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A Comprehensive Survey of Quantum and Quantum-Inspired Image Segmentation in the Context of Modern Segmentation Methods

Marie Gogolin

marie.gogolin@itwm.fraunhofer.de

Fraunhofer Institute for Industrial Mathematics and RPTU Kaiserslautern-Landau
https://orcid.org/0009-0002-4529-2070

Yannick Werner

DFKI German Research Center for Artificial Intelligence and RPTU Kaiserslautern-Landau
https://orcid.org/0009-0008-8315-7973

Alexander Geng

Fraunhofer Institute for Industrial Mathematics https://orcid.org/0000-0002-9955-4809

Paul Lukowicz

DFKI German Research Center for Artificial Intelligence and RPTU Kaiserslautern-Landau
https://orcid.org/0000-0003-0320-6656

Ali Moghiseh

Fraunhofer Institute for Industrial Mathematics https://orcid.org/0000-0001-9126-3495

Maximilian Kiefer-Emmanouilidis

DFKI German Research Center for Artificial Intelligence and RPTU Kaiserslautern-Landau
https://orcid.org/0009-0005-7065-3511

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A Comprehensive Survey of Quantum and Quantum-Inspired Image Segmentation in the Context of Modern Segmentation Methods

MARIE GOGOLIN, Fraunhofer Institute for Industrial Mathematics ITWM, Germany and RPTU Kaiserslautern-Landau, Germany
YANNICK WERNER, DFKI German Research Center for Artificial Intelligence, Germany and RPTU Kaiserslautern-Landau, Germany
ALEXANDER GENG, Fraunhofer Institute for Industrial Mathematics ITWM, Germany
PAUL LUKOWICZ, DFKI German Research Center for Artificial Intelligence, Germany and RPTU Kaiserslautern-Landau, Germany
ALI MOGHISEH, Fraunhofer Institute for Industrial Mathematics ITWM, Germany
MAXIMILIAN KIEFER-EMMANOUILIDIS, DFKI German Research Center for Artificial Intelligence, Germany and RPTU Kaiserslautern-Landau, Germany

Image segmentation remains one of the most extensively studied problems in computer vision, with applications ranging from medical image analysis and autonomous driving to remote sensing and industrial inspection. While deep learning approaches currently dominate the field, interest in quantum computing has motivated the development of quantum and quantum-inspired segmentation techniques that explore alternative strategies for image representation, optimization, and learning. This survey provides a comprehensive review of quantum and quantum-inspired image segmentation methods within the broader context of modern segmentation research. To establish this context, we first examine the evolution of image segmentation methodologies, covering classical image processing techniques, machine learning approaches, and contemporary deep learning architectures. We then organize the existing quantum image segmentation literature into four categories: quantum-inspired, tensor network-based, hybrid quantum-classical, and fully quantum methods. Across these categories, we analyze computational principles, image encoding and representation strategies, application domains, and datasets. We further compare quantum and quantum-inspired approaches with established segmentation paradigms in terms of supervision, scalability, and hardware requirements. Our analysis indicates that quantum-inspired methods currently represent the most developed direction, while hybrid approaches are emerging and fully quantum methods remain constrained by quantum hardware, data encoding costs, and scalability challenges. By connecting quantum image segmentation with the broader evolution of segmentation research, this survey provides a unified perspective on the field. It identifies current trends, open challenges, and promising future directions for researchers exploring the emerging role of quantum computing in image segmentation.

1 Introduction

Image segmentation is a foundational task in computer vision and image analysis. Its objective is to partition an image into meaningful regions based on characteristics such as semantic class, appearance, texture, or spatial structure. Modern image segmentation tasks are commonly categorized into three main types: semantic, instance, and panoptic segmentation. Semantic segmentation assigns a class label to every pixel, with pixels belonging to the same semantic

Authors' Contact Information: Marie Gogolin, marie.gogolin@itwm.fraunhofer.de, Fraunhofer Institute for Industrial Mathematics ITWM, Kaiserslautern, Rhineland-Palatinate, Germany and RPTU Kaiserslautern-Landau, Germany; Yannick Werner, DFKI German Research Center for Artificial Intelligence, Kaiserslautern, Rhineland-Palatinate, Germany and RPTU Kaiserslautern-Landau, Germany, yannick.werner@dfki.de; Alexander Geng, Fraunhofer Institute for Industrial Mathematics ITWM, Kaiserslautern, Rhineland-Palatinate, Germany, alexander.geng@itwm.fraunhofer.de; Paul Lukowicz, DFKI German Research Center for Artificial Intelligence, Kaiserslautern, Rhineland-Palatinate, Germany and RPTU Kaiserslautern-Landau, Germany, Paul.Lukowicz@dfki.de; Ali Moghiseh, Fraunhofer Institute for Industrial Mathematics ITWM, Kaiserslautern, Rhineland-Palatinate, Germany, ali.moghiseh@itwm.fraunhofer.de; Maximilian Kiefer-Emmanouilidis, DFKI German Research Center for Artificial Intelligence, Kaiserslautern, Rhineland-Palatinate, Germany and RPTU Kaiserslautern-Landau, Germany, maximilian.kiefer@dfki.de.

class receiving the same label. In contrast, instance segmentation aims to identify individual object instances and assigns a separate segmentation mask to each of them. The third category is panoptic segmentation, which combines both perspectives by assigning a semantic class label to every pixel and a unique instance identifier to each countable object [109]. These segmentation types enable downstream tasks such as object tracking and scene understanding. Domains in which image segmentation plays a pivotal role include medical image analysis (e.g., isolating anatomical structures), autonomous driving (e.g., distinguishing roads, pedestrians, and vehicles), and remote sensing (e.g., mapping land cover).

Over the decades, image segmentation methodologies have undergone substantial evolution.Early segmentation systems primarily relied on manually specified image properties and explicit decision rules, including intensity discontinuities, region similarity, clustering, and graph-based formulations. Although classical approaches are generally efficient and interpretable, their performance can deteriorate in the presence of noise, heterogeneous regions, and complex textures [69, 143, 220, 226]. To address these limitations, data-driven machine learning strategies emerged, typically combining engineered image features with statistical learning models such as support vector machines (SVMs) and random forests. These approaches were subsequently advanced through end-to-end representation learning, ranging from convolutional neural networks (CNNs) to transformer-based architectures and, more recently, large-scale foundation models. Such methods have achieved state-of-the-art performance across a broad range of segmentation benchmarks and currently dominate modern segmentation research. However, this development does not imply a complete replacement of earlier paradigms. Classical and machine learning methods remain relevant in application domains where computational efficiency and interpretability are crucial or where training data are limited. Furthermore, hybrid approaches can combine the complementary strengths of different paradigms.

Deep learning has substantially improved image segmentation, but its practical deployment still involves important constraints. Training data are often expensive to obtain and annotate, particularly in medical imaging [196]. Model behavior can also be difficult to interpret, which is particularly important in safety-critical and medical applications where decisions may need to be explainable. Deep learning models are also prone to overfitting, which can limit their ability to generalize to unseen data. However, the extent of overfitting depends on factors such as the amount and diversity of training data, model architecture, regularization, data augmentation, and potential domain shifts. Furthermore, training these models can require substantial computational and hardware resources [22]. These challenges have motivated the exploration of alternative computational paradigms that may complement existing approaches.

One emerging research direction is the application of quantum computing concepts to image segmentation. Quantum and quantum-inspired methods draw on concepts from quantum computing and quantum information, including superposition and entanglement, as well as related representations such as tensor networks. Based on how quantum computation is incorporated, existing approaches range from quantum-inspired algorithms that run entirely on classical hardware to hybrid quantum-classical frameworks and fully quantum implementations that require quantum processors or simulators in the full computational pipeline. Although many of these methods remain at an early stage of development, they are being explored as alternative computational strategies for image segmentation.

Image segmentation has been extensively surveyed from classical and deep learning perspectives [31, 142, 183], while a substantial body of literature has investigated quantum image processing [34, 218]. However, the relationship between quantum and quantum-inspired segmentation methods and the broader segmentation landscape remains insufficiently explored. In particular, a unified perspective that positions emerging quantum approaches alongside established classical, machine learning, and deep learning paradigms, would facilitate a more comprehensive assessment of their capabilities, limitations, and potential future role. Moreover, while individual surveys and overviews have

addressed aspects of quantum image segmentation [158], these works do not provide a systematic comparison of quantum segmentation methods within the broader segmentation landscape, making it difficult for researchers to obtain an overview of the field.

To address these gaps, this survey reviews quantum and quantum-inspired image segmentation methods within the context of modern segmentation research. We first discuss the major paradigms of image segmentation, including classical, machine learning, and deep learning approaches, to establish the broader methodological landscape. Building upon this foundation, we organize the existing quantum image segmentation literature into four major categories: quantum-inspired methods, tensor network-based approaches, hybrid quantum-classical frameworks, and fully quantum algorithms. Quantum-inspired methods adapt concepts from quantum mechanics or quantum computing within classical computational frameworks and do not require quantum hardware. Tensor network approaches use structured tensor representations to compactly represent and process high-dimensional image data. Hybrid quantum-classical methods combine classical processing with quantum subroutines, while fully quantum methods perform the segmentation task within a quantum computational framework. We compare these quantum paradigms with established classical, machine learning, and deep learning approaches in terms of supervision, data and hardware requirements, computational cost, scalability, and interpretability. Within the quantum literature, we further compare methods according to their image encoding and representation techniques, datasets, and application domains. The resulting synthesis provides a structured overview of the field, identifies current challenges and research gaps, and highlights promising directions for future work.

The remainder of this paper is organized as follows. Section 2 reviews the major image segmentation paradigms, from classical image processing and machine learning to deep learning. Section 3 introduces the four-category taxonomy and the quantum computing concepts and image representations required to understand the surveyed methods. Section 4 presents the quantum and quantum-inspired approaches. Section 5 compares them with established segmentation paradigms, while Section 6 provides a more detailed comparison within the quantum and quantum-inspired literature. Section 7 discusses key research gaps, limitations, and future directions. Finally, Section 8 concludes the survey.

2 Non-Quantum Image Segmentation Paradigms

Before discussing quantum and quantum-inspired image segmentation, it is useful to review the major paradigms that have shaped the field. Image segmentation methods have evolved from mainly rule-based and optimization-driven classical techniques to increasingly data-driven machine learning and deep learning approaches. This section provides a concise overview of these paradigms, focusing on their key characteristics and limitations. Figure 1 summarizes these paradigms.

2.1 Classical Image Segmentation

Classical image segmentation methods established many of the concepts underlying modern approaches and remain relevant when computational resources or annotated data are limited. Applications include embedded systems [33], real-time industrial inspection [213], medical imaging [224], and agricultural analysis using small drone datasets [70], where efficiency, interpretability, and implementation simplicity remain important [224]. These methods can be grouped into thresholding, gradient-based, region-based, graph-based, clustering, and energy minimization approaches, each based on different assumptions and computational principles.

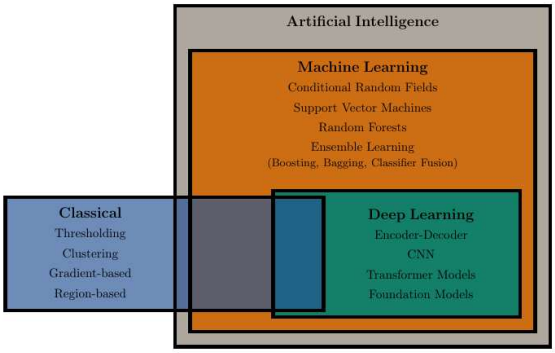


Fig. 1. Taxonomy of classical, machine learning and deep learning image segmentation paradigms, and their categories shown as a Venn diagram. The three paradigms can be combined in practice, as indicated by the overlap of the rectangles.

2.1.1 Thresholding. Thresholding provides a computationally simple approach for separating image regions according to intensity values. A seminal contribution in this area is Otsu's method, proposed by Nobuyuki Otsu in 1979. This method automatically determines an optimal threshold by maximizing the between-class variance of the gray-level histogram. The algorithm is nonparametric and unsupervised, requiring no prior assumptions about the underlying intensity distributions, which makes it computationally efficient and easy to implement. Furthermore, the method can be extended to multilevel thresholding for images containing more than two intensity classes. Another influential thresholding approach is the entropy-based method proposed by Kapur et al. [103] in 1985. Instead of relying on variance, the algorithm selects thresholds by maximizing the sum of entropies (a concept from information theory) in the segmented regions, making it suitable for images with multimodal gray-level distributions [103]. Other early thresholding methods include moment-preserving thresholding [202] and minimum error thresholding [112]. More recent methods encompass bi-level image thresholding [57], several nature-inspired methods such as differential evolution [192], particle swarm optimization (PSO) [107], and artificial bee colony optimization [104]; these have been adapted specifically for image segmentation tasks [44]. Additionally, iterative thresholding [212] and generalized histogram thresholding [15] have been proposed, with the latter being a framework which unifies and generalizes Otsu's method and minimum error thresholding.

2.1.2 Clustering. Clustering provides an unsupervised approach to image segmentation. Pixels or image regions are grouped according to similarity criteria such as intensity, color, or texture. Gaussian mixture models (GMMs) and k-means clustering are two prominent clustering families. GMMs represent data as a weighted sum of multiple Gaussian probability distributions. The expectation-maximization algorithm is commonly employed to estimate the GMM parameters by iteratively maximizing the likelihood of the observed data under the mixture model [50]. The posterior probabilities can then be used to assign each pixel to the most likely mixture component, resulting in a segmentation mask [102]. This approach has been extended in several directions, including superpixel segmentation [14], class-adaptive spatially constrained mixture models [150], and methods that integrate hidden Markov random fields with the expectation-maximization algorithm [231].

K-means divides the data into a predefined number of clusters by minimizing the within-cluster sum of squared distances to the corresponding centroids. It is computationally simple but can be affected by centroid initialization and outliers. A related extension is fuzzy c-means, a soft clustering approach formalized by Bezdek et al. [20], which allows data points to belong to multiple clusters with varying degrees of membership. Several adaptations incorporate additional spatial or nonlinear information [3, 102, 131, 227]. Further developments include spatially constrained k-means, which incorporates spatial information to reduce noise in segmentation maps [130, 137, 228]; kernel k-means, which handles nonlinear separability by implicitly mapping data into a higher-dimensional feature space [118, 129]; and the integration of k-means into hierarchical clustering frameworks [146].

2.1.3 Gradient-based. Gradient-based image segmentation focuses on identifying intensity transitions within an image, which often correspond to object boundaries. The image gradient provides a basis for detecting such boundaries by characterizing local intensity changes. It is a vector at each pixel that points in the direction of the greatest local intensity increase, with its magnitude indicating the rate of change. The gradient magnitude therefore measures the strength of local intensity transitions and can be used to construct an edge map. This map provides indicators of object boundaries and can be used in combination with contour models, watershed, region-growing, or graph-based methods to support segmentation [47].

Classically, edges can be detected by evaluating pixel intensity variations using filters such as Sobel, Prewitt, Laplacian, and Canny [29, 47]. These methods are complemented by active contour models, including gradient vector flow snakes, further incorporate image-derived forces with regularization terms that maintain contour smoothness [222]. Subsequent work has developed and extended gradient-based and active contour approaches for different segmentation applications [152, 166, 211, 229].

2.1.4 Region-based. Region-based segmentation methods identify connected image regions according to their spatial or intensity characteristics. A prominent example is the watershed transform, which interprets an image or its gradient as a topographic surface and simulates flooding from regional minima. The resulting catchment basins define the segmented regions, while watershed lines separate neighboring basins [106, 209]. To improve accuracy, various enhancements have been proposed. Some use genetic algorithms to guide the segmentation process [52], while others rely on marker-based methods to prevent over-segmentation [61, 78, 126, 230] or combine watershed with texture gradient analysis [91] or optimal thresholding [32].

2.1.5 Graph-based. Graph-based segmentation methods represent an image as a graph, where pixels are conceptualized as graph nodes with weighted edges, reflecting similarity. Segmentation can then be formulated through graph partitioning, region merging, or minimum-spanning-forest approaches. For example, Felzenszwalb and Huttenlocher [64] proposed an efficient graph-based method that iteratively merges regions based on the differences within regions and across their boundaries. Guimarães et al. [80] extend this approach to construct a nested hierarchy of segmentations, enabling multiscale image analysis.

2.1.6 Energy Minimization. Energy minimization provides a general framework for image segmentation by formulating the task as an optimization problem. Techniques like graph cuts [139, 208], random walker [55, 77, 108], and Markov random fields [48, 105] aim to minimize an energy function that balances data fidelity with spatial smoothness. For binary segmentation, exact solutions can be computed efficiently using max-flow/min-cut algorithms [26].

2.1.7 Limitations. Though classical methods are interpretable, relatively simple to implement, and computational efficient, they face challenges such as noise, uneven illumination, complex textures and often rely on handcrafted features [69, 143, 220, 226]. These limitations, together with the increasing availability of annotated image datasets and computational resources, motivated a shift toward data-driven segmentation approaches, including machine learning and, subsequently, deep learning methods such as CNNs.

2.2 Machine Learning Image Segmentation

Prior to the widespread adoption of deep learning, traditional machine learning played an important role in image segmentation, with methods including support vector machines (SVMs), conditional random fields (CRFs), random forests, and other ensemble models. These approaches typically depend on handcrafted feature extraction, as the quality of the extracted features strongly influences segmentation performance. Commonly used feature descriptors include the scale-invariant feature transform [136], histogram of oriented gradients [46], wavelet-based features [144, 179], and edge orientation histograms [66, 67].

2.2.1 Conditional Random Fields. CRFs were introduced by Lafferty et al. [121] as a probabilistic framework for modeling structured data, particularly sequence labeling. Kumar and Hebert [120] proposed a discriminative random field framework based on CRFs, where image regions are classified by incorporating spatial interactions from neighboring labels and observed data.

Krähenbühl and Koltun [117] introduced fully connected CRF models, in which dependencies are defined over all pixels rather than only local neighborhoods. More recently CRFs have increasingly been integrated with deep learning models such as deep neural networks [8] and CNNs [36]. Other approaches formulate iterative CRF inference as recurrent neural network architectures [145, 234].

2.2.2 Support Vector Machines. SVMs are supervised learning methods that classify data by learning a decision boundary in a potentially high-dimensional feature space, with kernel functions enabling nonlinear decision boundaries [42]. In image segmentation, SVMs are typically combined with handcrafted color, texture, shape, or intensity features. Early approaches integrated SVMs with level-set methods to learn image and curvature characteristics for segmentation [233]. Other methods applied SVMs directly to pixel- or superpixel-level features, sometimes combining them with fuzzy c-means clustering, saliency estimation, or SLIC superpixels [13, 189, 216, 217]. These approaches demonstrate the flexibility of SVMs for segmentation but rely strongly on the quality of the engineered features used for classification.

2.2.3 Ensemble Learning. Ensemble learning combines multiple classifiers to improve segmentation robustness and accuracy. Common strategies include boosting, bagging, and classifier fusion, where predictions from multiple models are aggregated to obtain a final segmentation. AdaBoost [68] is a prominent boosting approach that iteratively combines weak learners into a stronger classifier. Other boosting methods have also been applied to image segmentation [9, 125, 201].

Classifier fusion provides another ensemble strategy by combining the outputs of multiple classifiers. Kittler [111] developed a general theoretical framework for classifier combination, while Rohlfing et al. [172] applied classifier fusion to image segmentation by combining multiple segmentations into a consensus result. Like other traditional machine learning approaches, these methods generally depend on the quality of the underlying features and classifiers.

2.2.4 Random Forests. Random forests are ensemble learning methods introduced by Breiman [28] that combine multiple decision trees trained on randomly sampled training data and feature subsets. For a given input, the individual

trees vote for a class, and the final prediction is typically determined by majority voting. In image segmentation, random forests have been applied to pixel- and patch-based classification and can incorporate appearance, spatial, and contextual information. For example, Shotton et al. [187] proposed Semantic Texton Forests, which classify image pixels using randomized decision trees operating on local image patches. Subsequent approaches incorporated structural and contextual information to improve semantic labeling [75, 115], including spatial relationships and domain-specific features such as brain symmetry for medical image segmentation.

2.2.5 Limitations. Although machine learning methods can improve segmentation beyond purely handcrafted classical techniques, their performance is strongly influenced by the representation supplied to the learning algorithm. Designing informative features requires domain knowledge and substantial engineering effort, while fixed descriptors may have difficulty representing complex semantic relationships and may transfer poorly between datasets or imaging conditions [90, 182, 226]. Deep learning addresses this limitation by jointly learning task-relevant representations and prediction functions from image data, reducing the need for manually designed feature pipelines.

2.3 Deep Learning Image Segmentation

Deep learning has substantially changed image segmentation by enabling models, particularly convolutional neural networks (CNNs), to learn task-relevant representations as part of the training process. Rather than relying on a fixed set of manually designed descriptors, CNNs transform raw image intensities through successive layers into increasingly abstract representations that can capture local patterns, textures, structures, and higher-level object characteristics. Earlier segmentation pipelines typically depended on manually specified features, such as texture, color, and gradient descriptors, whose effectiveness could vary across tasks and datasets [153].

2.3.1 Convolutional Neural Networks. In 2015, Long et al. proposed the Fully Convolutional Network (FCN) architecture, which converted classification networks into fully convolutional architectures by replacing fully connected layers with convolutional layers. The FCN is trained end-to-end in a pixel-to-pixel manner, enabling it to predict dense outputs from inputs of arbitrary size [135].

Mask R-CNN addresses instance segmentation with a CNN architecture. It builds on Faster R-CNN [171] by adding an additional branch that predicts an object mask for each instance, operating in parallel with the existing branch for bounding box detection. This enables both object detection and segmentation mask prediction within a single architecture [87].

2.3.2 Encoder-Decoder Architecture. Another influential family of segmentation models is the encoder-decoder architecture. U-Net is one of the most prominent examples, extending the FCN concept with a contracting encoder path for capturing contextual information and a symmetric decoder path for precise localization through skip connections [173]. Numerous U-Net variants have since been proposed to address limitations such as feature blurring, limited receptive fields, and insufficient contextual information. These include architectures incorporating recurrent residual blocks, dense skip connections, dynamic receptive fields, squeeze-and-excitation modules, and attention mechanisms [16, 35, 89, 99, 148, 236]. Transformer-based variants such as UNETR further extend the encoder-decoder framework by using transformers to capture global and multi-scale contextual information [86].

Other encoder-decoder architectures follow different design principles. SegNet uses the pooling indices from the encoder to guide decoder upsampling, reducing memory requirements [11]. DeepLab instead employs atrous convolutions to enlarge the receptive field while preserving spatial resolution and uses atrous spatial pyramid pooling

to capture multi-scale information [37]. DeepLabV3+ further incorporates a decoder to improve the refinement of segmentation boundaries [38].

2.3.3 Transformer Architectures and Attention. In recent years, transformer-based and attention-driven architectures have emerged as powerful approaches for image segmentation, particularly due to their ability to model long-range dependencies and global context. The Segmentation Transformer [235] was one of the first transformer-based segmentation architectures, reformulating semantic segmentation as a sequence-to-sequence prediction task by processing image patches with self-attention. Segmenter [194] similarly adapts the Vision Transformer (ViT) [58] to semantic segmentation by producing patch-level embeddings that are converted into segmentation masks using linear or mask-transformer decoders. SegFormer combines a hierarchical transformer encoder with a lightweight multilayer perceptron decoder to efficiently integrate multi-scale features [221]. Mask2Former extends transformer-based segmentation to semantic, instance, and panoptic segmentation by using masked attention to focus each query on relevant image regions [40].

Attention mechanisms have also been incorporated into predominantly convolutional architectures. For example, SegNeXt replaces conventional self-attention with a convolutional attention mechanism to capture contextual information while retaining the efficiency of convolutional processing [81].

2.3.4 Foundation Models. Image segmentation can also be performed using foundation models. Foundation models are large-scale models pretrained on broad and diverse datasets, often exhibiting strong zero-shot and few-shot generalization capabilities. Depending on the application domain, they may be based on different architectures, such as large language models for text or transformer-based vision models for images. Their broad pretraining enables them to generalize to novel tasks and data distributions beyond those encountered during training [110]. Such models can be controlled or guided through the use of prompts. The Segment Anything Model (SAM) [110] is a promptable foundation model for image segmentation built on a ViT image encoder and has three main components: an image encoder, a flexible prompt encoder, and a fast mask decoder. First, the input image and a user-provided prompt are encoded. The transformer-based mask decoder then predicts segmentation masks corresponding to the provided prompt.

2.3.5 Limitations. Though deep learning models offer considerable advancements over traditional image segmentation techniques, they still face several limitations. One primary constraint is the reliance on large, annotated datasets for training [196], which are often difficult to obtain in important domains such as medical image segmentation. Several strategies can mitigate this limitation, including transfer learning [122], where pretrained models are fine-tuned on small, domain-specific datasets; data augmentation [186, 200], which applies transformations such as flipping, rotation, and scaling to expose the model to a more diverse set of inputs; and synthetic data generation using models like generative adversarial networks (GANs) to create realistic, annotated data [185, 224].

Another challenge is interpretability, which is particularly important in medical applications where experts may need to understand the basis of segmentation results. Explainability techniques such as layer-wise relevance propagation [10], as well as interpretable models such as decision trees [45] and linear models [133], can provide insights into model decisions [224]. Attention mechanisms additionally can focus segmentation models on relevant spatial regions and feature representations [79].

Deep learning models can also overfit, meaning they generalize poorly to unseen data. Techniques to prevent overfitting include dropout and regularization [170], data augmentation, integrated learning methods [39], and GAN-based training [160, 224]. Finally, a critical challenge is the high computational demand posed by deep learning [22]. Training models such as CNNs, FCNs, or transformers requires significant computational resources and long training

times. To alleviate this, approaches like model compression [85]–including pruning and quantization–can reduce model size; lightweight architectures such as EfficientNet [127, 197] improve efficiency; and distributed or parallel computing techniques, including the use of GPUs and TPUs, help reduce computational overhead [224].

3 Taxonomy of Quantum Image Segmentation Approaches

The field of quantum image segmentation has expanded in recent years, with an increasing number of publications proposing a wide variety of methodological approaches. As the body of literature continues to expand, the field becomes increasingly heterogeneous and more difficult to navigate, particularly for newcomers who are unfamiliar with the diverse, often physics-inspired, terminology. This heterogeneity reflects the broad range of computational paradigms employed, which differ fundamentally in how they incorporate quantum computing concepts and principles from quantum mechanics. As a result, the proposed methods vary considerably in terms of hardware requirements, algorithmic design, computational workflow, and practical applicability. This makes it challenging to compare existing approaches and identify research gaps and future opportunities.

Furthermore, the maturity of the published methods differs substantially across the literature, with some approaches already evaluated experimentally, while others remain largely conceptual or are limited by current quantum hardware. A taxonomy such as the one proposed in this survey provides a structured framework for organizing, comparing, and discussing the existing literature. It highlights the relationships, similarities, and differences between the various methodological paradigms, reveals current research trends, and facilitates the identification of promising directions for future research. Although it is possible to categorize the literature according to aspects such as the image representation technique or the underlying quantum computing paradigm, these criteria do not capture the full methodological diversity of quantum image segmentation approaches. Instead, they describe specific characteristics that can occur across different methodological categories. The proposed taxonomy therefore focuses on how quantum and quantum-inspired techniques are integrated into the overall segmentation approach.

Based on this criterion, we distinguish four main categories: quantum-inspired, tensor network-based, hybrid quantum-classical, and fully quantum methods. Tensor network methods are treated separately because, although often quantum-inspired, they use tensor network representations as their primary computational framework rather than directly adapting quantum algorithms. Figure 2 summarizes the taxonomy and its subcategories, which are based on the primary methodological mechanism.

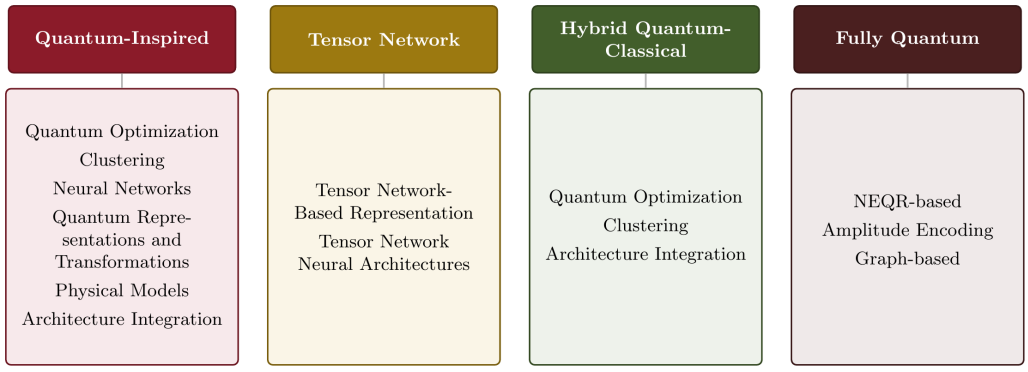


Fig. 2. Four-category taxonomy of quantum and quantum-inspired image segmentation methods and their subcategories.

3.1 Quantum-Inspired

Quantum-inspired methods employ mathematical concepts derived from quantum mechanics to develop or modify classical algorithms without requiring quantum hardware. Instead of exploiting physical quantum effects, they transfer selected principles to classical computation. Among the most important are quantum state representations and the principle of superposition.

In quantum mechanics, the fundamental unit of quantum information is the qubit. A qubit is represented by a vector in a two-dimensional complex Hilbert space and can occupy the computational basis states

$$|0\rangle = \begin{pmatrix} 1 \\ 0 \end{pmatrix}, \qquad |1\rangle = \begin{pmatrix} 0 \\ 1 \end{pmatrix}.$$

A general single-qubit state is given by

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle, \qquad \alpha, \beta \in \mathbb{C}, \qquad |\alpha|^2 + |\beta|^2 = 1, \tag{1}$$

where α and β are complex probability amplitudes. Their squared magnitudes, $|\alpha|^2$ and $|\beta|^2$, give the probabilities of measuring the qubit in the states $|0\rangle$ and $|1\rangle$, respectively. Before measurement, the qubit is described as a linear combination of both basis states, a property known as superposition [149].

Although quantum-inspired methods do not exploit physical quantum superposition, they can adopt mathematical representations inspired by quantum states, including normalized amplitude-based representations. These concepts have also motivated quantum-inspired optimization algorithms, such as quantum-behaved PSO, in which particle positions are modeled probabilistically rather than solely as deterministic point estimates. Depending on the formulation, such approaches can provide alternative data representations or optimization strategies while remaining fully executable on classical hardware.

3.2 Tensor Network

Tensor network approaches provide an alternative representation by expressing high-dimensional data through structured tensor decompositions. In image processing, an image can naturally be interpreted as a high-order tensor, with dimensions corresponding to spatial coordinates, color channels, or feature maps. Tensor networks compress these high-dimensional representations into interconnected low-order tensors, thereby reducing memory requirements and computational complexity while preserving the dominant information [154, 180]. Although tensor networks originated in quantum physics as representations of many-body quantum states [140], they can be efficiently simulated and implemented on classical hardware. Their ability to compactly represent high-dimensional image data has made them increasingly attractive for image classification, compression, and more recently, image segmentation [116].

Different tensor network architectures exist, including tree tensor networks, projected entangled pair states, and multiscale entanglement renormalization ansatz (MERA). The most fundamental and widely used structure is the matrix product state (MPS), in which a high-dimensional tensor is decomposed into a sequence of lower-order tensors. This decomposition can be obtained through successive singular value decompositions. The resulting representation is controlled by the bond dimension χ, which determines the amount of correlation that can be represented between different parts of the tensor. If χ is bounded, the storage complexity scales only linearly with the number of tensor components, allowing compact approximations of high-dimensional image data while preserving relevant spatial information [154, 180, 193].

3.3 Hybrid Quantum-Classical

Hybrid quantum-classical methods combine classical computation with quantum subroutines, distributing computational tasks between classical and quantum resources. Classical processors typically perform data preprocessing, optimization, and post-processing, whereas quantum hardware is used for feature mapping, optimization, or inference. This paradigm seeks to exploit the complementary strengths of classical and quantum computing while accommodating the limitations of current noisy intermediate-scale quantum (NISQ) hardware. The quantum component is typically implemented using either gate-based quantum computing or quantum annealing.

Gate-based quantum computing performs computations by manipulating quantum states through sequences of unitary quantum gates acting on qubits. Many algorithms employ fixed quantum circuits, while optimization tasks commonly rely on parameterized quantum circuits whose gate parameters are iteratively optimized by a classical optimizer. These methods are known as variational quantum algorithms (VQAs), with prominent examples including the variational quantum eigensolver [162] and the quantum approximate optimization algorithm (QAOA) [62]. Since many image segmentation tasks can be formulated as optimization problems, variational quantum circuits have become a common component of hybrid quantum image segmentation methods.

Quantum annealing is a specialized quantum computing paradigm designed for solving optimization problems. In quantum mechanics, the energy of a system is described by a mathematical operator called the Hamiltonian. For optimization tasks, a problem Hamiltonian is constructed such that its lowest-energy state (ground state) corresponds to the optimal solution of the encoded objective function. Instead of executing quantum circuits, quantum annealing searches for this solution by gradually transforming an initial Hamiltonian H_M into the problem Hamiltonian H_P,

$$H(t) = (1 - s(t))H_M + s(t)H_P, \tag{2}$$

where the interpolation parameter $s(t)$ increases smoothly from 0 to 1 during the annealing process. According to the adiabatic theorem [63], if this transformation is sufficiently slow, the system remains close to its ground state, such that measurement of the final state can yield the optimal solution. Because image segmentation is frequently formulated as graph partitioning, graph cuts, clustering, energy minimization, or quadratic unconstrained binary optimization (QUBO), quantum annealing appears as a natural candidate for optimization-based segmentation approaches.

Overall, hybrid quantum-classical methods form an active research direction in quantum image segmentation as they provide a flexible framework in which quantum routines can be integrated into established segmentation pipelines without requiring the entire algorithm to be executed on quantum hardware.

3.4 Fully Quantum

Fully quantum methods aim to perform image segmentation predominantly within a quantum computational framework. In these approaches, image data are represented as quantum states and processed using quantum algorithms, making the choice and cost of quantum data encoding a central consideration. Common image representation schemes include the Flexible Representation of Quantum Images (FRQI) [124], which encodes pixel intensities through rotation angles, and the Novel Enhanced Quantum Representation (NEQR) [232], which represents grayscale values using computational-basis states.

In addition to dedicated quantum image representations, general quantum data-encoding techniques are also used. Amplitude encoding maps the elements of a normalized classical vector to the amplitudes of a quantum state, while angle encoding represents individual features through qubit rotation angles [19, 167]. These approaches differ in

their qubit requirements, state-preparation procedures, and suitability for image data. Consequently, efficient state preparation remains a major practical challenge for fully quantum image processing, particularly as image size and data dimensionality increase.

4 Review of Quantum Image Segmentation Methods

This section describes the literature search process and reviews the literature on quantum image segmentation according to the taxonomy introduced in Section 3.

4.1 Methodology

A structured literature search was conducted to identify research on quantum and tensor network-based image segmentation published between January 2015 and through July 2026. The primary database used for the search was Lens.org, complemented by targeted searches in the ACM Digital Library and Google Scholar. AI-assisted tools were additionally used to identify potentially relevant publications and related work, but publications were included only after independent verification against the stated inclusion criteria. AI-assisted search was used as a supplementary tool rather than as an independent source for determining inclusion.

The primary search strings were "Quantum AND Image AND Segmentation" and "Tensor AND Network AND Image AND Segmentation". The search was intentionally broad to account for the heterogeneous terminology used across the field, where related approaches may be described using terms such as quantum-inspired optimization, quantum neural networks, quantum image processing, or quantum annealing.

Studies were included if they proposed, developed, or applied an image segmentation method incorporating quantum-mechanical principles, quantum computing, quantum-inspired concepts, or tensor network representations. A minimal conceptual connection to quantum mechanics or its underlying mathematical principles was required for inclusion. For tensor network approaches, the use of a tensor network representation as a primary computational framework was required. Studies were excluded if the term "quantum" was used only metaphorically or if there was no substantive connection to quantum-mechanical principles, quantum computation or tensor network methods. Publications were also required to address image segmentation as a central task rather than merely mentioning segmentation as a possible application of the proposed approach. No restriction was imposed on publication type, and preprints were retained because the field is relatively young, heterogeneous, and scattered across different research communities. Including preprints was considered important for capturing recent developments, emerging research directions, and methodological ideas that may not yet have appeared in peer-reviewed venues. For an overview, Table 1 lists the publication status and venue of each contribution included in this survey.

The screening process was performed in multiple stages. The first search string ("Quantum AND Image AND Segmentation") returned 12,454 publications, ranked by relevance in Lens.org. The first 200 records were screened based on title and abstract. The second search string ("Tensor AND Network AND Image AND Segmentation") returned 29,403 publications, of which approximately 100 records were screened. The results were then combined and checked for duplicates and methodological relevance. Publications whose relevance or methodological classification could not be determined from the title and abstract were examined in full text. After applying the inclusion criteria, 42 publications were selected for the final survey, comprising 19 quantum-inspired, four tensor network, eleven hybrid quantum-classical, and eight fully quantum approaches. The resulting collection was categorized according to the taxonomy introduced in Section 3 and forms the basis for the comparative analysis and discussion of research gaps presented in the remainder of this survey. The flowchart in Figure 3 depicts the search process.

Table 1. Overview of literature by segmentation paradigm, publication status, and venue.

Paradigm	Status	Publication	Literature
Quantum-Inspired	Peer-reviewed	Multimedia Tools and Applications	[199]
	Peer-reviewed	IEEE Access	[4]
	Peer-reviewed	Applied Soft Computing	[1, 113]
	Peer-reviewed	Research Anthology on Advancements in Quantum Technology	[157]
	Peer-reviewed	Applied Intelligence	[41]
	Preprint	arXiv	[54, 175]
	Peer-reviewed	Evolutionary Intelligence	[177]
	Peer-reviewed	tm – Technisches Messen	[190]
	Conf.	Applied Mechanics and Materials	[51]
	Conf.	IMPACT	[2]
	Peer-reviewed	Neural Computing and Applications	[82]
	Peer-reviewed	Signal, Image and Video Processing	[95]
	Peer-reviewed	Computational Intelligence	[168]
	Conf.+Peer-reviewed	ICASSP	[169]
	Peer-reviewed	PLoS One	[12]
	Peer-reviewed	International Journal of Theoretical Physics	[184]
	Peer-reviewed	Quantum Information Processing	[225]
Tensor Networks	Peer-reviewed	IEEE Transactions on Neural Networks and Learning Systems	[114]
	Peer-reviewed	Machine Learning for Biomedical Imaging (MELBA)	[181]
	Conf.+Peer-reviewed	SPIE Medical Imaging	[116]
	Peer-reviewed	Scientific Reports	[207]
Hybrid Quantum-Classical	Preprint	arXiv	[76, 123]
	Peer-reviewed	IET Radar, Sonar & Navigation	[164]
	Peer-reviewed	Scientific Reports	[101]
	Peer-reviewed	IEEE Computer Graphics and Applications	[205]
	Peer-reviewed	Frontiers in Digital Health	[98]
	Conf.+Peer-reviewed	IEEE/ACM SEC	[163]
	Peer-reviewed	IEEE Access	[132]
	Conf.+Peer-reviewed	IEEE IGARSS	[93]
	Conf.+Peer-reviewed	IEEE/CVF ICCV	[96]
	Conf.+Peer-reviewed	IEEE CBASE	[223]
Fully Quantum	Peer-reviewed	IEEE Transactions on Quantum Engineering	[134]
	Peer-reviewed	Quantum Information and Computation	[215]
	Peer-reviewed	Physica Scripta	[56]
	Peer-reviewed	Quantum Information Processing	[30]
	Peer-reviewed	Mathematics	[165]
	Conf.+Peer-reviewed	IEEE QCE	[138, 206]
	Preprint	arXiv	[203]

4.2 Quantum-Inspired Methods

The majority of the literature falls under the quantum-inspired category, with most studies focusing on medical and general image segmentation. Medical image segmentation is particularly relevant due to the limited availability of large annotated datasets, which poses challenges for data-driven methods, while the complexity of medical images can also limit traditional approaches [224]. Since many quantum-inspired methods operate without large supervised datasets, they may therefore be particularly relevant to this domain.

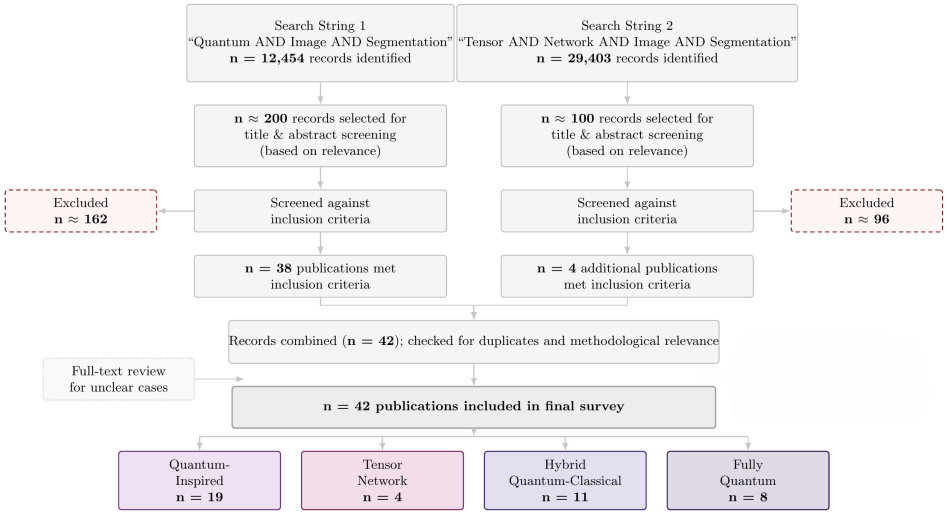


Fig. 3. Overview of the literature search and screening process, yielding 42 publications for the final survey: 19 quantum-inspired, 4 tensor network, 11 hybrid quantum-classical, and 8 fully quantum approaches.

4.2.1 Quantum Optimization. Quantum optimization methods incorporate quantum-mechanical concepts into optimization algorithms to improve the exploration and exploitation of complex search spaces.

One is provided by Deng et al. [51], who apply a quantum-behaved PSO algorithm to agricultural crop and weed images. The authors improve the original algorithm by introducing a multi-group and multi-stage optimization strategy.

Guo, Wei, and Xu [82] address sonar image segmentation by proposing a quantum-behaved variant of the PSO algorithm, in which particles are modeled according to quantum principles. Instead of using fixed positions and velocities, particles are represented by probability distributions, enabling broader exploration of the search space and improved convergence toward optimal solutions.

Rather et al. [169] further apply quantum-behaved PSO to the segmentation of kidney stone CT images, demonstrating the applicability of the algorithm to medical image segmentation.

Another approach is proposed by Bahaddad et al. [12]. Their multilevel segmentation method uses a two-dimensional quantum image representation. In this framework, the two-dimensional histogram of image intensities is treated as a quantum system. The quantum Rényi entropy is then used to measure the information content. The corresponding entropy-based fitness function is maximized using differential evolution and PSO algorithms to determine optimal thresholding values.

Several other nature-inspired optimization methods exist. Huo et al. [95] employ an improved quantum artificial bee colony algorithm in which qubit-space coordinates are used to encode the initial nectar source.

Elaziz et al. [1] extend the Marine Predators Algorithm into a quantum-inspired version. The authors incorporate a probability function derived from the Schrödinger wave function into the search process to enhance the exploration and optimization capabilities of the algorithm.

Choudhury et al. [41] propose an algorithm for segmenting hippocampus images based on the movement operation of the classical firefly algorithm. On the quantum side, this method incorporates quantum superposition and a quantum

update operation. The algorithm proceeds in two stages: in the first, quantum fireflies move toward comparatively brighter fireflies, and in the second, they are updated according to the global optimum using the quantum update operation.

Tariq-Jamal et al. [199] introduce the QGA-QR method, which combines entropy-based image analysis with quantum representations. First, classical Rényi and quantum Rényi entropies are used to quantify the information content of the image. Within the quantum framework, the digital image is expressed as a quantum system using FRQI. To solve the resulting complex optimization problem, the classical genetic algorithm and the quantum genetic algorithm are employed to determine optimal thresholding values by maximizing the entropy-based fitness functions.

Sayed [177] proposes a quantum-inspired algorithm based on the optimal foraging algorithm (OFA) for multilevel thresholding in image segmentation. The proposed quantum OFA enhances the classical OFA by integrating quantum operators, particularly interference, into the optimization process. This quantum-inspired extension improves the balance between exploration and exploitation.

4.2.2 Clustering. Quantum-inspired clustering methods incorporate quantum-mechanical or probabilistic principles into clustering algorithms to model uncertainty.

Sánchez and Martín-Landrove [175] address brain tumor segmentation using a dynamic quantum clustering algorithm. Data points are modeled with uncertainty, which determines the spread of their influence in the data space. A Parzen estimator is then used to define a potential function via the time-independent Schrödinger equation. The resulting potential surface contains minima at regions of high data density, which serve as cluster centers. Points are iteratively moved toward these minima to determine the clusters.

Rathee, Kaur, and Singh [168] propose a quantum-inspired image enhancement and segmentation framework motivated by the quantum probabilistic principles underlying magnetic resonance imaging. The method models uncertainty through fuzzy representations by first fuzzifying the image and then transforming it into a type-2 fuzzy set using the Hamacher T-conorm while incorporating neighborhood pixel information. The final segmentation is performed using fuzzy c-means clustering.

These two studies illustrate two distinct ways of incorporating quantum-inspired concepts into clustering-based segmentation: the first modifies the clustering mechanism itself, while the second introduces an uncertainty-aware representation before applying a conventional clustering algorithm.

4.2.3 Neural Networks. Quantum-inspired neural network approaches incorporate quantum-mechanical concepts into neural or self-organizing architectures.

Konar et al. [113] propose a Quantum-Inspired Self-Supervised Network (QIS-Net) for automatic brain MR image segmentation. QIS-Net consists of three layers of quantum neurons–input, intermediate, and output–represented as qubit-like quantum states. The intermediate and output layers are interconnected through bidirectional propagation of quantum states, enabling self-organization of image pixel intensities. Quantum observation is then used to extract the final segmentation after the superimposed quantum states interact with the environment. This eliminates the need for labeled data and extensive training.

Pal et al. [157] similarly employ a quantum-inspired self-organizing neural network for grayscale image segmentation. Their network uses a multilevel sigmoidal (MUSIG) activation function, with context-sensitive threshold values determined based on local image homogeneity. Guided by the principle of quantum superposition, these adaptive thresholds enable segmentation by distinguishing image regions according to their intensity.

These approaches show that quantum-inspired concepts can be incorporated both into the network dynamics themselves and into specific components, such as activation and thresholding mechanisms, within otherwise classical architectures.

4.2.4 Quantum Representations and Transformations. Quantum-inspired representation and transformation methods incorporate quantum state representations or quantum transformations into otherwise classical image-processing pipelines.

Domingo and Chehimi [54] address breast cancer segmentation in medical images by building an end-to-end quantum-enhanced framework for unsupervised mammography. As an initial step, they introduce a quantum-inspired image representation. To maximize contrast between background and tumor regions, the segmentation task is formulated as a QUBO problem which is solved classically.

Akinola et al. [4] introduce a novel image segmentation technique based on the Inverse Quantum Fourier Transform (IQFT). Each pixel intensity is encoded as a phase inspired by quantum-state representations, after which the IQFT is applied to extract phase information for automatic segmentation. The method does not require labeled training data and is therefore applicable to unsupervised segmentation.

4.2.5 Physical Models. Physical-model-based methods use mathematical models of quantum physical phenomena, such as quantum walks, to derive segmentation mechanisms directly from the behavior of quantum systems.

One early contribution is presented by Youssry et al. [225], who construct a Hamiltonian based on the image and solve the corresponding Schrödinger equation to segment the image by evolving and subsequently measuring the resulting quantum states.

Shi et al. [184] introduce a method based on the continuous-time quantum walk model. Since quantum walks based on individual pixels can be resource-intensive, the authors extend the model by using superpixels. A weighted graph is constructed, where nodes represent superpixels and edge weights reflect feature similarity between adjacent superpixels. After performing the quantum walk, segmentation is achieved by assigning each superpixel to a class.

Srinivasan et al. [190] propose a quantum-inspired, fermion-based segmentation method leveraging Anderson localization, where image irregularities induce local disorder and spatially localize the Hamiltonian eigenstates. This enables the detection and segmentation of structurally irregular features such as cracks.

4.2.6 Quantum-Inspired Deep Learning Architectures. Quantum-inspired deep learning approaches integrate quantum-inspired concepts into established neural network architectures such as U-Net.

Ahmad et al. [2] introduce QisNet, a quantum machine learning-inspired variant of the U-Net architecture for retinal image segmentation. The method incorporates quantum-inspired concepts, including entanglement-inspired skip connections and superposition-inspired activation functions, into the classical encoder–decoder architecture with the aim to enhance feature extraction and segmentation performance.

4.3 Tensor Network Methods

Tensor network-based approaches form a distinct category related to quantum-inspired methods. They can be divided into tensor network-based representations, which construct compact representations of image data, and tensor network neural architectures, which integrate tensor networks directly into neural segmentation models. Only a small number of studies were identified in this category, indicating that tensor networks remain largely unexplored for image segmentation.

4.3.1 Tensor Network-based Representation. Selvan et al. [181] utilize MPS tensor networks to perform patch-based image segmentation on medical images. In their method, image patches are first mapped into exponentially large feature spaces, allowing for pixel-wise classification into foreground and background through a linear decision hyperplane. This high-dimensional linear model is efficiently approximated using an MPS tensor network, with shared weights across non-overlapping patches. This results in a strided tensor network architecture.

More recently, Kopriva and Sitnik [116] propose a MERA-based semantic segmentation method for medical hyperspectral images. The MERA representation is used to generate pseudo-labels for cancerous and non-cancerous pixels, after which Grassmann representations and a nearest-subspace classifier are used to assign the remaining pixels to classes.

4.3.2 Tensor Network Neural Architectures. Konar et al. [114] introduce a shallow, self-supervised 3D tensor neural network–referred to as 3D-QNet–for volumetric segmentation of medical images. The 3D-QNet consists of three volumetric layers: input, intermediate, and output. These layers are interconnected via a third-order neighborhood structure, enabling voxel-wise processing in semantic segmentation tasks. Each layer is composed of quantum-inspired neurons modeled using qubit states, and tensor decomposition is incorporated within the quantum framework to accelerate convergence. The final segmented output volume is produced once the network reaches convergence.

Verma et al. [207] extend this idea further by performing volumetric medical image segmentation using qutrits—quantum systems with three orthogonal basis states—instead of qubits. They integrate these qutrits with tensor ring decomposition, with the aim to enhance the representational capacity of the network while maintaining computational efficiency.

4.4 Hybrid Quantum-Classical Methods

The third category comprises hybrid quantum-classical methods, which combine quantum resources with classical computational approaches. For a better overview, Table 2 summarizes the relevant contributions, indicating which parts of the segmentation pipeline are performed classically or using quantum resources, as well as the respective quantum hardware or simulator.

4.4.1 Quantum Optimization. Quantum optimization methods in the hybrid quantum-classical paradigm formulate segmentation as classical optimization problems, most often as QUBO formulations. In contrast to quantum-inspired optimization, these approaches employ actual quantum computational resources as part of the optimization process, particularly D-Wave quantum annealers, to solve or approximate the resulting problems.

Le et al. [123] introduce a quantum optimization method for geometric-constrained image segmentation. Their method integrates a graph-theoretic approach to optimal surface segmentation–formulated as a graph partitioning problem–with hybrid quantum-classical optimization. The segmentation problem is first formulated classically as a QUBO problem, after which the ground state of the corresponding Hamiltonian, which encodes the solution to the image segmentation problem, is estimated using a classical simulation of QAOA [62, 123].

Presles et al. [164] propose a hybrid quantum-classical expectation-maximization algorithm based on quantum annealing. Their approach first formulates image segmentation classically as a graph-cut problem and translates it into a QUBO formulation. The resulting QUBO problem is then solved using a D-Wave quantum annealer as the quantum optimization step, which is combined with classical optimization to segment medical images.

Venkatesh et al. propose Q-Seg [205], another quantum annealing-based approach formulated as a graph-cut optimization problem. The method uses the D-Wave quantum annealer to determine a low-energy segmentation mask.

Given an image consisting of n pixels, a grid graph $G(V, w)$ is constructed, where vertices represent pixels and edge weights encode similarity relationships between neighboring pixels. The resulting minimum-cut problem is formulated as a QUBO problem and mapped onto the quantum annealer. The lowest-energy sample is subsequently decoded into the final segmentation mask.

Jun and Lee [101] also employ a D-Wave quantum annealer to solve a QUBO formulation for computed tomography image segmentation. Their method minimizes the difference between a sinogram represented in a quantum superposition state and the experimentally acquired X-ray sinogram measured from multiple projection angles. To make the optimization feasible on current quantum hardware, the authors further reduce the number of required logical qubits by exploiting the known X-ray mass attenuation coefficients of the materials.

These approaches follow a common hybrid workflow in which the problem is classically formulated and mapped to a quantum optimization procedure. While Le et al. [123] investigate QAOA through classical simulation, Presles et al. [164], Q-Seg [205], and Jun and Lee [101] employ quantum annealing hardware. Thus, the quantum component primarily serves as an optimization backend, while problem formulation and solution decoding remain classical.

4.4.2 Clustering. Hybrid quantum-classical clustering methods combine classical feature processing with quantum clustering algorithms, such as q-means, to partition image data into clusters that can be used to define segmentation regions or classes.

Pramanik et al. [163] propose a generic hybrid quantum-classical pipeline for image classification and segmentation. Their pipeline consists of three stages: (1) detecting whether an image contains cracks, (2) clustering crack-containing images into two groups, and (3) classifying regions within the images. Quantum techniques, including quantum k-means (q-means) for segmentation and variational quantum classifiers for classification, are integrated with classical methods. The q-means components are evaluated using the AWS Braket Local Simulator on a conventional CPU, while principal component analysis is used classically for dimensionality reduction before the execution of the quantum components.

4.4.3 Hybrid Deep Learning Architectures. Hybrid architecture-integration methods incorporate parameterized quantum circuits or other quantum computational modules into established deep learning segmentation architectures, typically evaluated on simulators but potentially executable on quantum hardware. In contrast to quantum-inspired architecture-integration methods, these approaches use actual quantum computational operations for feature transformation or representation within an otherwise classical network.

Four methods were identified that incorporate structures of the U-Net encoder–decoder architecture. Xu et al. [223] propose the quantum-enhanced segmentation models QuantumUNet and QuantumHoverNet. In both models, a lightweight quantum layer is integrated into the network with the aim to improve the representation of complex visual features. The quantum components are evaluated using idealized quantum simulations on classical hardware.

A second method is proposed by Lim et al. [132], who replace the fully connected bottleneck layer of a U-Net with an eight-qubit variational quantum circuit simulated using PennyLane. Similarly, Hossain et al. [93] integrate a compact parameterized quantum circuit into the bottleneck of a classical U-Net, using a simulated quantum convolutional module to enrich compressed encoder features before decoding while keeping the quantum component shallow and parameter-efficient.

Jaincy and Pattabiram [98] introduce Q-SpinalNet, which combines a U-Net-style encoder–decoder with transformer-based attention, residual connections, and a simulated quantum neural network. The model is inspired by the modular information processing of the human spinal cord.

Other approaches incorporate quantum components into feature pyramid network (FPN)-based architectures rather than U-Net. Gharaibeh and Sharma [76] integrate an FPN gate into encoder architectures such as EfficientNetV2-L [198] for feature gating. The quantum component consists of a parameterized quantum circuit that learns to fuse lateral and top-down features. Islam et al. [96] combine a ResNet-50 [88] backbone with an FPN and attention mechanisms, with a parameterized quantum circuit serving as a feature enhancement module within the FPN.

Table 2. Overview of hybrid quantum-classical image segmentation approaches, indicating which parts are processed classically and which use quantum resources.

Group	Literature	Classical Part	Quantum Part	Computation
Clustering	[163]	Dimensionality reduction	Segmentation	AWS Braket Local Simulator
Quantum Optimization	[123]	QUBO formulation	Ground state estimation for segmentation	Simulation
	[164]	QUBO formulation	Ground state estimation for segmentation	D-Wave
	[205]	QUBO formulation	Ground state estimation for segmentation	D-Wave
	[101]	QUBO formulation	Ground state estimation for segmentation	D-Wave
Architecture Integration	[223]	Processing, Segmentation	Feature representation improvement	Idealized quantum simulation
	[132]	Processing, Segmentation	Global feature integration	PennyLane simulation
	[93]	Processing, Segmentation	Feature representation improvement	Simulation
	[98]	Processing, Segmentation	Improve generalization and robustness	Simulation
	[76]	Processing, Segmentation	Feature representation improvement	Simulation
	[96]	Processing, Segmentation	Feature representation improvement	Simulation

4.5 Fully Quantum Methods

The fourth and final category of algorithms consists of fully quantum algorithms, in which the segmentation algorithm is formulated as a quantum algorithm and its core computational operations are performed using quantum states and quantum circuits. These methods are designed for execution on quantum hardware, although practical evaluation may rely on quantum simulation.

4.5.1 NEQR-based. NEQR-based methods use NEQR to encode pixel intensities and spatial information into quantum states, which are subsequently processed by quantum circuits for segmentation.

Caraiman and Manta [30] employ threshold-based segmentation using a quantum oracle to construct a quantum circuit that performs the segmentation operation. Their algorithm operates on images represented using NEQR [232]. While this provides a compact quantum encoding, practical implementation is additionally constrained by state preparation, circuit depth, and repeated measurements for readout.

Liu et al. [134] introduce a quantum image segmentation method inspired by classical grayscale morphology. In their quantum formulation, morphological operations are applied directly to the quantum image representation, which is subsequently converted into a binary segmentation.

Wang et al. [215] also design a fully quantum circuit for segmenting NEQR images. Their approach is based on background subtraction for detecting dynamic objects in static scenes. An absolute-value subtractor, combining a quantum comparator and subtractor, is used to obtain a grayscale image containing the detected object.

Another approach based on the NEQR image representation is proposed by Prodan, Manta, and Zvoristeanu [165]. Their method aims to avoid quantum RESET operations, which can disrupt the entanglement structure between auxiliary qubits and the image data register during computation. Instead, the authors allocate dedicated auxiliary qubits for each stage of the segmentation pipeline, thereby preserving the intended entanglement structure throughout the computation.

Dong et al. [56] propose a dual-threshold quantum image segmentation algorithm, which segments grayscale NEQR images into three regions. Pixel values above a high threshold and below a low threshold are assigned fixed values, while intermediate values remain unchanged. The authors design an quantum comparator and a scalable quantum circuit to implement the segmentation process.

4.5.2 Amplitude Encoding. Amplitude Encoding-based methods encode image features into the amplitudes of quantum states. Madeira et al. [138] propose a quantum anomaly segmentation algorithm based on a patch-based quantum autoencoder. The method reconstructs the quantum states of embedded image patches and computes an anomaly map directly from quantum measurements using a SWAP test, thereby avoiding explicit reconstruction of the input image.

4.5.3 Graph-based. Graph-based methods formulate image segmentation as an optimization problem over a graph representation, which is encoded into a quantum algorithm for optimization. Unlike the hybrid approaches discussed in Section 4.4, these methods formulate both the segmentation objective and its optimization within a quantum computational framework.

Tse et al. [203] formulate image segmentation as graph optimization problems, including max-flow/min-cut and normalized cut, and employ QAOA [62] to solve them. Venkatesh et al. [206] follow a similar optimization-based strategy using a VQA for semantic image segmentation. Their method combines Parametric Gate Encoding, Ancilla Basis Encoding, and Adaptive Cost Encoding to encode the segmentation problem into a variational quantum circuit and identify the segmentation mask.

Table 3. Overview of fully quantum image segmentation methods and the quantum hardware or simulator used for the experiments.

Group	Literature	Method	Computation
NEQR	[30]	Thresholding with quantum oracle	Conceptual
	[134]	Grayscale morphological operations and quantum binarization	IBM-Q
	[215]	Background difference	IBM-Q
	[165]	Avoid quantum RESET, dedicated ancilla qubits	Qiskit StatevectorSimulator
	[56]	Dual-threshold with quantum comparator	IBM-Q
Amplitude Encoding	[138]	SWAP-test measurements of reconstructed quantum states	PennyLane simulation
Graph	[203]	QAOA	Conceptual
	[206]	Parametric Gate Encoding, Ancilla Basis Encoding, and Adaptive Cost Encoding	QASM simulator

5 Positioning Quantum and Quantum-Inspired Approaches within the Image Segmentation Landscape

To contextualize quantum and quantum-inspired image segmentation within the broader field, classical, machine learning, deep learning, quantum-inspired, and quantum approaches are compared across several characteristics. This comparison considers supervision, data requirements, computational requirements and scalability, interpretability, hardware requirements, and application domains. Together, these characteristics highlight the trade-offs between classical, traditional machine learning, deep learning, and quantum approaches. To further place these paradigms into context, Figure 4 presents a historical timeline of both non-quantum and quantum image segmentation methods.

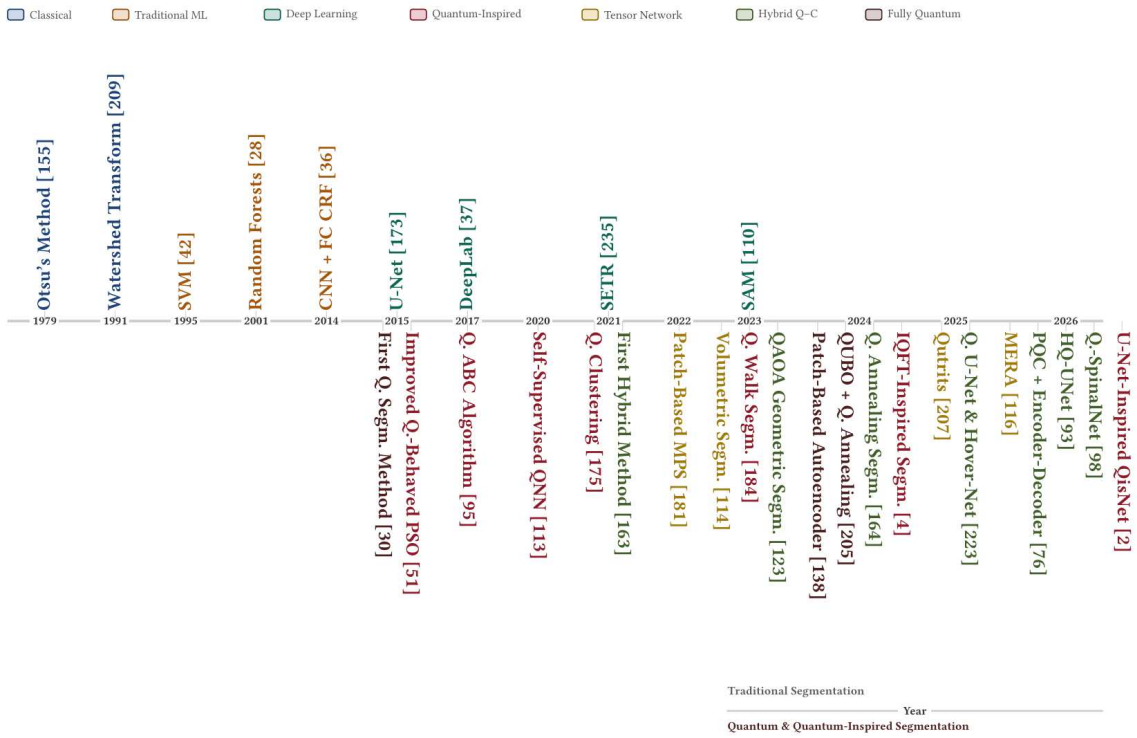


Fig. 4. Evolution of image segmentation methods from early classical techniques to quantum and quantum-inspired approaches. Traditional methods are placed above the axis, and quantum and quantum-inspired methods below. Note that Q. = Quantum and FC = Fully-Connected.

Owing to space constraints, not every surveyed quantum image segmentation method could be included in the timeline. Nevertheless, the selected works reflect the temporal development of the four proposed categories.

Several observations can be drawn from the timeline. First, quantum image segmentation is not a recent development. The earliest contribution identified in our search dates to 2015, coinciding with the publication of U-Net [173], one of the most influential encoder–decoder architectures for biomedical image segmentation. Thus, quantum image segmentation emerged alongside the early development of modern deep learning-based segmentation rather than only after its later dominance.

Second, the timeline suggests a substantial increase in research activity after 2020. In particular, the quantum literature has diversified rapidly between 2023 and 2026, during which a large number of new methods were proposed.

Third, hybrid quantum-classical and quantum-inspired approaches account for most recent publications, indicating that integrating quantum techniques into established classical and deep learning frameworks is currently the most active research direction. This trend is also reflected in recent methods that extend established architectures such as U-Net with quantum components, including QuantumUNet [223], HQ-UNet [93], QisNet [2], and Q-SpinalNet [98].

Fourth, tensor network methods, although represented by comparatively few publications, show increasing methodological diversity, ranging from MPS representations to qutrit-based tensor networks and MERA-based approaches.

Finally, fully quantum methods remain the smallest category despite containing some of the earliest contributions. This observation is consistent with the practical limitations of current quantum hardware, which continue to restrict the development and evaluation of large-scale fully quantum image segmentation methods.

5.1 Supervision

The supervision requirements differ considerably across image segmentation paradigms. Classical image segmentation methods are typically non-learning-based, as they rely on manually designed rules, thresholds [103, 155, 202, 212], or optimization criteria [14, 50, 55] rather than labeled training data. Traditional machine learning approaches often require labeled data for supervised learning and typically rely on handcrafted feature extraction [75, 121, 187, 216]. Most deep learning approaches are trained in a supervised manner and depend on large annotated datasets [37, 87]. Recent advances in transformer-based architectures [40, 86, 194] and large foundation models such as SAM [110] have further increased the importance of large-scale pretraining datasets, while simultaneously reducing the amount of task-specific annotated data required through transfer learning and prompt-based adaptation [110]. In the quantum domain, several hybrid quantum-classical approaches also employ supervised learning [76, 93, 163]. However, many of the surveyed quantum and quantum-inspired segmentation methods either formulate image segmentation as a thresholding, clustering or optimization problem [54, 56, 165, 199, 203, 215] or rely on self-supervised [113] and self-organizing learning strategies [157]. As a result, many of these approaches reduce and in some cases eliminate the dependence on labeled datasets.

5.2 Data Requirements

Generally, there is a trend that more data-driven learning paradigms require larger amounts of training data. Classical image segmentation algorithms typically require no data because segmentation decisions are derived directly from image characteristics rather than learned from examples [26, 50]. Traditional machine learning approaches usually require a moderate amount of labeled data to train discriminative models, such as the method proposed by Bai and Wang [13]. Deep learning methods generally require more training data than conventional machine learning approaches, particularly when trained from scratch, as they learn feature representations directly from data. This applies to CNNs [87], transformer-based architectures [40, 86, 194], and foundation models [110]. For instance, the SAM model was pretrained on the SA-1B dataset, which contains over 11 million images and more than one billion segmentation masks [110].

In contrast, many quantum and quantum-inspired segmentation methods do not require datasets of comparable size. Depending on the approach, they either avoid model training by formulating segmentation as an optimization problem [164, 177, 199, 205] or use smaller datasets in hybrid learning settings [163]. However, quantum components do not inherently reduce data requirements. Hybrid approaches extending deep learning architectures such as U-Net generally retain similar data requirements to their classical counterparts [93, 98] and are typically trained on established datasets

such as CBIS-DDSM [176] and LandCover.ai [24]. Overall, quantum and quantum-inspired methods may be particularly relevant for applications where annotated data are scarce, such as medical image segmentation [224].

5.3 Computational Requirements and Scalability

Many classical segmentation algorithms are computationally efficient and can often operate in real time or near real time on conventional hardware [14, 15, 64, 112]. Since they typically do not require training data, they can be directly applied to new images without a training stage. However, their scalability depends on the specific algorithm, as some optimization-based approaches become computationally demanding for high-resolution images or complex image structures [183].

Traditional machine learning models introduce additional computational overhead during training but typically have substantially lower inference costs. For example, tree-based ensemble methods require the construction of multiple models during training, whereas prediction only involves aggregating the outputs of the trained models through voting or averaging procedures [9, 27, 28, 201]. Furthermore, the scalability of traditional machine learning algorithms can be improved through dimensionality reduction, parallel processing, and distributed implementations [83].

Deep learning methods require substantially greater computational resources, particularly during training, where multiple GPUs or specialized AI accelerators are commonly employed, particularly for large models and datasets [86, 87, 110]. Consequently, they incur considerable costs in terms of training time, energy consumption, and hardware requirements. Nevertheless, with sufficient computational resources, deep learning models scale well and can efficiently process large datasets through distributed training and specialized hardware acceleration.

Quantum-inspired algorithms are executed entirely on classical hardware and therefore do not incur quantum hardware overhead. Their computational requirements are instead determined by the underlying classical implementation and optimization procedure. In contrast, hybrid and fully quantum approaches may introduce additional overhead associated with data encoding and quantum state preparation [215], quantum circuit execution [56], quantum annealing [101], and measurement operations. The choice of data encoding can itself become a limiting factor, particularly for large and high-dimensional images. On current NISQ hardware, these components can become a significant practical constraint.

Finally, scalability remains one of the primary challenges for quantum computing approaches. While quantum-inspired algorithms implemented on classical hardware can often achieve scalability comparable to conventional methods, hybrid and fully quantum algorithms remain constrained by the limited number of usable qubits, restricted circuit depths, noise, and hardware connectivity limitations [21]. Consequently, most existing quantum image segmentation methods remain restricted to relatively small images and problem instances [56, 165, 215]. However, recent hybrid quantum-classical approaches have demonstrated progress toward improved scalability by integrating quantum components into larger classical architectures and enabling experiments on larger-scale images [76, 93, 98, 132]. A common strategy in these approaches is to operate the quantum components on compressed feature representations rather than encoding the complete image using dedicated quantum image representations such as NEQR.

5.4 Interpretability

As image segmentation methods become increasingly complex and data-driven, their decision-making processes generally become less transparent. Classical algorithms typically exhibit a high degree of interpretability, as segmentation decisions are based on explicit mathematical rules or optimization criteria, allowing the decision-making process to be comparatively transparent [14, 50, 155, 212]. Traditional machine learning methods, such as SVMs and random forests,

can provide a greater level of interpretability, although the interactions between handcrafted features and learned decision boundaries become less transparent [174]. In contrast, deep learning methods are commonly regarded as black boxes due to their large number of parameters and complex internal representations, making it difficult to explain how specific segmentation decisions are obtained. This has motivated extensive research in explainable artificial intelligence [53], particularly for safety-critical applications such as medical image analysis, where understanding the reasons behind a model's predictions or segmentation decisions is often as important as the predictions themselves.

The interpretability of quantum and quantum-inspired methods varies substantially with the underlying computational paradigm. Optimization-based approaches are often relatively interpretable because the segmentation objective is defined through explicit objective functions or energy models [164, 165, 177, 199, 205]. However, the optimization process and the contribution of individual variables to the final solution may still be difficult to understand. Tensor network methods offer greater mathematical transparency through their structured factorization and explicit network topology, although individual tensor components may remain difficult to interpret semantically. Further, variational quantum algorithms and quantum neural networks can inherit the explainability challenges of classical deep learning, as learned quantum representations and individual circuit parameters may be difficult to relate to meaningful image features [93, 98, 163].

5.5 Hardware

Hardware requirements differ substantially across image segmentation paradigms. Classical and traditional machine learning methods typically run on conventional hardware such as CPUs and GPUs [14, 117, 216]. Deep learning commonly relies on GPUs or TPUs for efficient training [86, 87, 110]. Quantum-inspired methods are generally executed on conventional hardware, such as CPUs [41, 54], and require no quantum devices. Hybrid quantum-classical approaches combine classical computation with quantum circuits or annealing, using either physical quantum processors [56] or simulators [138, 164]. Fully quantum methods are designed for quantum hardware, including IBM Quantum processors [134] and D-Wave systems [205], although many are still evaluated using simulators. Their practical deployment therefore remains dependent on the availability and capabilities of current quantum hardware.

However, despite increasing access to cloud-based quantum hardware, most hybrid quantum-classical and fully quantum image segmentation approaches are still evaluated using quantum simulators rather than physical devices, as shown in Table 3. Simulator-based evaluations should further distinguish ideal from noisy simulations that model hardware imperfections. Experimental studies in quantum image processing confirm the importance of distinguishing simulator-based results from executions on physical quantum hardware. Geng et al. [74] evaluate quantum image processing workflows on superconducting and trapped-ion quantum computers and show that hardware noise, gate errors, and limited circuit resources can substantially affect the fidelity of image processing operations. Such hardware-level effects should therefore be reported explicitly when evaluating quantum image segmentation methods. Limited qubit availability, noise, connectivity constraints, and the computational overhead of repeated circuit evaluations remain important practical limitations, particularly for encoding and processing the high-dimensional spatial information of images.

5.6 Application Fields

Classical segmentation methods remain relevant in embedded systems, industrial inspection [128], and applications that require computational efficiency or high interpretability. Traditional machine learning approaches remain useful in scenarios where handcrafted features are informative and only limited training data are available [128]. Deep learning

methods currently represent the predominant paradigm in modern image segmentation and are applied across numerous domains, including medical image analysis [16, 89], autonomous driving [59, 221], satellite image interpretation [214], robotics [33], and general-purpose computer vision [110].

In contrast, quantum and quantum-inspired methods in the surveyed literature primarily target medical image segmentation [41, 54, 96, 168, 175] and general-purpose image segmentation [82, 95]. Although their application scope is currently more limited than that of established segmentation paradigms, they represent an emerging research direction. Section 6.1 provides a detailed comparison of the application domains covered by the surveyed quantum image segmentation methods.

6 Comparison of Quantum Image Segmentation Approaches

To characterize the current state of quantum image segmentation research in greater detail, the surveyed approaches are compared along three dimensions: application field, image encoding and representation, and datasets.

6.1 Domain Distribution

The surveyed quantum image segmentation literature is strongly concentrated in two application fields: medical imaging, with 17 works and general images, with 16 works including synthetic images, grayscale test patterns, and natural RGB images. These works span the major quantum segmentation categories, including quantum-inspired approaches [4, 12, 157, 184, 223], fully quantum methods [56, 134, 206, 215], and hybrid quantum-classical approaches [123, 132].

The medical domain represents the largest category, with contributions primarily distributed across quantum-inspired methods [41, 54, 113, 175, 177, 199, 207] and tensor network approaches [114, 116, 181, 207]. This strong focus is consistent with the importance of accurate segmentation in medical imaging, where complex image structures and limited annotated data pose challenges for conventional data-driven approaches.

Further application fields include remote sensing and satellite image analysis, represented by three hybrid quantum-classical approaches [93, 164, 205]. Other contributions address infrastructure inspection and anomaly segmentation, particularly crack detection in concrete structures [138, 163, 190]. Isolated contributions also target agricultural image segmentation [51], sonar image processing [82], and geophysical exploration [76].

Overall, quantum image segmentation has been explored across several specialized domains but remains strongly concentrated on medical and general image segmentation. In contrast, established application areas such as robotics, autonomous driving, embedded systems, and industrial inspection remain largely unexplored. Table 4 provides an overview of the surveyed quantum approaches categorized by application field.

Table 4. Application fields of quantum and quantum-inspired image segmentation approaches.

Application Domain	**Literature**
Medical	[2, 41, 54, 96, 98, 101, 113, 114, 116, 168, 169, 175, 177, 181, 199, 207, 223]
General	[1, 4, 12, 30, 56, 95, 123, 132, 134, 157, 165, 184, 203, 206, 215, 225]
Anomaly Detection	[138, 163, 190]
Remote Sensing/Satellite Images	[93, 164, 205]
Geophysical Exploration	[76]
Agriculture	[51]
Sonar Images	[82]

6.2 Image Encoding and Representation

Regarding image encoding and representation, 12 of the 19 quantum-inspired approaches rely on intensity- or histogram-based mappings, which are computationally simple and avoid explicit quantum state preparation. Examples include methods that map pixel intensities to quantum-inspired phase representations [4] and graph-based representations in which image regions or superpixels form graph nodes [184]. Interestingly, Tariq-Jamal et al. [199] use a quantum-inspired representation inspired by FRQI, despite being classified as quantum-inspired rather than fully quantum. Another approach [12] uses a two-dimensional entropy-based representation.

Tensor network methods employ representations that are closely tied to the structure of the tensor network. Verma et al. [207] combine angle-based encoding with tensor ring decomposition, whereas Selvan et al. [181] represent images through local patches that are mapped to high-dimensional feature spaces and subsequently approximated using a MPS tensor network.

Most surveyed hybrid approaches do not rely on quantum-native image encodings such as FRQI or NEQR. Instead, they typically pass classically derived features or problem representations to the quantum component, including CNN-based embeddings [163] or intensity- and graph-based representations [123, 164, 205]. Hybrid U-Net-based approaches further reduce the encoding burden by applying quantum circuits to compressed feature representations extracted by the classical network rather than encoding the complete image [93, 132]. In contrast, fully quantum methods frequently rely on dedicated quantum image encoding schemes such as NEQR and related representations (e.g., [56, 134, 215]), as well as amplitude-based and graph-based formulations. Table 5 provides an overview of the image representation techniques used across the surveyed methods.

Table 5. Overview of image representation techniques used in quantum and quantum-inspired image segmentation approaches.

Category	Image Representation Method	Literature
Quantum-Inspired	FRQI-inspired	[199]
	Phase/Quantum-inspired pixel intensities encoding	[4, 113, 157]
	Classical histogram/pixel-domain representation (+ quantum-inspired optimization)	[1, 2, 12, 41, 51, 82, 95, 168, 169, 175, 177, 190]
	Graph-based	[184]
	Custom quantum-inspired image transformation	[54, 225]
Tensor Networks	Volumetric Tensor Representation	[114]
	Patch-based tensor representation	[181]
	MERA	[116]
	Volumetric qutrit angle encoding	[207]
Hybrid Quantum-Classical	Graph-based Ising/QUBO Encoding	[101, 123, 164, 205]
	Classical features	[98]
	Classical features + angle encoding	[76, 93, 96, 132, 163, 223]
Fully Quantum	NEQR	[30, 56, 134, 165, 215]
	Amplitude encoding	[138, 206]
	Graph-based, Ising/QUBO representation	[203]

6.3 Datasets

Dataset usage in the surveyed quantum image segmentation literature is highly heterogeneous. Among the medical imaging studies that use publicly available datasets, several rely on established benchmarks, including the InBreast dataset [54, 147], TCGA-derived imaging data [161, 175, 178], and the BraTS brain MRI benchmark [114, 141, 207]. More recent hybrid quantum-classical approaches have also been evaluated on datasets such as CBIS-DDSM [98, 176] and MoNuSeg [119, 223]. Additional domain-specific datasets include MVTec AD [17, 138] and the Kaggle surface crack detection dataset [156, 163] for anomaly and defect segmentation, as well as LandCover.ai [24, 93] for remote sensing. The HairWidthCracks dataset [72] provides a further example of a domain-specific resource for evaluating segmentation of fine structural defects.

For general-purpose natural-image segmentation, Akinola et al. [4] employ the Flowers dataset [151] and PASCAL VOC 2012 [60], while Shi et al. [7, 184] use the BSDS500 dataset. More recently, Ahmad et al. [2] evaluate their method on retinal image datasets including DRIVE [191], STARE [92], and CHASE-DB [65]. Despite these examples, dataset usage remains highly inconsistent. Among the 16 surveyed studies addressing general image segmentation, 13 do not report a specific standardized benchmark dataset and instead rely on grayscale, synthetic, or otherwise unspecified images. This is particularly common among fully quantum approaches, which are often restricted to small-scale image representations due to current limitations in quantum hardware, data encoding, and computational resources. Table 6 summarizes the datasets used across the surveyed studies.

7 Research Gaps and Future Outlook

The analysis of existing quantum and quantum-inspired image segmentation approaches reveals substantial research activity in exploring the potential of quantum technologies for image analysis. However, the reviewed literature also highlights several open challenges that currently limit their practical applicability and their transition toward real-world applications. While classical and deep learning-based segmentation methods benefit from mature evaluation frameworks, large-scale datasets, and highly optimized architectures, quantum approaches remain constrained by scalability, data representation, and integration with modern learning paradigms. The following sections discuss these key research gaps and outline future directions toward more comparable, scalable, and practically relevant quantum image segmentation methods.

7.1 Standardized Evaluation and Benchmarking

A major limitation identified across the reviewed quantum image segmentation literature is the absence of consistent evaluation protocols. Classical and deep learning approaches are typically assessed using established benchmark datasets, including Cityscapes, COCO, BraTS, and PASCAL VOC, together with widely adopted metrics such as the Dice coefficient, Intersection over Union (IoU), mean Intersection over Union (mIoU), and boundary-aware measures [142].

The situation is considerably less consistent for quantum and quantum-inspired approaches. Existing studies differ in their choice of datasets, image resolutions, preprocessing procedures, experimental configurations, and evaluation metrics, which makes direct comparison between reported results difficult. In particular, performance obtained on small or synthetic images cannot readily be compared with results from methods evaluated on large-scale, high-resolution benchmark datasets. The problem becomes even more pronounced for hybrid and fully quantum approaches, where limitations of current quantum hardware, together with the costs associated with image encoding and circuit execution,

Table 6. Overview of datasets used in quantum and quantum-inspired image segmentation approaches by paradigm. The custom dataset category includes studies using only synthetic or generic grayscale images, as well as studies using datasets that were not specified or only generally described without naming a publicly available source, such as MRI, crop, or sonar images.

Paradigm	Dataset	Literature
Quantum-Inspired	TCGA-LGG [161], Brain Neoplasia data, TCGA-GBM [178]	[175]
	INbreast data [147]	[54]
	Flower data [151], Caltech-UCSD Birds 200-2011 [210], Pascal VOC 2012 [60], xView2 challenge data [84]	[4]
	BSD 500 data [7]	[184]
	Hairline crack width data [72]	[190]
	DRIVE [191], STARE [92], CHASE [65]	[2]
	Only custom	[1, 12, 41, 51, 82, 95, 113, 157, 168, 169, 177, 199, 225]
Tensor Networks	2D/3D biomedical images, MoNuSeg [119], Lung CXR [97], BraTS [141], DRIVE [191], STARE [92], CHASE [65]	[181]
	BraTS [141], LiTS17 [23]	[114]
	BraTS [141], Spleen data	[207]
	Only custom	[116]
Hybrid Quantum-Classical	Kaggle Surface Crack Detection data [156]	[163]
	SAR images, MSTAR data [204]	[164]
	Synthetic, DeepGlobe18 [49], Sen1Floods11 [25]	[205]
	2018 TGS Salt Identification data [94]	[76]
	LandCover.ai [24]	[93]
	CVC-ClinicDB [18], Kvasir-SEG [100], CVC-ColonDB [195], ETIS-LaribPolypDB [188]	[96]
	CBIS-DDSM [176]	[98]
	Only custom	[101, 123, 132, 223]
Fully Quantum	MVTEC-AD anomalies data [17], BUSI data [5]	[138]
	Only custom	[30, 56, 134, 165, 203, 206, 215]

can restrict experiments to comparatively small inputs. As a result, many quantum segmentation studies cannot yet be evaluated under conditions comparable to those routinely used for classical and deep learning segmentation.

Recent hybrid quantum-classical studies have begun to move toward more realistic experimental settings by evaluating their methods on application-relevant datasets [93, 223]. Nevertheless, a broadly accepted benchmarking procedure for quantum image segmentation has not yet been established. Future studies should therefore work toward common evaluation protocols that specify shared datasets, image resolutions, preprocessing procedures, evaluation metrics, and experimental settings, while also requiring comparisons with strong classical and deep learning baselines. General benchmarking frameworks developed for quantum AI could provide useful methodological foundations for such an effort. For example, Morbiducci et al. [43] propose QuantAI, an end-to-end benchmarking framework designed to facilitate reproducible and comparable evaluations of quantum AI workflows across different methods and execution environments. Although QuantAI is not designed specifically for image segmentation, its emphasis on controlled experimental configurations, systematic performance assessment, and reproducible benchmarking is relevant to the development of dedicated quantum image segmentation benchmarks. Such evaluations should not be restricted to traditional techniques,

such as Otsu thresholding, but should also incorporate representative learning-based baselines, including U-Net and DeepLab, as well as suitable foundation-model-based approaches such as SAM when the segmentation task and evaluation protocol allow a meaningful comparison. Establishing common benchmarks of this kind would provide a more reliable basis for assessing the actual advantages, limitations, and practical applicability of future quantum image segmentation methods, while improving reproducibility and comparability across studies.

7.2 Image Representation and Encoding Bottleneck

One of the most fundamental challenges identified across quantum and hybrid quantum-classical image segmentation methods is the representation and encoding of classical image data in quantum form. Unlike classical segmentation algorithms, which operate directly on pixel arrays or learned feature representations, quantum algorithms require the input data to be encoded into quantum states before processing. Consequently, many existing methods rely on dedicated quantum image representations, such as NEQR, FRQI, or angle encoding, despite their well-known limitations.

These encoding schemes are primarily designed to represent classical image information in quantum states rather than to provide task-specific representations optimized for segmentation. Although mathematically elegant, their practical implementation can involve costly state preparation, introduce additional computational overhead, and typically encode low-level pixel intensities instead of the hierarchical feature representations that have proven highly effective in modern deep learning [110, 173]. Experimental evidence from quantum image processing further illustrates these practical limitations. Geng et al. [71, 73] investigate an improved FRQI implementation on superconducting quantum processors and demonstrate that state preparation, hardware noise, and limited circuit depth remain major obstacles to reliable image encoding on NISQ devices. These findings underline that the logarithmic qubit requirements often associated with quantum image representations do not directly imply efficient end-to-end image processing. As a result, they can become a bottleneck that limits both computational efficiency and segmentation performance.

Future research should therefore investigate task-adaptive quantum representations instead of pixel-based encodings. Recent work also explores structured decompositions as a means of reducing the cost of quantum image encoding. Pangeva et al. [159] investigate Schmidt decomposition-based methods for quantum image encoding, suggesting that image structure and correlations may be exploited before mapping data to quantum states. While this work is currently available as a preprint, such decomposition-based encodings represent a promising direction for reducing the gap between theoretically compact quantum representations and practically implementable state-preparation circuits. Further steps in this direction have already been taken by Hossain et al. [93], Islam et al. [96], and Xu et al. [223], where quantum circuits operate on learned feature representations rather than raw image data. Similar concepts are explored in broader quantum machine learning approaches such as QuKAN [219], which, although not designed for image segmentation, demonstrates the potential of applying quantum circuits to compact learned feature representations rather than directly encoding high-dimensional raw data.

Another promising direction is the use of graph-based representations, as adopted by Venkatesh et al. [205]. Since many segmentation problems are naturally formulated as graph optimization tasks, representing pixels or superpixels as graph nodes provides a representation that is inherently aligned with the underlying segmentation objective. However, the resulting graph must still be mapped to the available quantum optimization architecture, and the associated encoding and embedding costs remain important considerations. Tensor network representations constitute a further promising alternative. By treating images as high-dimensional tensors and compressing them through tensor decompositions, tensor network methods provide compact representations that may be processed efficiently on classical hardware while also offering a natural bridge toward quantum-inspired and future quantum image segmentation approaches. However,

the survey reveals that tensor-based representations remain largely unexplored within image segmentation, with only a limited number of contributions investigating their potential.

7.3 Scalability Towards Real-World Images

Although an n-qubit quantum system has a state space of dimension 2^n,this representational capacity does not directly translate into efficient processing of large classical images. Current quantum image segmentation approaches nevertheless remain limited to relatively small image sizes, particularly in fully quantum settings. Many fully quantum methods are therefore evaluated on binary or grayscale images and small synthetic examples (e.g., [56, 165, 215]). As image resolution and feature dimensionality increase, the required number of qubits, state-preparation operations, circuit depth, hardware connectivity, and measurement operations can become substantial. On current quantum hardware, noise, gate errors, and finite coherence times further restrict the size and complexity of circuits that can be executed reliably.

Overcoming this scalability limitation remains a fundamental challenge, particularly for fully quantum approaches based on gate-based quantum computing. The ability to process larger and more complex images is closely tied to future advances in quantum hardware, including increased qubit numbers, improved error rates, and longer circuit execution capabilities. However, scalability is not solely a hardware problem: it also depends on how much information must be represented and processed by the quantum component. In the near term, research should therefore focus on hybrid, tensor network-based, and quantum-inspired methods that can improve segmentation performance while reducing the burden of image representation and encoding and remaining compatible with current computational limitations. At the same time, continued evaluation of advances in quantum hardware will be essential to determine when fully quantum image segmentation becomes practically feasible.

7.4 Reproducibility

A further research gap identified across the surveyed literature concerns the reproducibility of quantum and quantum-inspired image segmentation methods. Although many studies report promising results, the information required to independently reproduce them is often incomplete. A number of studies do not provide publicly accessible source code, quantum circuits, trained parameters, complete hyperparameter configurations, or sufficiently detailed descriptions of preprocessing and experimental settings. For quantum methods, reproducibility is further complicated by hardware-dependent factors such as qubit connectivity, transpilation, noise, calibration, measurement shots, and backend configuration. This makes it difficult to verify reported results and perform reliable comparisons, particularly because outcomes can depend strongly on implementation-specific choices such as image encoding, circuit configuration, optimization settings, and hardware or simulator configurations.

Future work should therefore establish more transparent and reproducible experimental protocols. Where possible, authors should provide source code, relevant configurations, preprocessing details, and evaluation procedures together with their publications. Hardware-based experiments should additionally document the relevant device and execution settings. Combined with standardized benchmarks and evaluation protocols, such practices would enable independent verification and more meaningful comparisons between quantum, quantum-inspired, and established classical and deep learning methods.

7.5 Integration with Deep Learning and Foundation Models

The current quantum image segmentation literature remains only partially connected to the broader deep learning community. Although several recent approaches integrate quantum components into established architectures such as U-Net [93, 98, 132, 223], many surveyed quantum and quantum-inspired methods are developed independently from modern segmentation architectures. In particular, transformer-based models and foundation models have received very limited attention, despite their increasing importance in modern image segmentation, as demonstrated by approaches such as SAM [110].

Future research should therefore investigate how quantum components can be integrated into modern deep learning architectures, for example by enhancing attention mechanisms, feature extraction modules, or vision foundation models and their adaptation mechanisms. In particular, the learned latent representations produced by modern segmentation networks may provide a more suitable interface for quantum processing than raw image data, potentially reducing the encoding and scalability bottlenecks discussed in the previous sections. Initial exploratory work has also investigated the integration of quantum components with foundation models such as SAM [6], suggesting a possible research direction, although further investigation and peer-reviewed validation are still required.

8 Conclusion

In conclusion, when compared with classical, traditional machine learning, and deep learning approaches, quantum and quantum-inspired methods occupy an intermediate position between optimization-driven and data-driven paradigms. Classical segmentation methods are predominantly unsupervised and rely on handcrafted rules or explicit optimization criteria, whereas traditional machine learning approaches introduce supervised learning but still depend on engineered feature representations. Deep learning methods, in contrast, achieve state-of-the-art performance across many domains but require large annotated datasets, substantial computational resources, and often exhibit limited interpretability. Within this context, quantum and quantum-inspired approaches are particularly characterized by reformulating segmentation as optimization or clustering problems, reducing dependence on labeled data, and maintaining comparatively high interpretability when based on explicit objective functions. Nevertheless, they remain constrained by scalability limitations and, in hybrid or fully quantum settings, additional hardware-related overhead. Table 7 summarizes the key differences between the investigated segmentation paradigms.

Table 7. Comparison of image segmentation paradigms across key characteristics.

Dimension	Classical	Traditional ML	Deep Learning	Quantum / Q-Inspired
Supervision	Unsupervised	Supervised	Supervised	Mixed
Data Requirements	Low	Moderate	High	Low–Moderate
Computational Cost	Low	Moderate	High	Moderate–High
Scalability	Moderate	Moderate	High	Low-Moderate
Interpretability	High	Moderate	Low	Moderate–High
Hardware Needs	CPU	CPU	GPU/TPU	CPU/QPU

The comparison across application fields, encoding strategies, and datasets reveals a clear dominance of medical and general image segmentation within the quantum literature, as well as a strong reliance on intensity- and graph-based representations in quantum-inspired methods. While some studies employ established benchmark datasets such as BraTS, InBreast, and PASCAL VOC, their use remains relatively uncommon. Furthermore, all quantum and hybrid

approaches require some form of quantum state preparation. Fully quantum methods frequently rely on dedicated quantum image encodings, such as NEQR, whereas hybrid methods typically employ task-specific data encodings or, more recently, compressed feature representations extracted by classical networks, such as U-Net-based architectures, before quantum processing.

Overall, several image segmentation techniques considered in this survey demonstrate promising potential. Some approaches achieve performance comparable to classical optimization solvers such as Gurobi [54], and in certain cases even approach the accuracy of state-of-the-art supervised models such as U-Net [93, 113, 114, 190]. However, the lack of standardized benchmarks makes such comparisons difficult to interpret and prevents a direct assessment of their practical advantages. General benchmarking initiatives such as in [43] may provide a useful starting point for developing reproducible, segmentation-specific evaluation frameworks that account for both task-level quality and quantum hardware constraints.

Quantum-inspired and tensor network-based methods currently appear to be the most mature and practically applicable directions, as they are frequently evaluated on real-world datasets and larger-scale image representations. Furthermore, hybrid and quantum optimization-based approaches demonstrate the ability to reduce dependence on large annotated datasets by formulating segmentation as clustering or graph optimization problems. Recent hybrid architectures that integrate quantum components into established segmentation frameworks, such as U-Net, also represent an important first step toward combining quantum methods with modern deep learning paradigms. In contrast, many fully quantum approaches remain largely exploratory and are often restricted to small-scale or synthetic grayscale images due to current hardware limitations. Overall, the field currently represents an active and heterogeneous research landscape with a broad range of methodological approaches. The surveyed literature suggests that near-term advances in quantum image segmentation are most likely to emerge from quantum-inspired, tensor network-based, and hybrid approaches, while fully quantum implementations remain a longer-term research direction. However, there is not yet robust evidence of a practical advantage over strong classical and deep learning baselines.

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