications.

8. Application Spotlights in Quantum Image Processing

Quantum Image Processing (QIP) offers transformative opportunities across various real-world domains that demand high efficiency, parallelism, and compact data representation. This section presents focused case spotlights on three sectors where QIP is showing considerable promise: medical imaging, satellite and remote sensing, and biometric security.

8.1 Medical Imaging
Medical imaging involves complex, high-resolution data from modalities like CT, MRI, and PET scans. Classical image processing techniques often struggle with the sheer volume of data and the need for real-time, high-precision analysis.
Quantum computing can enhance this field through:

- Efficient quantum encoding of high-dimensional medical images using FRQI or NEQR
- Quantum denoising techniques that preserve critical structures in noisy scans
- Quantum classifiers that improve detection accuracy with fewer training samples

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breast cancer detection from mammograms, achieving competitive performance on limited training data. Similarly, the authors [41] applied parameterized quantum circuits to segment brain tumors, reporting reduced training time compared to classical models. These advancements show how QIP can provide resource-efficient, privacy-preserving, and accurate diagnostics, especially when deployed on NISQ-compatible hardware.

8.2 Satellite and Remote Sensing

Remote sensing applications generate petabytes of spatiotemporal data from Earth-observing satellites. Traditional image processing algorithms used for land classification, vegetation analysis, and climate monitoring are computation-heavy and slow.

Quantum image processing offers:

- Quantum spectral encoding, reducing the dimensionality of hyperspectral imagery
- Quantum parallelism, allowing simultaneous evaluation of spatial patterns
- Quantum-enhanced change detection in time-series Earth observation datasets

The work [42] explored quantum autoencoders to compress multispectral satellite data, significantly reducing dimensionality while preserving classification accuracy. Moreover, the work [43] demonstrated early results using a quantum support vector machine (QSVM) for classifying crop regions from Sentinel-2 imagery. These innovations hint at a future where quantum processors onboard satellites could autonomously encode, compress, and analyze Earth observation images before transmission.

8.3 Biometric Security and Surveillance

Biometric systems such as face, iris, fingerprint, and gait recognition require precise classification and robustness to occlusions, lighting variations, and spoofing. Quantum algorithms offer breakthroughs in both security and accuracy.

Key contributions include:

- Quantum pattern matching, using amplitude amplification to locate biometric features
- QCNNs (Quantum Convolutional Neural Networks), optimized for low-data training
- Quantum cryptographic encoding for secure transmission of biometric templates

The work [44] implemented a hybrid quantum-classical face recognition system and achieved higher accuracy on grayscale facial datasets with fewer qubits. Additionally, the authors [45] proposed a quantum secure iris recognition algorithm using Bell-state-based feature encoding to ensure tamper-proof identity verification. These developments mark the convergence of quantum machine learning and cybersecurity, especially important in defense, smart surveillance, and border control applications.

In summary, application spotlights in quantum image processing highlight early use cases in medical imaging, remote sensing, and secure visual data processing, where hybrid quantum–classical models are explored for feature extraction, enhancement, and confidentiality. While current demonstrations are limited to small-scale datasets, these studies illustrate how quantum techniques may complement classical pipelines in high-complexity or security-sensitive imaging scenarios.

9. Benchmarks and Datasets for Quantum Image Processing

The development of robust and generalizable quantum image processing (QIP) techniques depends significantly on the availability of standardized datasets and benchmarks. Unlike

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MNIST, CIFAR-10, ImageNet, and medical imaging repositories—quantum image processing still lacks widely accepted datasets or evaluation protocols specifically designed for quantum circuits or simulators.

9.1 Use of Classical Datasets in Quantum Settings

Most current QIP experiments repurpose classical datasets after dimensionality reduction. For instance, the MNIST handwritten digit dataset is frequently used by reducing image size (e.g., from 28×28 to 4×4 or 8×8) to fit the limited number of qubits on today's Noisy Intermediate-Scale Quantum (NISQ) hardware.

For example, the work [46] demonstrated variational quantum classifiers using downsampled MNIST digits encoded via amplitude encoding and fed to a hybrid quantum-classical pipeline, emphasizing feasibility over scalability. While these studies are valuable, they cannot generalize to full-resolution or high-dimensional images due to qubit limitations and circuit depth constraints.

To bridge this gap, several researchers have proposed modifications to classical datasets to suit quantum experimentation:

- Binarized versions of grayscale images
- Cropped or low-resolution MRI/X-ray scans
- Synthetic datasets created for demonstrating quantum encoding models (e.g., FRQI, NEQR)

However, these approaches often suffer from loss of visual fidelity, limited variability, and lack of domain-specific context, particularly in high-stakes areas like medical imaging or remote sensing.

9.2 Emerging Quantum-Specific Datasets

A growing body of work aims to construct quantum-native datasets or simulated environments for benchmarking QIP algorithms. For instance, the work [47] introduced the Q-MNIST dataset—a quantum-encoded version of MNIST images using amplitude and phase encoding, suitable for simulation on Qiskit and PennyLane backends.

In another effort, the work [48] proposed a quantum circuit-based dataset generator, which outputs parametrized patterns designed to test the resilience of quantum edge detectors and filters. These quantum-specific datasets aim to simulate scenarios involving entanglement-aware pixel dependencies and probabilistic sampling [49] during decoding—something not present in classical counterparts.

Despite these efforts, there is still no universal benchmark that evaluates quantum image processing tasks across frameworks (e.g., Qiskit, Qibo, PennyLane, and Braket) or across representations (e.g., FRQI, NEQR, 2D-NEQR).

9.3 Toward Standardized Benchmarking Protocols

To encourage reproducibility and cross-platform validation, there is a strong need for community-driven initiatives to establish benchmarking standards. Inspired by classical projects like ImageNet, OpenML, or Medical Segmentation Decathlon, quantum image researchers have begun proposing metrics tailored to quantum environments:

- Quantum Fidelity: Used to compare expected and measured quantum states post-processing
- Circuit Depth and Gate Count: As complexity metrics impacting hardware feasibility
- Noise Robustness: Evaluating how performance degrades on real quantum backends

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Efforts like the QMLBench initiative (in preprint) aim to consolidate such metrics across simulation and hardware-based runs.

Without well-defined benchmarks, it becomes difficult to objectively evaluate progress in QIP, particularly for applications in quantum edge detection, compression, and classification.

Table 4 gives a comparative analysis of the datasets and their suitability for QIP. This table includes classical datasets adapted for quantum use, as well as quantum-native or simulated datasets designed specifically for benchmarking quantum image algorithms.

Table 4: Datasets for Quantum Image Processing – Comparison and Suitability

Dataset	Type	Size / Format	Used In	Quantum Encoding Applied	Suitability for QIP
MNIST	Classical	28×28 grayscale images	Wilson et al. (2021) [46]	Amplitude / Basis Encoding	Widely used (downsized to 4×4 or 8×8); good for classification
CIFAR-10	Classical	32×32 RGB images	Simulated QNNs in image classification	FRQI / NEQR (channel-split)	High memory demand; limited by current qubit count
MedMNIST	Classical (Medical)	Variable (RGB, gray)	Used in medical QML experiments	Binarization or grayscale compression	Excellent for low-resolution QML trials in healthcare
Q-MNIST	Quantum-Encoded	8×8 amplitude encoding	Wang et al. (2022) [47]	Amplitude Encoding	Designed for Qiskit/Pennylane simulation; suitable for VQC
Quantum Bars & Stripes	Synthetic (Quantum-native)	N×N binary images (N ≤ 8)	Educational demos, edge detection	NEQR / FRQI	Good for testing quantum edge filters and circuits
Synthetic Quantum Patterns	Quantum Circuit–Generated	User-defined (4×4 – 16×16)	Tian et al. (2023) [48]	Parametric FRQI / QFT	Tailored for benchmarking quantum Image Processing and vision pipelines
Fashion-MNIST (Compressed)	Classical	28×28 grayscale	Emerging QML applications	PCA + Quantum Amplitude Encoding	Moderate complexity; useful for testing hybrid models

In summary, Benchmarks and datasets for quantum image processing are currently adapted from classical image datasets such as MNIST, Fashion-MNIST, and MedMNIST, often reduced in resolution to meet qubit constraints. The absence of quantum-native benchmarks and

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reproducible datasets tailored to hybrid quantum–classical image experiments.

10. Hybrid Quantum-Classical Models in Image Processing

The Noisy Intermediate-Scale Quantum (NISQ) era is characterized by quantum processors with limited qubits and gate fidelity. As a result, fully quantum pipelines for complex image processing tasks are currently impractical. To bridge this hardware limitation, researchers have turned to hybrid quantum-classical models, which combine the power of classical deep learning with quantum computing's advantages in encoding, optimization, and parallelism.

10.1 Motivation for Hybrid Models

Hybrid models leverage the strengths of both paradigms:

- Classical Front-End: Handles tasks such as feature extraction, dimensionality reduction, and preprocessing, which are computationally efficient on GPUs or CPUs.
- Quantum Back-End: Performs classification, regression, or optimization using quantum circuits, variational quantum classifiers (VQCs), or quantum kernels.

This architecture significantly reduces the number of qubits required and enables execution on near-term quantum devices. For example, the authors [5] explored transfer learning using a classical convolutional neural network (CNN) as a feature extractor, followed by a variational quantum circuit for classification. This approach achieved comparable accuracy to full CNNs with fewer parameters.

10.2 Types of Hybrid Architectures

Several hybrid designs have been proposed in the context of image processing:

(i) Quantum Neural Layers

These models embed quantum circuits within neural networks, acting as quantum layers that learn trainable parameters.

- Example: A CNN processes image patches, and the final dense layer is replaced with a quantum circuit for classification.
- The work [49] applied such hybrid networks for semantic segmentation, reporting smoother boundaries and lower training times compared to pure CNNs.

(ii) Quantum Kernels with Classical SVMs

This method uses quantum circuits to compute kernel functions in high-dimensional Hilbert spaces, which are then fed to classical SVMs.

- The authors [6] introduced this approach using the quantum feature map concept, which has been adopted for low-dimensional grayscale image classification.

(iii) Quantum Autoencoders

Hybrid quantum autoencoders (QAE) compress visual data using quantum circuits, followed by classical decoding layers for tasks such as image denoising or compression.

- A work [51] proposed a QAE for reducing quantum state dimensionality, which has been adapted for low-resolution medical images.

10.3 Practical Implementations and Simulators

Popular frameworks supporting hybrid quantum-classical models include:

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- Qiskit Machine Learning (IBM's native interface for hybrid models)
- TorchQuantum (open-source framework optimized for PyTorch-based quantum layers)

For example, the Pennylane-Qiskit-TensorFlow stack allows seamless gradient backpropagation from quantum layers through classical neural networks, facilitating end-to-end training.

In summary, hybrid quantum-classical models provide a pragmatic pathway for integrating quantum computing into real-world image processing tasks. By offloading heavy preprocessing to classical systems and utilizing quantum circuits for decision layers or optimization, these models strike a balance between current hardware limitations and algorithmic innovation. As quantum hardware improves, these hybrid models are likely to evolve into fully quantum pipelines or serve as benchmarks for comparison.

11. Quantum Security in Image Processing

In an era of increasing cyber threats and data breaches, image processing systems—especially those used in domains like healthcare, surveillance, and defence—require robust mechanisms for ensuring security, privacy, and integrity. Quantum computing, along with quantum information science, offers novel capabilities to not only process images efficiently but also secure image data using the fundamental principles of quantum mechanics.

Unlike classical encryption, which can be theoretically broken by future quantum computers, quantum security methods rely on quantum no-cloning, entanglement, and quantum key distribution (QKD) to achieve provably secure communication and authentication.

11.1 Quantum Secure Image Transmission

The most direct application of quantum security in image processing is quantum key distribution (QKD), which enables two parties to share a secret key using quantum states. This key can then be used for symmetric encryption of sensitive image data (e.g., in teleradiology or remote surveillance).

For instance, the work [52] proposed a quantum image encryption technique based on the fractional-order chaos system and QKD for encrypting medical images transmitted over open networks. Their approach demonstrated superior resistance to brute-force, noise, and statistical attacks compared to classical methods.

11.2 Quantum Watermarking and Steganography

Quantum watermarking embeds ownership or integrity verification data within the quantum representation of an image. Unlike classical watermarking, quantum techniques allow tamper detection at the quantum state level, making them highly secure.

The work [53] introduced a quantum watermarking scheme using the quantum Fourier transform (QFT), demonstrating its applicability in securing high-value satellite imagery. The watermark, encoded in the phase of qubits, could be extracted even after image perturbations or noise, preserving fidelity and ownership.

Quantum steganography further enables hiding images or messages within other quantum states, with detection only possible by authorized receivers aware of the encoding mechanism.

11.3 Quantum Image Authentication and Integrity Verification

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transmission or storage. Unlike classical hash functions or digital signatures, quantum image authentication protocols exploit entanglement or Bell-state measurements to verify authenticity.

The work [54] proposed an authentication protocol for NEQR images using controlled quantum gates and quantum hash functions. Their model successfully identified even minute modifications in image data, offering a highly sensitive method for forensic image validation. In forensic and legal contexts, this capability could prove invaluable for verifying medical records, satellite intelligence, or surveillance evidence.

11.4 Challenges and Prospects

While the theoretical foundation for quantum-secure image processing is strong, several practical challenges remain:

- Current quantum devices have limited qubits and coherence time for full-scale encryption or watermarking
- Implementation of quantum cryptographic protocols requires integration with quantum communication infrastructure (e.g., QKD networks)
- There is limited standardization of quantum image security protocols across platforms

Nevertheless, as quantum networks mature (e.g., China's QUESS satellite or Europe's OpenQKD project), the fusion of QIP and quantum cryptography is likely to be a pivotal area in secure digital infrastructure.

In summary, Quantum image security offers a paradigm shift in how visual data is protected, authenticated, and transmitted. From secure encryption and watermarking to quantum-level authentication, these techniques promise tamper-proof, privacy-preserving systems that are resilient to classical and quantum attacks alike. As quantum communication hardware advances, quantum-secured image processing systems will become essential in critical applications such as medical diagnostics, remote sensing, and national defence.

12. Analytical Framework

While the preceding sections have examined quantum image processing from multiple perspectives—ranging from representation models and learning paradigms to benchmarking, security, and applications—it is important to consolidate these discussions into a unified perspective. Given the interdisciplinary nature of quantum image processing, researchers often face challenges in systematically navigating design choices, comparing methodologies, or identifying suitable pathways for practical implementation. To address this, Table 5 presents a consolidated analytical framework that synthesizes the key dimensions explored throughout this survey. Rather than introducing new concepts, the framework organizes existing ideas into a structured pipeline that reflects how quantum image processing systems are typically conceived, developed, and evaluated. It highlights the logical progression from problem definition and data representation to computational modeling, benchmarking, application deployment, and security considerations, while explicitly acknowledging the constraints imposed by current NISQ-era quantum hardware. The framework is intended to serve as a guiding reference for researchers and practitioners—helping them position their work within

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design choices, and identify open research gaps.

Table 5: Analytical Framework

Layer	Framework Component	What It Addresses	Key Design Choices	Evaluation Focus
Problem Definition	Image Processing Task	Identifies the objective of processing	Classification, enhancement, compression, restoration	Task relevance, clinical/operational usefulness
Data Representation	Quantum Image Encoding	Maps classical images to quantum states	FRQI, NEQR, 2D-NEQR, amplitude encoding	Qubit efficiency, encoding complexity
Computational Model	Processing Architecture	Performs learning or transformation	Fully quantum vs. hybrid quantum–classical models	Circuit depth, trainability, hardware feasibility
Learning & Optimization	Model Training Strategy	Optimizes quantum parameters	VQCs, QCNNs, quantum kernels	Convergence, stability, noise tolerance
Benchmarking & Metrics	Dataset & Evaluation	Enables fair performance comparison	MNIST variants, Q-MNIST, synthetic datasets	Fidelity, SSIM, PSNR, gate count
Application Mapping	Domain Deployment	Links methods to real-world use	Medical imaging, remote sensing, biometrics	Accuracy, reliability, interpretability
Security & Trust	Quantum Security Layer	Protects sensitive image data	QKD, watermarking, authentication	Privacy, tamper resistance
Practical Constraints	NISQ Reality Check	Ensures near-term feasibility	Qubit limits, noise, simulators	Scalability, reproducibility

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13. Conclusion

Quantum computing has emerged as a promising paradigm for addressing the growing computational demands of image processing, particularly in scenarios where classical methods face scalability, optimization, or security limitations. This survey has systematically reviewed the evolution of quantum image processing, spanning representation models, hybrid learning architectures, tools and simulators, benchmarking datasets, security considerations, and emerging application domains. Rather than positioning quantum approaches as direct replacements for classical pipelines, the paper emphasizes their role as complementary

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constraints.

a. Summary of Key Contributions

This survey makes several key contributions to the existing literature. First, it presents a structured taxonomy of quantum image processing techniques, linking classical image processing tasks—such as classification, enhancement, compression, and restoration—to their quantum and hybrid counterparts. Second, it critically examines quantum image representation models, highlighting trade-offs among qubit efficiency, circuit depth, and noise sensitivity. Third, the paper evaluates hybrid quantum–classical architectures, offering analytical insights into practical challenges including data transmission latency between classical and quantum processors, convergence behavior during training, and robustness to hardware noise in NISQ-era devices.

Additionally, this work consolidates a diverse set of tools, frameworks, simulators, and datasets, providing a practical reference for researchers seeking to implement or benchmark quantum image processing algorithms. The inclusion of security-aware image processing and application-driven case spotlights further broadens the scope of the survey, emphasizing both technical feasibility and real-world relevance. Collectively, these contributions offer a cohesive and comparative perspective that extends beyond isolated algorithmic studies.

b. Future Research Directions

Future research in quantum image processing should move beyond broad conceptual goals toward quantifiable and implementation-driven targets. One immediate priority is the design of noise-aware hybrid architectures that explicitly model hardware constraints. For example, future studies should benchmark hybrid quantum–classical image classifiers under fixed circuit depths (e.g., ≤20 two-qubit gates) and evaluate performance degradation across standardized noise models, reporting metrics such as accuracy drop per noise channel and convergence stability across training epochs.

Another critical direction involves data encoding and transmission efficiency. Research efforts should quantify classical-to-quantum data loading overhead by measuring end-to-end latency for different encoding schemes (e.g., amplitude vs. angle encoding) and correlating it with achievable image resolution and qubit count. Establishing encoding efficiency metrics—such as information density per qubit or reconstruction fidelity per circuit depth—would enable objective comparison across methods.

In the context of training convergence, future work should focus on adaptive optimization strategies tailored for hybrid models, including layer-wise training, parameter freezing, and noise-aware gradient estimation. Measurable outcomes could include reductions in training epochs to convergence or improvements in loss stability under noisy execution. Additionally, systematic ablation studies are needed to determine the minimal quantum circuit depth required to outperform classical baselines on fixed-size image tasks.

Explainable quantum image processing (QXAI) should progress from conceptual proposals to operational interpretability tools, such as visualizing quantum feature maps or measuring the sensitivity of output states to pixel perturbations. These methods should be validated against classical explainability benchmarks to assess their added value. Finally, as hardware evolves, large-scale validation on real quantum devices—using standardized datasets and reproducible protocols—will be essential to demonstrate practical advantage and guide the transition from simulation-based studies to deployment-oriented research.

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computational imaging—offering both theoretical insights and practical solutions for next-generation intelligent systems.

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