Contributions:

| Chapter | Initial Writing | Changes | Proofreading |
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| 0. Abstract | Lorenz | Jonas | Liselotte |
| 1. Introduction | Michael | Lorenz | Jonas |
| 2. Literature Review | Lorenz, Jonas | Liselotte | Liselotte |
| 3. Specific Architectures | Michael, Liselotte, Lorenz | Jonas | Michael |
| 4. Analysis | Michael | Michael | Lorenz |
| 5. Addressing Limitations | Jonas | Michael | Lorenz |
| 6. Conclusion | Liselotte | Michael | Jonas |

We used a shared Zotero literature database to keep track of the literature and to make sure that we all had access to the same sources. We also used a shared latex document to write the report together. We had regular meetings to discuss the progress and to make sure that everyone was on the same page and to update the team members regarding the content which was written within the indicidual chapters.

# Quantum Computer Vision

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***Abstract*—Our analysis of current literature suggests that quantum computer vision has the potential to drastically increase the efficiency of image processing when compared to traditional approaches. Quantum computing's inherent advantages, such as reduced computational complexity and increased generalization capabilities, present significant opportunities for advancements in tasks like image classification, segmentation, and medical imaging. However, current implementations remain in their early stages, relying heavily on classical image processing methods due to the limitations of available quantum hardware. Even though there are already multiple quantum image representations (QIRs), hybrid quantum-classical models, and specific architectures like Quantum Image Transformers (QiT) and Quantum Convolutional Neural Networks (QCNNs), future research should focus on optimizing quantum image encoding, improving quantum memory management, and developing full quantum pipelines to fully leverage quantum computing's potential in computer vision.**

## I. Introduction

With the rapid advancement of quantum technologies, researchers have begun exploring their applications across a growing number of fields. One such area is quantum computer vision, which has emerged at the intersection of quantum computing and artificial intelligence. Though still in its infancy, this field holds strong potential to revolutionize image processing.

The field of computer vision is especially interesting in the context of quantum computing due to the high computational complexity of traditional image processing tasks. Quantum computing has the potential to drastically increase the efficiency of computer vision by decreasing the need for large amounts of data and reducing the computational complexity of tasks. This way it could help to make classical image processing techniques such as compression, augmentation, and classification more efficient and open up completely new possibilities for image processing.

This review provides a concise yet comprehensive overview of the current state of quantum image processing, covering both foundational concepts and recent practical implementations. The paper is structured as follows: first, an introduction to the field is presented, with references to key literature. Next, we examine major implementations and architectures that have been developed. Finally, we discuss findings, limitations, and potential future directions before concluding the review.

## II. Literature Review

### A. *Quantum Gates and Qubits*

Quantum computing leverages the principles of quantum mechanics, where quantum bits (qubits) serve as the basic units of information [1]. Unlike classical bits, which represent either 0 or 1, qubits can exist in a superposition of both states simultaneously [2]. This ability allows quantum computers to process information in parallel, providing a potential computational advantage over classical systems [1].

To manipulate qubits, quantum gates are applied. These gates are unitary operations that change the state of qubits [1]. Examples include the Hadamard gate, which creates superposition, and the CNOT gate, which can generate entanglement between qubits [2]. Quantum gates differ from classical logic gates in that they preserve the overall probability of the system, while altering the probabilities of individual qubit states [2].

A quantum circuit is a sequence of quantum gates applied to qubits, forming the basis for executing quantum algorithms [2]. The design of quantum circuits is central to realizing practical quantum computation, and their complexity grows with the number of qubits and gates involved [3]. However, quantum circuits are sensitive to noise and errors, which is why robust error correction and gate fidelity remain active areas of research [4]. These challenges are particularly pronounced in the current Noisy Intermediate-Scale Quantum (NISQ) era, where quantum devices operate with limited qubits and high susceptibility to decoherence and operational errors [4]. Addressing these limitations is critical for achieving reliable quantum computations [3].

### B. *Quantum Image Representations*

Quantum image representations aim to harness quantum computing's power to process and analyze image data more efficiently than classical approaches [5], [6]. Traditional image processing typically involves encoding images as classical data, where each pixel is represented by a specific color value [6]. However, quantum images utilize quantum states to represent image data, offering the potential for significant computational advantages, such as faster processing and the ability to handle complex image transformations [5].

A quantum image representation typically uses quantum registers to encode the pixel information of an image [6]. One common approach is to encode pixel values in the amplitudes of quantum states, where each quantum state corresponds to a pixel in the image [6], [7]. These representations exploit quantum properties like superposition and entanglement to store and manipulate multiple pixel values simultaneously [8]. This allows for parallel processing of images, enabling quantum algorithms to execute complex operations more efficiently than classical counterparts [8].

Several quantum image representations (QIR) have been proposed, with two notable approaches being quantum associative memory (QAM) [9] and quantum image encoding (QIE) [10]. QAM uses quantum states to store patterns, enabling faster recognition and retrieval of image data [9]. QIE, on the other hand, focuses on encoding classical images into quantum states while preserving the essential features of the image for processing [10]. Both techniques leverage quantum gates and quantum circuits to manipulate image data efficiently [9], [10]. Overall all QIRs consist of three notable parts: the image color model, the image coordinate model and the image color encoding model. For the image color model the color can either be stored in binary, greyscale or RGB format [6], [11], [12]. Binary means that only a black and white image representation is stored, greyscale means that the image color is stored in a single channel and RGB means that image color is stored in three channels [13]. For the image coordinate model the image can either be stored in a cartesian coordinate system, in a log-polar system or in a multi-dimensional system [6]. In the Cartesian coordinate system images are stored in a 2D grid, in the log-polar system images are stored using log-polar sampling which is good for scale- and rotation-invariant processing. In turn, in multidimensional systems images are stored in a multidimensional grid which is useful for example for medical images [6]. For the image color encoding, angle parameter or basis state encoding are typically used. In the angle parameter encoding color values are stored in the qubit rotation angle. In this case the retrieval is probabilistic which means it requires multiple measurements. If the basis state encoding is used, the color information is stored in the computational basis states of the qubits. This makes the retrieval deterministic [6].

While quantum image representations offer theoretical advantages, practical implementation remains challenging due to the sensitivity of quantum states to noise and the complexity of quantum circuit design [4]. Ongoing research focuses on improving the fidelity of quantum image representations and developing quantum error correction methods to make them viable for real-world applications in image processing and computer vision [4].

### *C. Edge Detection and Image Segmentation*

Edge detection and image segmentation are fundamental techniques in classical image processing used to identify boundaries and separate different regions within an image [14]. Edge detection highlights significant changes in intensity between neighboring pixels, while image segmentation partitions an image into distinct areas based on color, texture, or intensity to facilitate analysis [14]. These techniques are widely used in computer vision applications, including object recognition, medical imaging, and autonomous vehicles [15], [16].

In quantum computing, edge detection and image segmentation can benefit from quantum parallelism and quantum image representations, enabling faster processing and more efficient handling of complex image data compared to classical algorithms [17], [18]. Quantum algorithms for these tasks have the potential to outperform classical approaches by leveraging quantum gates and circuits to perform parallel computations on quantum images, reducing the time and resources needed for large-scale image processing tasks [19].

### *D. Quantum Convolutional Neural Networks*

Convolutional neural networks (CNNs) have become a cornerstone of classical machine learning, particularly in image processing tasks such as object recognition, image classification, and even video analysis [24], [25]. However, CNNs face limitations when processing large datasets or high-dimensional data, often requiring significant computational resources [25]. Quantum Convolutional Neural Networks (QCNNs) aim to address these limitations by incorporating quantum computing techniques into the convolutional network framework, offering the potential for faster computation and greater efficiency in tasks like feature extraction and pattern recognition [26].

The core concept behind QCNNs is the use of quantum circuits to perform the operations that are typically carried out by classical convolutional layers [27]. In a classical CNN, the convolutional layer applies filters or kernels to the input image to extract spatial hierarchies of features [28]. Each layer applies a linear transformation and non-linear activation function to progressively capture complex features [25]. Quantum convolution, on the other hand, exploits quantum mechanics properties such as superposition and entanglement to perform these operations in a quantum state [27]. This allows QCNNs to process information in parallel, dramatically increasing computational efficiency for particular task types [29].

One key advantage of QCNNs is their ability to encode data into quantum states, as discussed in *B. Quantum Image Representations*, leveraging quantum parallelism to simultaneously explore multiple possibilities [30]. By using quantum gates and measurements, QCNNs apply transformations to these quantum states that mimic the convolution operations in classical networks, allowing them to learn and classify patterns more efficiently than classical methods, again, for particular tasks. [27].

QCNNs also benefit from quantum entanglement, a phenomenon where qubits become correlated in a way that classical bits cannot [31]. This entanglement can be used to encode higher-order relationships between data points, which is particularly useful in tasks such as image segmentation or feature recognition [32]. In contrast to classical neural networks that struggle with high-dimensional data, QCNNs can utilize quantum entanglement to capture complex patterns in data, which could improve their performance on tasks

| QIR Model | Key Features | Supports Color | Retrieval |
|---|---|---|---|
| Qubit Lattice Representation (QLR) [7] | First QIR, inefficient | Greyscale | Probabilistic |
| Flexible Representation for Quantum Images (FRQI) [20] | Uses angle encoding for color | Greyscale | Probabilistic |
| Multi-Channel Representation of Quantum Images (MCQI) [8] | RGB support | RGB | Probabilistic |
| Novel Enhanced Quantum Representation (NEQR) [11] | Basis state encoding | Greyscale | Deterministic |
| Caraiman's Quantum Image Representation (CQIR) [21] | Supports histogram equalization | Greyscale | Deterministic |
| Quantum Log-Polar Image (QUALPI) [22] | Log-polar image processing | Greyscale | Deterministic |
| Simple Quantum Representation (SQR) [12] | Thermal/Infrared imaging | Greyscale | Probabilistic |
| Quantum States for M Colors and N Coordinates (QSMC & QSNC) [23] | Image compression | RGB | Probabilistic |
| Normal Arbitrary Quantum Superposition State (NAQSS) [13] | Multi-dimensional images | RGB | Probabilistic |

TABLE I: Quantum Image Representations and Their Characteristics

like medical imaging, speech recognition, or video processing [32].

## III. Comparison of Specific Architectures

### A. QIR Systems

Since 2003, several QIR systems have been developed, each for use in specific scenarios. [5], [33] A comparison of the major ones can be seen in Table I.

### B. Architecture Review

In this section, a number of prominent publications from the research community aligned with Quantum Computer Vision will be reviewed.

*1) Quantum Vision Transformers:* The Quantum Image Transformer (QiT), an adapted Vision Transformer (ViT) which was proposed by Cherrat et al. [34], brings ViT's approach into the realm of quantum computing, splitting an image into tiles and analyzing inter-tile relationships via attention. Cherrat introduces three potential architectures: an Orthogonal Patchwise Neural Network, a Quantum Orthogonal Transformer, and a Compound Transformer.

The Orthogonal Patchwise Neural Network (OPNN) [34], the simplest approach, uses quantum circuits to analyze individual tiles. The Quantum Orthogonal Transformer (QOT) [34] mirrors the classical ViT but employs quantum circuitry to analyze inter-tile relationships. Finally, the Compound Transformer (CT) [34] is the most advanced, leveraging superposition to process all tiles simultaneously—akin to mixing all necessary colors required to create a goal color at once instead of sequentially.

Cherrat tested these approaches on medical imagery with only 6 qubits available, a major limitation. Despite this constraint, this experiment's results gave reason for optimism. When the performance of the classical ViT, the OPNN, the QOT and the CT were compared in terms of accuracy on 12 individual medical datasets, the OPNN was best in 1 case, the QOT in 1, the ViT in 5, and the CT also in 5, meaning that advantages over current approaches were found using QiT architectures [34].

*2) A quantum convolutional network and ResNet (50)-based classification architecture for the MNIST medical dataset:* Quantum Computer Vision holds great promise for society as a whole, with one of the most promising fields being medical imaging, with potential benefits in personalized medicine and earlier disease detection. Hassan et al.'s [35] work on a hybrid QCNN approach to classify medical images from the MedMNIST dataset [36]. They propose a novel Medical Quantum Convolutional Neural Network (MQCNN), which aimed to eliminate classical techniques' struggles with complex and/or voluminous data by only using a classical architecture for base feature extraction, followed by then leveraging a QCNN architecture for classification. The chosen classical architecture in this case was ResNet50 [37].

Hassan et al. managed to achieve a classification accuracy of 99.09% on the MedMNIST's 58,954 64x64 images, which proved to be superior to either the QCNN or ResNet50 on their own, by a margin of  0.5% for the ResNet50 [37] and  1.5% for the QCNN [26]. While this is only a minimal improvement in terms of accuracy, any improvement shows a potential for superior performance in the future. This study highlights the potential of hybrid quantum-classical architectures in medical imaging.

*3) Quantum Machine Learning-Based Framework to Detect Heart Failures in Healthcare 4.0:* Another study, from the medical subdomain of QCV, conducted by Munshi et al., [38], aimed to begin the shift of the current medical mindset from a reactive approach to a more predictive one. They aimed to implement a Quantum ML based framework that could improve the detection rate of heart failures in Healthcare 4.0. To accomplish this, they used a standard heart rate failure dataset consisting of the health records of 918 patients, acquired from Kaggle.

Two different architectures were tested, with varying degrees of success. The first implementation was a 'Variational Quantum Classifier' (VQC), which employed a quantum circuit representation to classify the data/make predictions. The VQC also contained an optimizer (COBYLA), to tune the parameters and configuration of the quantum circuit in order to minimize the requisite loss function [38]. The authors also proposed a 'Quantum Support Vector Classifier' (QSVC) model, which leveraged quantum kernels and circuits to separate quantum converted data points with a hyperplane, porting the classical technique of the same name into the quantum realm. These architectures were compared and contrasted using IBM's Quantum Lab as the experimental platform.

The QSVC model comfortably outperformed the VQC model on every metric used, for example, achieving an accuracy score of 82% compared to the VQC's 76% [38]. The main difference in the two architectures' results lay in their false negative rate, which was over two times greater for the VQC model than the QSVC model.

*4) Hybrid Quantum ResNet for Diagnosis from Liver Biopsy Image Classification:* Building on the potential of MCQNN's [35] and QSVC's [38] in medical image classification, another hybrid/Quantum-Classical approach to QCV in the medical sector is proposed here. Lusnig et al. integrate quantum layers with deep learning to enhance the diagnosis of hepatic steatosis [39].

The Hybrid Quantum ResNet, incorporates a Quantum Depth Infused (QDI) layer into the ResNet18 [37] architecture. In this model, ResNet extracts 1,000 features, which are then reduced to 100 through a fully connected layer. These features are subsequently mapped onto 5 qubits using 20 data reuploading layers. Variational layers with over 105 variational gates process the quantum state, after which measurements convert the quantum information back into classical data for final classification. [39] The model architecture is based on transfer learning, allowing it to leverage pre-trained models to enhance performance and adaptability across different datasets. Additionally, this architecture facilitates the efficient encoding and transformation of significant amounts of information with very few qubits, maximizing computational depth while minimizing quantum resource requirements and therefore remaining feasible for near-term NISQ hardware. [4]

This architecture demonstrates a 97% accuracy rate, which is 1.8% higher than classical models, and requires 1.75 times fewer parameters. [39] It exhibits strong generalization capabilities on small datasets and potentially supports federated learning, thereby ensuring compliance with GDPR regulations.

*5) Hybrid Quantum Neural Networks for Multi-Class Image Classification:* Finally, another study in this field, which utilises a hybrid approach to QCV, this time outside of the medical domain, was conducted by Shi et al. [40]. Their study focused on exploring various Hybrid Quantum Neural Network (HQNNs) architectures and construction methods for multi-class image classification, specifically addressing challenges posed by high-dimensional data in quantum neural networks (QNNs), such as the barren plateau problem. The architectures compared in the study were evaluated on the MNIST [40] and FashionMNIST [40] datasets.

Further, the authors also compare the use of Principal Component Analysis (PCA) for dimensionality reduction with leveraging CNNs for their feature extraction abilities as a preprocessing step for QNNs. The QNNs are then used for classification based on the reduced feature set. [40] Notably, their approach involves using a complete QNN rather than just integrating it as a layer within a classical neural network, as in the case of Hassan et al.'s MCQNN [35].

While PCA performs well in binary classification problems, achieving an F1 score of 80%, this performance does not translate to the tested multi-class problems, where the F1 score drops to around 40%. Employing a CNN to extract relevant features from the image data significantly improves these results, yielding an accuracy of 73%. [40]. Based on these findings, Shi et al. [40] propose their own construction method for an HQNN. The resulting model incorporates amplitude encoding and quantum rotation gates. Additionally, they introduce an efficient quantum rotation gate variant capable of fitting any single-variable function, along with a fully connected entanglement parametric quantum circuit (PQC) model. The evaluation of this model also shows improvements over previous HQNN models, increasing the F1 score by 5% to 78%. However, while this represents an improvement over traditional HQNNs, the proposed model is still outperformed by a simple classical CNN [40].

## IV. Analysis, Findings, and Limitations

### *A. Theoretical Limitations of Quantum Computing in CV*

Quantum computing faces several significant challenges that currently limit its practical application in computer vision. While theoretical possibilities are promising, the actual quantum speedup remains uncertain for many CV algorithms. Current quantum devices often struggle to outperform classical computers in real-world tasks, and the anticipated exponential speedup may not materialize for all applications [2].

Hardware constraints pose substantial barriers. Today's quantum computers have limited qubit counts and suffer from decoherence, making it difficult to maintain quantum states long enough for complex computations [2]. Error rates in quantum gates remain high, necessitating error correction that consumes additional qubits and computational resources [4]. The requirement for near-absolute zero temperatures also makes scaling challenging.

Data encoding presents another fundamental challenge. Converting classical image data into quantum states is non-trivial and can be computationally expensive [7], [8], [41]. Quantum interference, while essential for quantum advantage, can also cause unwanted effects when encoding visual data. The process of mapping high-dimensional image data to quantum states must be done carefully to preserve important features while remaining computationally feasible [8].

The resource requirements for quantum CV systems are substantial. Quantum memory for storing image data, specialized quantum circuits for processing, and classical pre- and post-processing hardware all contribute to high implementation costs [5], [17]. Additionally, the need for quantum error correction significantly increases the number of physical qubits required for reliable computation, often by orders of magnitude compared to the logical qubits needed for the algorithm itself.

These limitations suggest that near-term applications of quantum computing in computer vision may be best suited for specific, well-defined tasks rather than general-purpose CV applications.

### B. Practical Analysis

*1) Analysis and Findings:* Through the analysis of several bleeding-edge architectures and publications, it has become evident that Quantum Computer Vision holds great promise for both the scientific community and society as a whole. Further , from the examination of various implementation results, it is clear that, regardless of application or architecture, using quantum techniques in the examined cases consistently resulted in both efficiency and accuracy improvements. Most examined architectures achieved performance boosts in terms of both speed and the number of parameters required when compared with entirely classical approaches [34]–[36], [39], [40]. These improvements in results are particularly promising in the field of medical imaging, where significant speedups could lead to a vast array of potential applications, such as live surgery quantum simulations [42]. Further, image classification accuracy was similarly affected by these architectures, with some individual implementations achieving almost 2% higher accuracy than their classical counterparts [39].

However, while such ideas are alluring, the reality remains that hybrid classical-quantum approaches will be more prevalent in the near future, due to the challenges mentioned in the theoretical analysis section. Despite this, the integration of quantum techniques with classical systems has shown to be a viable path forward. For instance, hybrid models can leverage the strengths of both paradigms, using classical preprocessing to reduce noise and normalize data before feeding it into quantum models for more complex tasks. The potential of such systems is exemplified by Hassan et al's results, where a hybrid architecture, combining a QCNN with a classical IP architecture, ResNet50, outperformed both single-concept models individually [35].

*2) Critiques and Limitations:* Quantum computing, despite its immense theoretical potential, remains in its early stages, and faces numerous foundational challenges. Within this broader field, as expected, Quantum Computer Vision (QCV) shares many of the same limitations, making large-scale practical applications difficult. This section discusses the primary practical limitation, and potential societal implications should QCV achieve anything even approaching widespread adoption.

One of the biggest practical obstacles to QCV is the immaturity of its algorithmic design. Unlike classical computer vision, where CNNs and deep learning models have undergone decades of refinement, QCV is still in its infancy. Current quantum algorithms for image processing, such as Quantum Fourier Transforms [43] or Quantum Boltzmann Machines [44], are constrained by inefficient data encoding methods, as detailed in previous sections. Furthermore, transferring classical image data into a quantum system is computationally expensive, often nullifying any theoretical speed advantage. As quantum hardware advances, so too must the algorithms that run on it, but at present, this remains a significant bottleneck.

Should QCV become widely accessible, it risks exacerbating existing societal inequalities, especially in the medical sector. Quantum technology is resource-intensive, requiring specialized infrastructure, which may be monopolized by tech giants and wealthy nations. This could widen the technological divide, granting disproportionate power to entities that control quantum computing resources. Ethical considerations must be addressed to prevent QCV from being used in ways that reinforce biases or limit access to its benefits. For example, should quantum medical imaging become available to only a select few, this could significantly impact gaps in healthcare standards between the wealthy and the less fortunate. In summary, while QCV certainly holds promise for the future, algorithmic design limitations and broader societal implications highlight the need for careful, responsible development to ensure both a rapid and ethical development cycle.

Another significant limitation is handling high-dimensional datasets, as current quantum systems have restricted qubit counts and struggle with processing substantial amounts of information. Additionally, it is worth noting that the majority of research papers in this field rely heavily on quantum simulators rather than actual quantum computers [39], [40], which may not fully capture the real-world challenges and noise characteristics present in physical quantum systems.

## V. Addressing Limitations

### A. Quantum Image Encoding Optimization and Adaptive Solutions

The challenge of efficient quantum image encoding remains a critical bottleneck in quantum image processing. While established models like FRQI, NEQR, and QSMC have laid important groundwork, as shown in Table I, they each have specific limitations that need to be addressed. A promising direction is the development of adaptive quantum encoding systems that can dynamically select optimal encoding schemes based on input characteristics.

The implementation of an agent-based approach for autonomous encoding selection presents an innovative solution. Such a system could analyze image properties like complexity, color distribution, and spatial relationships to determine the most efficient encoding strategy. This could be achieved through reinforcement learning agents that optimize encoding choices based on performance metrics like fidelity, compression ratio, and processing speed.

A particularly promising avenue is the development of hybrid encoding schemes that combine the strengths of multiple approaches. For instance, FRQI's efficiency in handling color information could be combined with NEQR's superior spatial resolution preservation. This hybrid approach could be implemented on distributed quantum systems, allowing for parallel processing and better resource utilization.

### B. Quantum Memory Management and Optimization

The exponential growth of quantum memory requirements with increasing qubit count presents a significant challenge. Compressed quantum state representations offer a way to reduce memory requirements while maintaining essential information. These techniques leverage quantum state properties like entanglement and superposition to achieve more efficient storage. Quantum tensor networks, particularly Matrix Product States (MPS) and Projected Entangled Pair States (PEPS), provide a structured approach to representing quantum states with reduced memory overhead.

The current hybrid quantum-classical paradigm serves as a practical intermediate solution. By intelligently distributing computational tasks between classical and quantum processors, advantages of both systems can be maximized. Classical computers can handle data preprocessing, feature selection, and post-processing, while quantum processors focus on computationally intensive tasks that benefit from quantum parallelism.

### C. Advancing Towards Full Quantum Approaches

While hybrid approaches currently dominate the field, the ultimate goal is to develop full quantum solutions that can handle entire image processing pipelines. This includes quantum feature extraction, which currently relies heavily on classical preprocessing. Development of more sophisticated quantum circuits capable of direct feature extraction from quantum image representations is essential, along with the implementation of quantum convolutional operations that can process spatial information efficiently. Additionally, the creation of quantum-native dimensionality reduction techniques will play a crucial role in advancing full quantum approaches.

### D. Error Mitigation and Correction Strategies

Error correction remains crucial for reliable quantum image processing. A comprehensive approach to error mitigation should include the development of specialized error correction codes for quantum image processing operations and implementation of error estimation techniques that can predict and account for hardware-specific noise patterns. Integration with existing quantum error correction frameworks while minimizing additional qubit overhead is essential, as is the creation of adaptive error mitigation strategies that can adjust to changing noise conditions during processing.

### E. Accessibility and Development Infrastructure

The limited accessibility of quantum computing resources significantly impacts research progress. Development of more sophisticated quantum simulators that can better approximate real quantum hardware behavior remains valuable for algorithm development and testing, despite computational limitations with increasing qubit counts. Creation of cloud-based quantum computing platforms with improved queue management and resource allocation systems could include implementation of priority queues for time-critical research and better scheduling algorithms to maximize hardware utilization.

Investment in educational quantum computing platforms can help researchers and students gain experience with quantum algorithms without requiring access to actual quantum hardware. This democratization of quantum computing resources is crucial for advancing the field.

## VI. Conclusion

The intersection of quantum machine learning and computer vision presents a promising field with several key advantages. The quantum approach offers potential for faster computation through quantum parallelism enabled by superposition, demonstrated improvements in accuracy, and notably better generalization capabilities that enable effective learning from small datasets. This latter advantage is particularly significant for medical image classification applications, where large annotated datasets are often difficult to obtain.

However, several important limitations currently constrain the field's practical applications. Hardware constraints in the NISQ era restrict implementations to few qubits and introduce high operational errors. A significant challenge lies in processing high-dimensional data, which is particularly problematic for computer vision tasks. This limitation has led to fully quantum approaches falling short of theoretical expectations, with very few successful practical implementations. Furthermore, many current implementations do not fully utilize quantum image representations, indicating additional challenges in leveraging quantum advantages.

Hybrid approaches have emerged as a practical compromise, combining classical machine learning for feature extraction with quantum computing for classification. These approaches have shown success in either mimicking classical architectures like Tranformer and QCNN or integrating quantum layers such as quantum-inspired variational layers. Notably, these hybrid methods have demonstrated improvements over classical approaches while maintaining performance with reduced data requirements.

To advance the field further, development of standardized benchmarking tools for comparing different quantum image encoding schemes is necessary. Creation of automated optimization tools for quantum circuit design specific to image processing tasks will streamline development processes. Implementation of quantum-specific image processing libraries that can seamlessly integrate with existing classical frameworks will facilitate adoption of quantum techniques.

The path forward requires a balanced approach that acknowledges current hardware limitations while pushing the boundaries of what's possible with quantum computing. Significant research opportunities remain in exploring how to better exploit quantum computing's potential for computer vision tasks, particularly in medical imaging where it could revolutionize diagnostic processes. As quantum hardware continues to improve, the focus should shift from hybrid solutions to full quantum implementations, while maintaining backward compatibility with existing classical systems. This ongoing development could lead to breakthrough advances in medical diagnosis and other critical computer vision applications.

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