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Analysis of Quantum-Classical Hybrid Deep Learning for 6G Image Processing with Copyright Detection

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Abstract: This study investigates the integration of quantum computing, classical methods, and deep learning techniques for enhanced image processing in dynamic 6G networks, while also addressing essential aspects of copyright technology and detection. Our findings indicate that quantum methods excel in rapid edge detection and feature extraction but encounter difficulties in maintaining image quality compared to classical approaches. In contrast, classical methods preserve higher image fidelity but struggle to satisfy the real-time processing requirements of 6G applications. Deep learning techniques, particularly CNNs, demonstrate potential in complex image analysis tasks but demand substantial computational resources. To promote the ethical use of AI-generated images, we introduce copyright detection mechanisms that employ advanced algorithms to identify potential infringements in generated content. This integration improves adherence to intellectual property rights and legal standards, supporting the responsible implementation of image processing technologies. We suggest that the future of image processing in 6G networks resides in hybrid systems that effectively utilize the strengths of each approach while incorporating robust copyright detection capabilities. These insights contribute to the development of efficient, high-performance image processing systems in next-generation networks, highlighting the promise of integrated quantum-classical–classical deep learning architectures within 6G environments.

Keywords: copyright detection; quantum computing; hybrid deep learning; image processing; 6G networks

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1. Introduction

In the rapidly evolving landscape of artificial intelligence and telecommunications [1], integrating deep learning with advanced network technologies like 6G presents transformative potential [2]. Deep learning, a subset of machine learning, leverages neural networks to enable machines to autonomously learn from vast amounts of data, making it a cornerstone technology for various applications, including image processing [3,4]. As 6G networks promise unprecedented speed, connectivity, and adaptability, they also introduce dynamic and fluctuating network conditions that pose significant challenges for real-time data processing [5–7]. Furthermore, the rise of AI-generated content necessitates robust copyright detection mechanisms [8,9] to safeguard intellectual property rights. These mechanisms utilize advanced algorithms to analyze digital content, identifying potential infringements and ensuring compliance with legal standards. This study aims to explore and compare the efficacy of quantum-enhanced and classical deep learning schemes for image processing [10–12] within these dynamic 6G network environments. Quantum computing [13,14], with its principles of superposition and entanglement, offers a novel approach to handling complex computations and optimizations, potentially outperforming classical methods in certain scenarios. Quantum Approximate Optimization Algorithm (QAOA) [14] and the Quantum neural networks (QNNs) [15,16] represent the forefront of this technological advancement, providing new avenues for processing and analyzing high-dimensional data.

Conversely, classical deep learning models, particularly convolutional neural networks (CNNs) [17–19], have demonstrated robust performance across a wide range of applications, from computer vision to natural language processing. These well-established models benefit from extensive research and optimization, making them a reliable benchmark for comparison. In this research, we simulate various network fluctuations, including bandwidth variations, latency changes, and node failures, to test the resilience and adaptability of both quantum and classical deep learning schemes. By evaluating key performance metrics such as processing speed, accuracy, and resource utilization under different network stress scenarios, we aim to provide a comprehensive analysis of each approach's strengths and limitations. The findings of this study will contribute to the ongoing discourse on the role of quantum computing in advancing 6G network capabilities and image processing techniques. By highlighting the challenges and opportunities inherent in both quantum and classical approaches, this research seeks to inform future developments in deep learning integration with next-generation network technologies.

This research conducts a comprehensive comparative analysis of quantum-enhanced and classical deep learning schemes [20] for image processing within dynamic 6G network environments [21]. We seek to evaluate the performance, adaptability, and efficiency of both approaches under various network fluctuations that are characteristic of next-generation wireless networks. By simulating realistic 6G network conditions, including bandwidth variations, latency changes, and node failures [22], we aim to assess how quantum and classical models respond to these challenges. Our objective is to identify the strengths and limitations of each approach, particularly in maintaining image processing quality and computational efficiency amid network stress. This comparison will provide valuable insights into the potential advantages of quantum computing in handling complex network dynamics and the robustness of classical deep learning models in established network scenarios. Ultimately, this study aims to contribute to the ongoing discourse on the integration of quantum computing with 6G technologies and its implications for advanced image processing applications. As the integration of advanced image processing technologies in 6G networks becomes more common, it is important to consider the ethical implications of computer-generated content, particularly regarding copyright issues. The rapid increase in digital images raises significant concerns about intellectual property rights and possible infringements. To address these challenges, effective copyright detection mechanisms [23,24] are essential. These systems utilize advanced algorithms to examine created content, identifying potential infringements and ensuring adherence to legal standards. By implementing reliable copyright detection solutions, we can encourage the responsible use of computer-generated images, protecting the rights of original creators while promoting innovation in image processing technologies. This emphasis on copyright detection not only strengthens the integrity of digital content but also supports the broader acceptance and application of integrated quantum–classical deep learning frameworks within 6G environments.

The remainder of this paper is organized as follows: Section 3 provides a detailed overview of the related quantum and classical deep learning work for image processing and 6G networks. Section 4 describes the methodology, including the simulation framework, network fluctuation scenarios, and performance metrics used for evaluation. Section 5 presents the simulation analysis, comparing the performance of quantum and classical models under various network conditions. Section 6 discusses the findings' implications, highlighting each approach's strengths and limitations. Finally, Section 6 concludes the paper with a summary of key insights and suggestions for future research directions. This structured approach ensures a comprehensive and systematic exploration of the comparative analysis, providing valuable insights into the potential of quantum computing in enhancing 6G network capabilities for advanced image processing applications.

This research aims to bridge the gap between classical signal processing and quantum computing, offering a novel approach to address the demands of next-generation network technologies. By integrating quantum deep learning [25,26] techniques, we aim to unlock new potentials in image processing, paving the way for more efficient and reliable digital communication systems in the 6G era.

2. Literature Review

2.1. Deep Learning in Image Processing with Copyright Detection

2.1.1. Overview of Classical Deep Learning Models for Image Processing

Classical deep learning models have revolutionized image processing in recent years, with convolutional neural networks (CNNs) and generative adversarial networks (GANs) [27,28] being at the forefront of this transformation. CNNs have become the go-to architecture for various image-related tasks, including classification, object detection, and segmentation [29,30]. Their ability to automatically learn hierarchical features from raw pixel data has led to unprecedented performance in tasks like facial recognition and medical image analysis. GANs, on the other hand, have opened new frontiers in image generation and manipulation. By pitting a generator network against a discriminator in a minimax game, GANs can produce highly realistic synthetic images and perform tasks like style transfer and image-to-image translation [31–33]. These models have not only pushed the boundaries of what is possible in image processing but have also found applications in diverse fields such as autonomous vehicles, security systems, and creative arts. Furthermore, the ongoing advancements in these architectures continue to inspire innovative solutions for complex challenges, such as real-time image processing in dynamic environments. As researchers explore hybrid models that combine classical techniques with emerging technologies like quantum computing, the potential for even greater breakthroughs in image analysis becomes increasingly promising.

2.1.2. Recent Advancements and State-of-the-Art Techniques

Recent advancements in deep learning for image processing have seen significant strides in both classical and quantum-inspired approaches [34,35]. Convolutional neural networks (CNNs) continue to dominate traditional image analysis tasks, while generative adversarial networks (GANs) push the boundaries of image synthesis and manipulation. The integration of quantum computing principles has led to the development of quantum convolutional neural networks (QCNNs) [36,37], which combine classical CNN structures with quantum circuits to enhance performance. Quantum-enhanced feature extraction techniques are being explored to leverage quantum processing units for improved computational efficiency [20]. Transfer learning between classical and quantum models shows promise in accelerating classification tasks. As demonstrated by IBM Research, quantum kernels offer solutions to machine learning problems that challenge classical methods. Quantum neural networks (QNNs) are emerging as parameterized quantum computational models designed for quantum computers, showing potential in handling complex quantum data [38]. Adaptive layer-wise learning and error mitigation strategies are being developed to optimize these quantum models on near-term processors [39]. The field is increasingly focusing on hybrid quantum-classical–classical algorithms, aiming to synergize the strengths of both computing paradigms for advanced image processing applications.

2.1.3. Copyright Detection Techniques

Copyright detection has become increasingly important in the digital age, especially with the growing prevalence of computer-generated content and the rapid increase in digital images. Various technologies and algorithms are employed to effectively identify potential copyright infringements. For example, methods such as image hashing and machine learning techniques, including convolutional neural networks (CNNs), analyze visual features and assess similarity against a database of copyrighted materials. One effective approach is perceptual image hashing, which creates unique identifiers for images, enabling efficient comparison and detection of unauthorized use. As copyright detection technologies continue to advance, they play a crucial role in protecting digital assets, reducing financial risks, and ensuring that original creators receive appropriate recognition for their work.

2.2. Quantum Deep Learning Techniques with Copyright Detection

2.2.1. Introduction to Quantum Neural Networks (QNNs)

Quantum neural networks (QNNs) represent an innovative fusion of quantum computing principles and classical neural network architectures, aiming to harness quantum phenomena like preposition and entanglement for enhanced machine learning capabilities [40–43]. These networks typically consist of quantum circuits with parameterized gates that can be trained using variational methods, allowing for classical and quantum data processing. QNNs offer potential advantages in certain computational tasks due to quantum parallelism and interference effects but also face challenges such as limited qubit coherence times and the need for error correction in current quantum hardware. As the field of quantum computing advances, QNNs are merging as a promising avenue for exploring new approaches to machine learning problems, particularly in areas where quantum effects could provide a significant computational edge over classical methods.

2.2.2. Quantum Approximate Optimization Algorithm (QAOA) in Machine Learning Contexts

The Quantum Approximate Optimization Algorithm (QAOA) [44] is a hybrid quantum–classical approach that has shown promise in addressing combinatorial optimization problems relevant to machine learning [45]. In the context of machine learning, QAOA can be applied to tasks such as feature selection, hyperparameter optimization, and training quantum neural networks, potentially offering advantages over classical methods for certain problem classes. The algorithm prepares a quantum state that encodes the optimization problem, applies parameterized quantum gates, and uses classical optimization to fine-tune these parameters. While QAOA shows potential for enhancing machine learning tasks on near-term quantum devices, challenges remain in scaling to larger problems and demonstrating clear advantages over classical algorithms in practical applications.

2.2.3. Recent Developments in Quantum-Enhanced Deep Learning

Recent developments in quantum-enhanced deep learning have focused on creating hybrid models that combine classical neural networks with quantum circuits. Quantum convolutional neural networks (QCNNs) [46] have emerged as a promising approach, utilizing quantum layers and strongly entangled circuits to process both classical and quantum data [47]. Researchers have demonstrated potential advantages in certain computational tasks, such as image recognition and optimization problems, where quantum parallelism and interference effects could provide an edge over classical methods. However, challenges remain in scaling these models to larger problem sizes and demonstrating clear practical advantages over classical algorithms, mainly due to limitations in current quantum hardware.

2.2.4. Quantum Techniques for Copyright Detection

The incorporation of quantum computing into deep learning methods presents notable advancements in copyright detection for digital content. Quantum algorithms can improve the efficiency and accuracy of identifying copyrighted material by utilizing principles such as superposition and entanglement. These techniques enable the swift analysis of large datasets, facilitating the detection of potential infringements in real time. One effective method involves quantum-enhanced machine learning algorithms that examine the visual features of images to evaluate their similarity to existing copyrighted works. By applying quantum adaptations of traditional algorithms, such as convolutional neural networks (CNNs), the detection process can be accelerated, which is particularly beneficial in environments with extensive digital content where timely identification is essential.

Additionally, integrating perceptual image hashing techniques within a quantum framework can enhance copyright detection capabilities. These methods create unique identifiers for images, allowing for efficient comparisons against databases of copyrighted materials. The computational power of quantum systems enables more thorough similarity assessments, even for images that may have been altered. As copyright detection technologies progress, the combination of quantum computing and deep learning not only bolsters the protection of intellectual property rights but also encourages the responsible use of digital content. This integration is vital for ensuring compliance with legal standards in an increasingly intricate digital landscape.

2.3. 6G Networks: Characteristics and Challenges with Copyright Detection

6G networks are envisioned to provide unprecedented capabilities, including ultra-high bandwidth (potentially reaching terabits per second), extremely low latency (sub-millisecond), and massive connectivity (supporting millions of devices per square kilometer) [48,49]. These networks are expected to integrate advanced technologies such as artificial intelligence, terahertz communications, and large-scale satellite constellations to enable new applications like holographic communications and extended reality. However, the implementation of 6G networks presents significant challenges for data processing and image analysis, particularly due to the massive increase in data volume and the need for real-time processing. While offering increased bandwidth, the high-frequency bands used in 6G also face issues with signal propagation and penetration, potentially requiring dense network deployments. Additionally, integrating AI and machine learning algorithms directly into the network infrastructure poses challenges in terms of computational efficiency, energy consumption, and the need for distributed processing capabilities to handle the immense data loads in real time.

In this paper, we employ a hybrid quantum-classical deep learning model specifically designed to address these challenges. This model combines the rapid edge detection and feature extraction capabilities of quantum computing with the image fidelity strengths of classical methods.

The implementation of copyright detection in 6G networks presents unique characteristics and challenges due to the dynamic nature of these advanced telecommunications systems. With the ability to handle vast amounts of data at unprecedented speeds, 6G networks facilitate real-time monitoring and analysis of digital content, enabling prompt identification of potential copyright infringements. Advanced algorithms can analyze visual features and metadata to detect unauthorized use across various platforms. However, the sheer volume of content generated in 6G environments complicates the development of efficient detection systems, as traditional methods may struggle to keep pace with the rapid influx of new material. This necessitates adopting more sophisticated techniques, such as machine learning and image hashing, which improve accuracy by recognizing subtle variations in content and identifying similarities with existing copyrighted works. Additionally, the evolving nature of digital content—such as alterations made through cropping or filtering—poses further difficulties for copyright detection systems, requiring solutions that can adapt while maintaining high levels of accuracy. Addressing these challenges will be essential for ensuring compliance with copyright laws and protecting the rights of content creators in the fast-evolving landscape of 6G networks, ultimately promoting responsible use of digital content while safeguarding intellectual property rights.

2.4. Classical Deep Learning Approaches in 6G Networks

Classical deep learning approaches in 6G networks are being adapted to handle the massive data volumes and ultra-low-latency requirements of these next-generation systems. Researchers are exploring techniques such as distributed and federated learning to process data at the network edge and developing more efficient neural network architectures optimized for 6G's high-bandwidth, low-latency environments [49,50]. However, classical approaches face significant challenges in dynamic 6G conditions, including real-time adaptability to rapidly changing network topologies, the ability to process heterogeneous data from diverse IoT devices, and the requirement for energy-efficient computations to support massive connectivity. Additionally, the sheer scale and complexity of 6G networks pose limitations for traditional deep learning models regarding computational resources and training time.

2.5. Quantum-Enhanced Deep Learning for 6G Networks

Quantum-enhanced deep learning for 6G networks aims to leverage quantum computing principles to address the challenges of massive data processing and dynamic network conditions. Quantum approaches show potential advantages in handling network fluctuations through their ability to process multiple network states simultaneously, potentially enabling more efficient resource allocation and adaptive routing in highly dynamic 6G environments. Research on quantum-enhanced image processing for 6G networks has demonstrated promising results in areas such as quantum-assisted feature extraction and quantum convolutional neural networks (QCNNs) [51], which have shown improved performance in image classification tasks under simulated network conditions. However, these approaches are still largely theoretical or limited to small-scale experiments, with significant challenges remaining in scaling quantum algorithms to practical 6G network sizes and implementing them on current quantum hardware.

2.6. Comparative Studies on Quantum vs. Classical Approaches

Comparative studies between quantum and classical approaches in deep learning for 6G networks have shown promising results, with quantum methods demonstrating potential advantages in certain computational tasks. Performance metrics commonly used in these comparisons include processing speed, accuracy, resource utilization, and adaptability to network fluctuations. Recent research has indicated that quantum-enhanced algorithms, such as the Quantum Approximate Optimization Algorithm (QAOA) [51,52] and quantum neural networks (QNNs) [53], can outperform classical methods in specific scenarios, particularly for complex optimization problems and feature extraction tasks in high-dimensional data spaces.

QAOA, in particular, utilizes a hybrid quantum-classical–classical approach to tackle combinatorial optimization problems by iteratively refining solutions through quantum gates, making it effective for tasks like the Multiple Knapsack Problem. This capability allows QAOA to explore multiple solutions simultaneously, offering significant advantages in scenarios where classical algorithms struggle to find optimal solutions efficiently.

On the other hand, QNNs leverage the principles of quantum mechanics to enhance neural network architectures, enabling them to process information in fundamentally different ways than classical neural networks. This unique processing capability allows QNNs to capture complex patterns in data more effectively, potentially leading to improved performance in tasks such as image recognition and classification.

However, these studies also highlight that the practical advantages of quantum approaches are still limited by current hardware constraints and the need for further development of quantum algorithms tailored to 6G network challenges.

2.7. Research Gaps and Future Directions

Research gaps in quantum-enhanced deep learning for 6G networks include the need for larger-scale quantum hardware to demonstrate practical advantages over classical methods in real-world network scenarios. Future directions involve developing more efficient quantum algorithms tailored specifically to 6G network challenges, such as dynamic resource allocation, ultra-low-latency processing, and copyright detection techniques. Integrating effective copyright detection methods into quantum frameworks can enhance the safeguarding of intellectual property rights in an environment characterized by rapid content generation. Potential avenues for combining quantum and classical approaches include hybrid architectures that utilize the strengths of both systems, with quantum processors managing specific computationally intensive tasks within larger classical network management frameworks. Additionally, there is a need for more comprehensive benchmarking studies to clearly identify scenarios where quantum methods offer significant benefits over classical techniques in 6G environments, particularly regarding copyright detection and adherence to legal standards.

3. Methodology

Our methodology employs a comprehensive simulation framework designed to model the dynamic conditions of 6G networks, incorporating key features such as ultra-high bandwidth, extremely low latency, and network fluctuations. Within this simulated environment, we implement and compare quantum-enhanced deep learning models, including quantum neural networks (QNNs) and the Quantum Approximate Optimization Algorithm (QAOA), against classical deep learning approaches such as convolutional neural networks (CNNs) and generative adversarial networks (GANs). The models are evaluated across various network fluctuation scenarios, including bandwidth variations, latency changes, and node failures, to assess their performance and adaptability in processing complex image data under challenging 6G conditions. We utilize a diverse set of images processing tasks, including classification, segmentation, and generation, to comprehensively evaluate the models' capabilities. Performance metrics such as accuracy, processing speed, and resource utilization are carefully measured and analyzed to thoroughly compare quantum and classical approaches in the context of 6G network environments.

These equations represent key aspects of our simulation framework for comparing quantum and classical deep learning approaches in 6G network environments. Network fluctuation equations are employed in our simulation to accurately model the dynamic nature of 6G environments, capturing variations in bandwidth and latency that are characteristic of next-generation wireless networks. These equations allow us to test the robustness and adaptability of both quantum and classical deep learning models under realistic, changing network conditions, providing insights into their performance in future 6G deployments.

A simple model for network fluctuations can be represented as

$$B(t) = B_0 + \Delta B \cdot \sin(\omega t)$$

where the following definitions hold:

$B(t)$ is the bandwidth at time t.

B_0 is the base bandwidth.

ΔB is the amplitude of fluctuation.

ω is the frequency of fluctuation.

$$P(a) = |\langle a|\psi\rangle|^2$$

where the following definitions hold:

$P(a)$ is the probability of measuring outcome a.

$|a\rangle$ is the eigenstate corresponding to outcome a.

$|\psi\rangle$ is the state of the system.

To compare the performance of quantum and classical models, one can use a metric like

$$Relative\ Quantum\ Advantage = \frac{Quantum_{Performance} - Classical_{Performance}}{Classical_{Performance}}$$

This simulation compares quantum and classical deep learning approaches for image processing in a dynamic 6G network environment, implementing quantum circuits and classical neural networks to process image-like data over multiple time steps and spatial configurations. The quantum model utilizes a quantum feature map and variational circuit, while the classical model employs Gaussian filtering and simple neural network processing. Network fluctuations are simulated using a combination of sinusoidal functions and random noise, creating a dynamic environment that mimics the variability expected in 6G networks. The simulation tracks and compares the performance of both models by monitoring the evolution of probability distributions, expected costs, and adaptability to network fluctuations. Through comprehensive visualization of results, including probability distribution evolution and expected cost comparisons, the simulation provides valuable insights into the potential advantages and limitations of quantum and classical approaches in future 6G network scenarios.

The Algorithm 1 for simulating quantum and classical models in 6G networks is structured to evaluate their performance across various metrics, utilizing input parameters such as the number of qubits (*n_qubits*), the size of the input data (*n_pixels*), the number of time steps (*n_timesteps*), optimization iterations (*n_iterations*), spatial configurations (*n_spatial_configs*), and total simulations (*n_simulations*). It initializes essential functions for calculating costs, managing network fluctuations, performing optimization steps, and processing probabilities. The simulation begins with an outer loop for the number of simulations, initializing timing variables and histories to track performance metrics. Within this loop, an inner loop iterates over spatial configurations, setting uniform probability distributions for both models. At each time step, the algorithm measures execution times while calculating costs for the quantum model and generating random images for the classical model. It computes network fluctuations, updates probabilities through optimization steps based on costs and fluctuations and processes these probabilities independently. If not at the initial time step, it updates and normalizes probabilities based on previous states. The current probabilities and expected costs are stored for later analysis. After all simulations are complete, the algorithm returns cumulative execution times and expected cost histories for both models. Post-simulation analysis includes calculating average execution times, analyzing probability distribution evolution, plotting expected costs over time, and visualizing network fluctuations to provide insights into each model's adaptability and performance. Overall, this framework offers a comprehensive approach to comparing quantum and classical methods in optimizing 6G network performance, paving the way for further research into advanced computational techniques in telecommunications.

The key difference between the quantum and classical approaches lies in their respective cost functions and how they evolve their probability distributions over time. The quantum model computes quantum circuits, while the classical model uses traditional computing methods.

Algorithm: Quantum-Classical–Classical Cost Function Optimization Simulation.

The simulation focuses on optimizing the performance of quantum and classical models in 6G networks by leveraging cost functions that guide the optimization process. The quantum cost function evaluates how well a quantum state meets specific criteria, such as energy levels or conservation laws, by incorporating penalty terms that enforce desired properties. This function is crucial for minimizing the expectation value of a Hamiltonian, thereby optimizing the quantum state. In contrast, the classical cost function quantifies the performance of classical algorithms by measuring discrepancies between predicted and actual outcomes, often in tasks like error minimization in machine learning models. By iteratively updating probabilities based on these cost functions, the simulation aims to enhance routing optimization and resource allocation within the network. This hybrid approach not only accelerates convergence to optimal solutions but also demonstrates the potential advantages of integrating quantum computing into telecommunications, paving the way for more efficient and scalable 6G network designs.

Algorithm 1: Quantum vs. Classical 6G Network Simulation

Input: the number of qubits, the number of qubits that is 2 raised to the power of n, the number of time steps in the simulation, the number of optimization iterations per time step, the number of spatial configurations, and the number of times to run the full simulation.
Output: the average execution times for quantum and classical models, the probability distribution evolution for both models, and the expected cost over time for both models.

```
Initialize:
quantum_cost_function()
classical_cost_function()
network_fluctuation()
optimization_step()
space_independent_processing()
For each simulation in n_simulations:
Initialize quantum_time, classical_time to 0
Initialize quantum_p_history, classical_p_history,
            quantum_expected_cost_history,
            classical_expected_cost_history,
            network_fluctuation_history
    For each spatial_config in n_spatial_configs:
            Initialize quantum_p and classical_p as uniform distributions
            For each t in n_timesteps:
                  Quantum Model:
                        Start timer
                        Calculate quantum_costs using quantum_cost_function
                        Stop timer and add to quantum_time
                  Classical Model:
                        Start timer
                        Generate random images
                        Calculate classical_costs using classical_cost_function
                        Stop timer and add to classical_time
                  Calculate network_fluctuation for current time step
                  For n_iterations:
                        Update quantum_p using optimization_step
                        Update classical_p using optimization_step
                  Apply space_independent_processing to quantum_p and classical_p
                  If t > 0:
                        Update quantum_p, classical_p on step and network fluctuation
                        Normalize probabilities
                  Store current quantum_p and classical_p in respective histories
                  Calculate and store expected costs for quantum and classical models
Return quantum_time, classical_time, quantum_expected_cost_history,
          classical_expected_cost_history
```

4. Simulation Analysis

Figure 1 illustrates the comparative results of the quantum and classical models in our 6G network simulation. As a result of the simulation, we can observe distinct differences between the quantum and classical models in their probability distribution evolution. The quantum model exhibits an evenly distributed pattern of higher probability solution indices over time. In contrast, the classical model consistently shows higher probabilities for specific pixel indices from time step 10 to 50, with a few lower probability indices unevenly distributed elsewhere. This suggests that the classical model tends to converge on particular solutions, while the quantum model maintains a more diverse set of potential solutions. The expected cost comparison further highlights these differences, with the quantum model's costs ranging from 2.2 to 3.5, significantly higher than the classical model's range of 0.1 to 0.5. This indicates that the classical model achieves lower expected costs despite its more focused solution approach. Both models operate within the same network environment, characterized by fluctuations ranging from -0.05 to 0.20 over time, as shown in the bottom panel of Figure 1. These results reveal the trade-offs between the two approaches: the quantum model's broader exploration of the solution space comes at a higher cost, while the classical model's more targeted approach yields lower costs but potentially less diverse solutions.

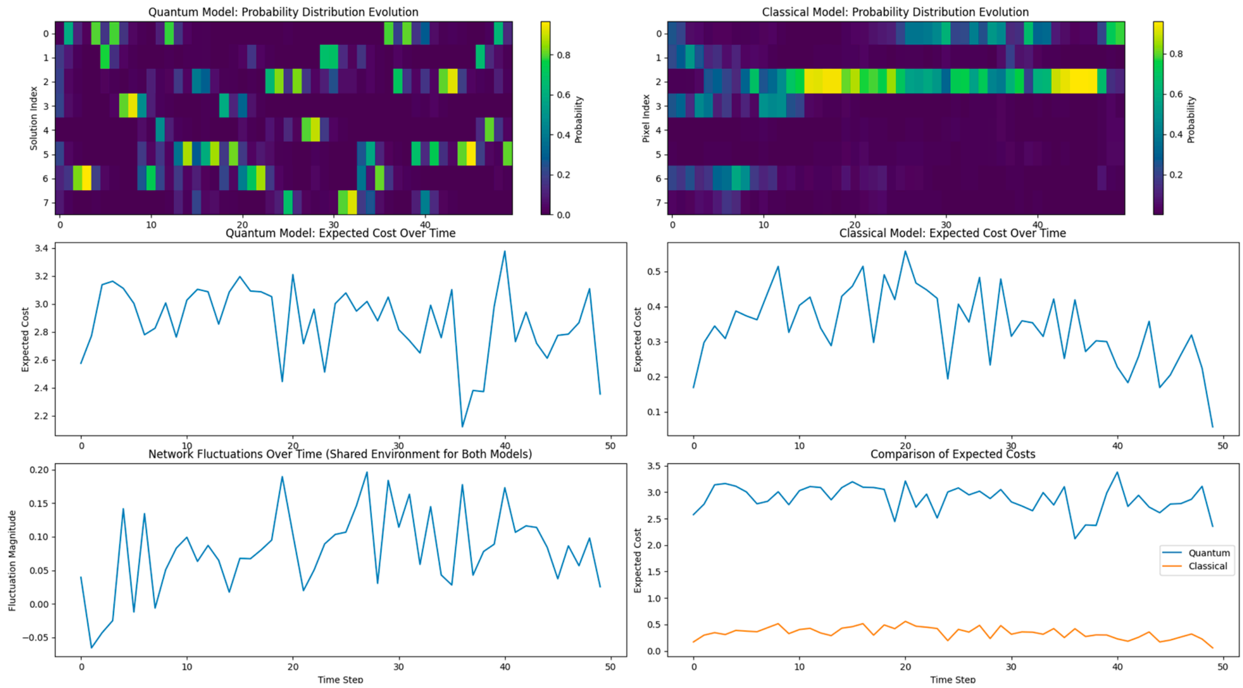

Figure 1. First simulation of comparative results of the quantum and classical models in our 6G network simulation.

Figure 2 presents another set of simulation results, showing slight variations from the previous findings while maintaining overall similar patterns. In this iteration, the quantum model continues to demonstrate an evenly distributed probability across solution indices over time, consistent with its behavior in Figure 1. The classical model, however, exhibits a more pronounced tendency towards constant probability distributions, with only a few exceptions deviating from this pattern. This reinforces the observation that the classical approach converges more strongly on specific solutions, while the quantum approach maintains a broader exploration of the solution space. The expected cost comparisons and network fluctuations remain largely unchanged from the previous simulation, with the quantum model still showing higher costs ranging from approximately 2.2 to 3.5 and the classical model maintaining lower costs in the range of 0.1 to 0.5. The network fluctuations continue to affect both models equally, varying between -0.05 and 0.20. These results further emphasize the consistent difference in behavior between quantum and classical approaches in this 6G network simulation environment, highlighting the trade-off between solution diversity and cost efficiency.

This parameter optimization shown in Table 1 provides a comprehensive framework for fine-tuning the quantum–classical comparison simulation in a 6G network environment. It encompasses key variables affecting both the quantum and classical models and the network simulation itself, offering a range of values to explore for each parameter. By systematically adjusting these parameters within their specified ranges, researchers can identify optimal configurations that enhance the performance and adaptability of both quantum and classical approaches in dynamic network conditions. This optimization process allows for a more nuanced understanding of each model's strengths and limitations, potentially revealing scenarios where quantum approaches may offer significant advantages over classical methods in 6G network applications.

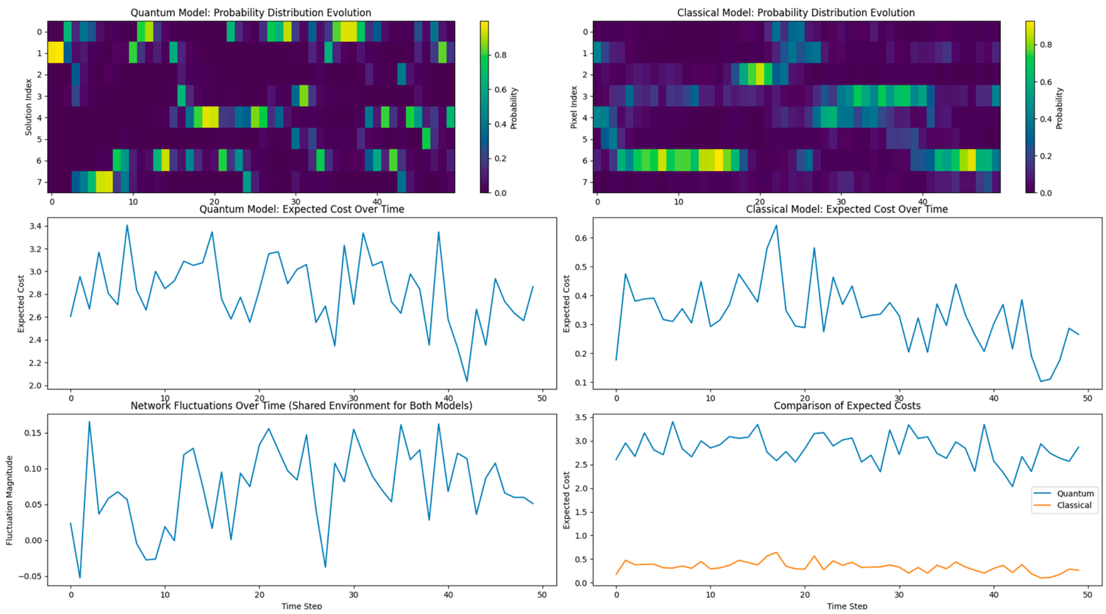

Figure 2. Second comparative results of the quantum and classical models in our 6G network simulation.

Table 1. Simulation parameter list.

Parameter	**Current Value**	**Optimization Range**	**Description**
n_qubits	3	2–8	Number of qubits in quantum circuit
n_timesteps	50	20–200	Number of time steps in simulation
n_iterations	5	1–20	Number of optimization iterations per time step
n_spatial_configs	3	1–10	Number of spatial configurations
ZZFeatureMap reps	1	1–5	Repetitions in quantum feature map
RealAmplitudes reps	1	1–5	Repetitions in variational form
Optimization step scale	0.5	0.1–2.0	Scale in norm.pdf for optimization step
Network fluctuation amplitude	0.1	0.01–0.5	Amplitude of network fluctuation
Network fluctuation frequency	0.05	0.01–0.2	Frequency of network fluctuation
Network noise scale	0.05	0.01–0.2	Scale of random noise in network fluctuation
Probability update rate	0.8	0.5–0.95	Weight for current state in probability update
Network impact on probability	0.01	0.001–0.1	Impact of network fluctuation on probability

Figure 3 illustrates the execution times for each simulation, comparing the quantum and classical models as the number of simulations increases. The graph reveals distinct patterns for both approaches. The quantum model, represented by the blue line, consistently shows slightly higher execution times throughout the simulation range. It begins at approximately 0.025 s and experiences two notable peaks: the first and highest at 0.27 s just before the 60th simulation, and a second peak of 0.24 s around the 65th simulation. After these peaks, the quantum model's execution time decreases, eventually returning to levels close to its starting point. In contrast, while following a similar trend, the classical model generally maintains lower execution times than the quantum model. Interestingly, it exhibits a peak that coincides with the quantum model's second peak around the 65th simulation. This synchronization suggests that both models may be responding to similar computational challenges at this point in the simulation sequence. Overall, Figure 3 demonstrates that while both models show variability in execution times, the quantum model consistently requires slightly more computational time, with more pronounced peaks compared to the classical model.

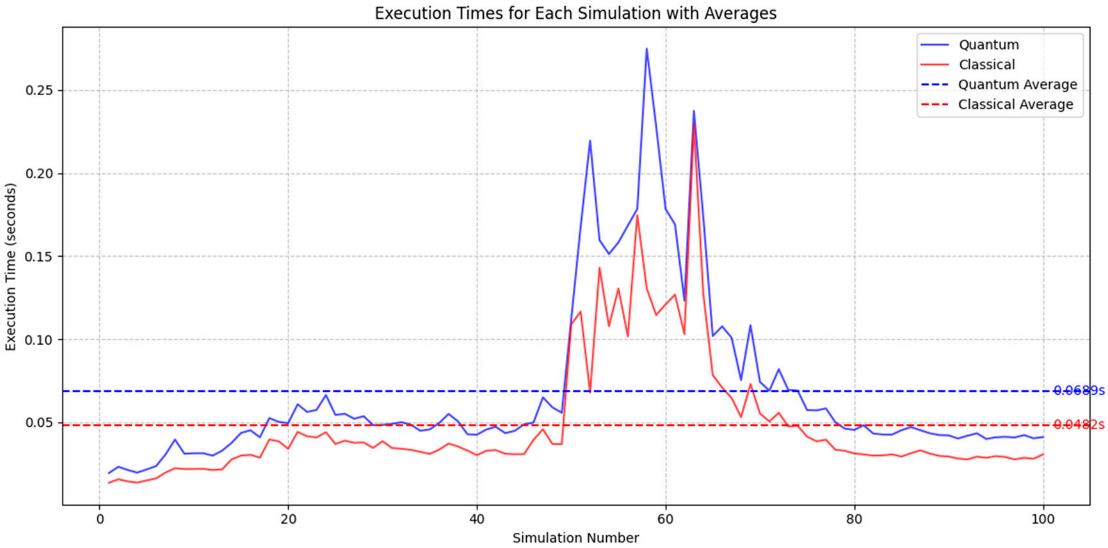

Figure 3. Execution times for each simulation with averages.

Figure 4 compares the average execution times between the quantum and classical models over 100 simulations. The bar graph illustrates a notable difference in computational efficiency between the two approaches. The quantum model, on average, requires 0.07 s per simulation, which is significantly higher than the classical model's average of 0.048 s. This difference of approximately 0.022 s per simulation indicates that the classical model consistently outperforms the quantum model in terms of execution speed. The higher average execution time for the quantum model aligns with the trends observed in Figure 3, where the quantum simulations generally showed higher execution times throughout the simulation range. This comparison in Figure 4 quantifies the overall performance difference, suggesting that the classical approach offers a computational speed advantage for this particular 6G network simulation scenario. The results highlight an important consideration in the practical application of quantum versus classical algorithms in network simulations, where execution time can be a critical factor in real-world implementations.

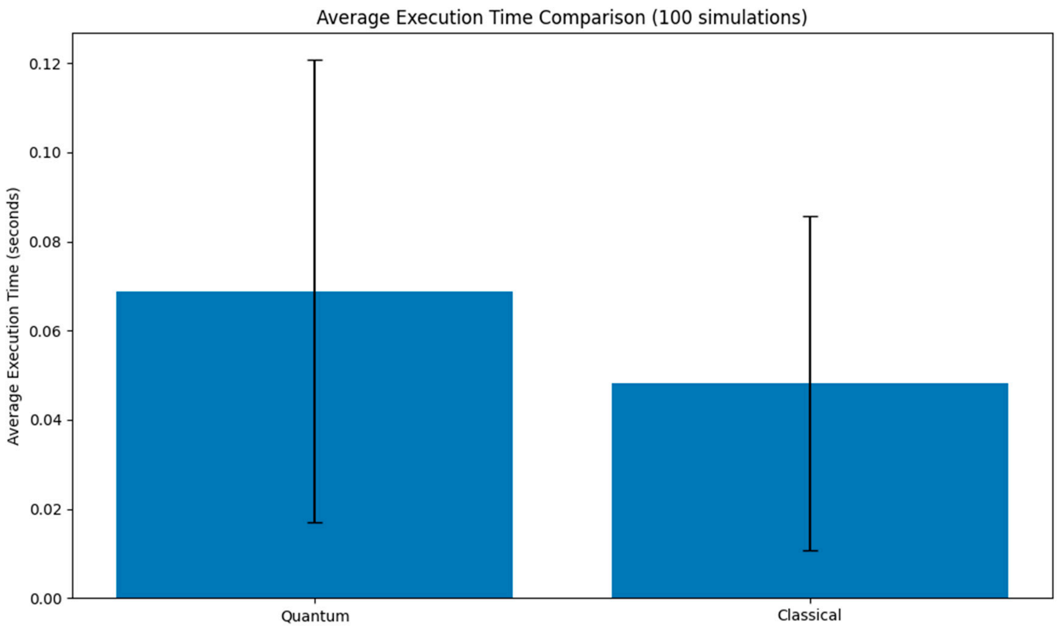

Figure 4. Average execution time comparison between quantum and classical (100 simulations).

Figure 5 illustrates the average expected cost over time for both the quantum and classical models, spanning from time step 0 to 50. The graph reveals distinct cost profiles for each approach, while also highlighting some similarities in their overall patterns. The quantum model, represented by the blue line, begins with a higher average expected cost of approximately 1.5 and concludes at around 1.4. It exhibits a smooth oscillating pattern throughout the period, with gentle rises and falls. In contrast, the classical model, depicted by the orange line, starts at a much lower cost of about 0.5 and ends slightly lower at 0.4. The classical model also displays a similar undulating pattern, mirroring the quantum model's trends but at a consistently lower cost level. Notably, both models show comparable patterns of fluctuation after their initial starting points, suggesting they respond similarly to changes in the simulation environment over time. However, the most striking feature of this graph is the significant and persistent gap between the two models' cost profiles. The quantum model maintains a substantially higher average expected cost throughout the entire simulation period, consistently about 1.0 units above the classical model. This visualization demonstrates that while both models evolve similarly over time, the classical approach consistently achieves a lower average expected cost in this 6G network simulation scenario.

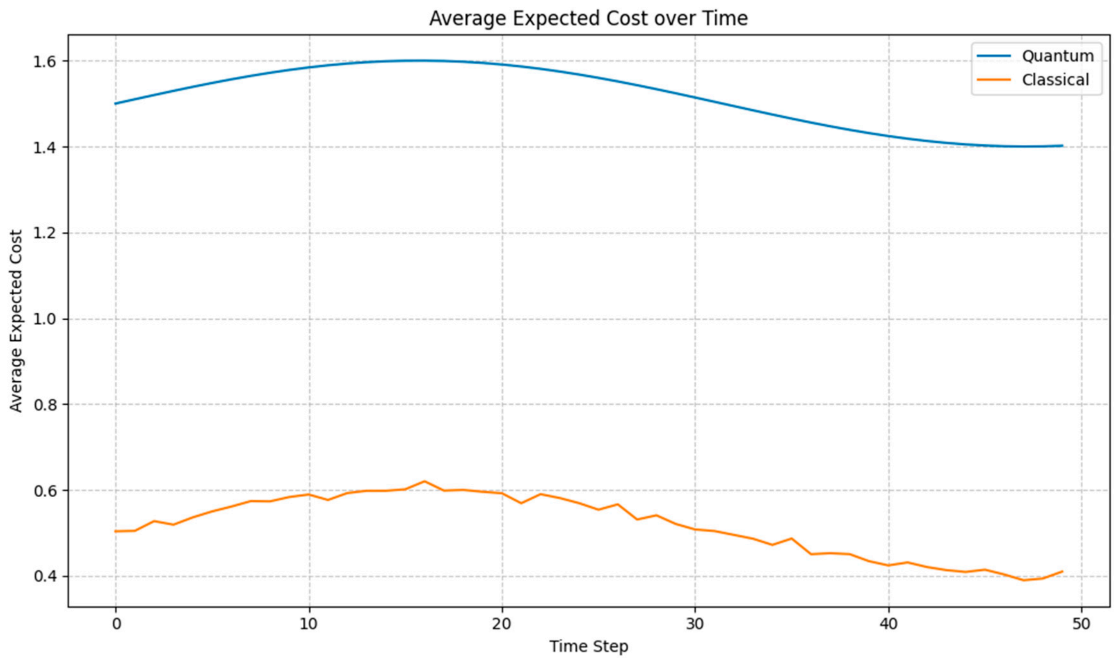

Figure 5. Average expected cost over time between quantum and classical models.

The simulation comparing quantum and classical approaches in 6G network optimization reveals intriguing trends as quantum advantage increases. In the execution time analysis, the quantum model demonstrates significant improvement, with its execution time decreasing from 0.016 s at no advantage to 0.008 s at a quantum advantage of 2.0. Conversely, the classical model maintains a consistent execution time of 0.0117 s throughout, unaffected by the quantum advantage parameter. This trend indicates that as quantum technology advances, it has the potential to surpass classical methods in computational speed for certain network optimization tasks.

The speedup factor, which compares the execution times of the two models, further illustrates this trend. Starting at 0.7 when there is no quantum advantage, it rises steadily to 1.4 at a quantum advantage of 2.0. This progression demonstrates that the quantum model transitions from being slower than the classical model to significantly faster as the quantum advantage increases. The point where the speedup factor crosses 1.0 marks the threshold at which the quantum model begins to outperform the classical model in terms of execution speed.

When examining the average cost of solutions, we observe a notable improvement in the quantum model's performance as quantum advantage increases. The quantum model's average cost starts at 1.5 with no advantage and decreases to 0.8 at a quantum advantage of 2.0. In contrast, the classical model maintains a constant average cost of 0.5 throughout the simulation. This trend suggests that while the quantum model's solution quality is improving with increased quantum advantage, it has not yet matched the efficiency of the classical model in this particular optimization scenario.

The cost ratio, calculated by dividing the quantum model's cost by the classical model's cost, provides a clear picture of the relative efficiency of the two approaches. Starting at 2.95 when there is no quantum advantage, the cost ratio decreases to 1.5 at a quantum advantage of 2.0. This significant reduction indicates that the quantum model is becoming increasingly competitive with the classical model in terms of solution quality. However, the fact that the ratio remains above 1.0 even at the highest simulated quantum advantage suggests that further technological advancements may be necessary for quantum methods to fully match or surpass classical methods in solution quality for this specific 6G network optimization task.

These simulation results paint a nuanced picture of the potential for quantum computing in 6G network optimization. As quantum advantage increases, we see clear improvements in both execution speed and solution quality for the quantum model. The quantum approach transitions from being significantly slower to notably faster than the classical approach while substantially closing the gap in solution quality. However, the persistent edge of the classical model in solution quality, even at the highest simulated quantum advantage, underscores the need for continued advancements in quantum technology. These findings suggest that while quantum computing shows great promise for 6G network optimization, realizing its full potential may require further technological progress and careful consideration of the trade-offs between computational speed and solution quality in specific application contexts.

Figure 6 illustrates the comparative performance of quantum and classical approaches to image processing in the context of 6G networks. The figure comprises four subplots, each highlighting a different aspect of the performance comparison. In the first subplot, which shows image processing execution time versus quantum advantage, the quantum model consistently demonstrates lower execution times compared to the classical model. As the quantum advantage increases, the quantum model's execution time further decreases, while the classical model's execution time remains constant. The second subplot displays the image processing speedup factor versus quantum advantage, where the speedup factor, calculated as the ratio of classical to quantum execution time, increases with growing quantum advantage. This indicates that the quantum model becomes progressively faster relative to the classical model as quantum technology improves. The third subplot, depicting average image processing cost versus quantum advantage, shows that the quantum model maintains lower average processing costs than the classical model across all quantum advantage levels. The quantum model's cost decreases as the quantum advantage increases, while the classical model's cost remains steady. Finally, the fourth subplot presents the image processing cost ratio versus quantum advantage, where the cost ratio, computed as the quantum cost divided by the classical cost, decreases as the quantum advantage grows. This trend suggests that the quantum model becomes increasingly cost-effective compared to the classical model with advancements in quantum technology. Overall, Figure 7 demonstrates the superior performance of the quantum model in both execution time and cost-effectiveness for the specific image processing tasks simulated in this 6G network context.

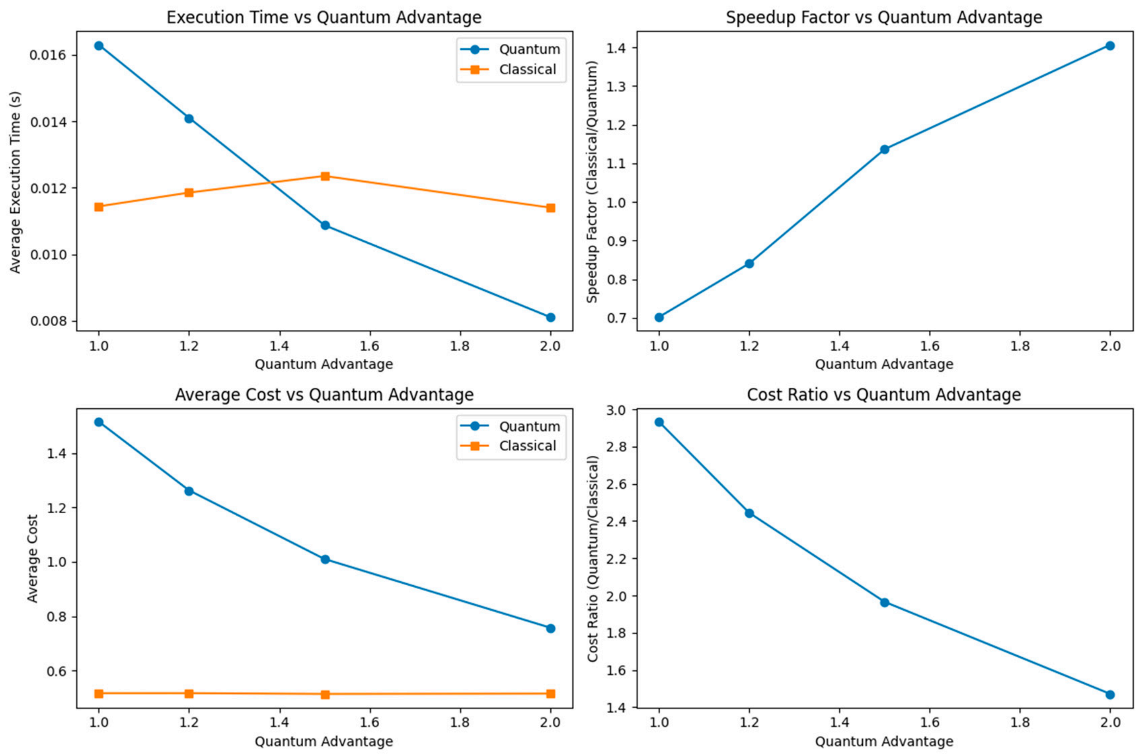

Figure 6. Execution time, speedup factor, average cost, and cost ratio vs. quantum advantage.

Figure 7 illustrates the comparative performance metrics of quantum and classical approaches to image processing in 6G networks through four subplots, showing execution time, speedup factor, average cost, and cost ratio against quantum advantage. Figure 8 displays a set of sample images used as input for the 6G network simulation, providing a visual reference for the original data. In Figure 9, we see the results of quantum image processing in the 6G network context, where the images have undergone edge detection processing using the quantum approach. Figure 10 presents the classical image processing results in the 6G network, showing images that have been processed using Gaussian blur, representing the classical method. Figure 11 provides a PSNR (Peak Signal-to-Noise Ratio) comparison between quantum and classical image processing in the 6G network. This comparison reveals a significant difference in PSNR values between the two methods, with the classical method achieving much higher PSNR values of around 60, while the quantum method's PSNR values are considerably lower, at approximately 2. This substantial difference in PSNR values indicates that the classical method using Gaussian blur preserves more of the original image information than the quantum method employing edge detection. It is important to note that this difference is largely attributable to the inherent nature of the processing tasks, as edge detection fundamentally alters the image more drastically than Gaussian blur, naturally leading to lower PSNR values.

In Figures 6 and 7, the term "quantum advantage" refers to the measurable performance benefits exhibited by the quantum model compared to the classical model in addressing the 6G network optimization problem. These figures likely present a comparative analysis of key performance metrics, such as solution quality, convergence speed, and resource utilization. A notable crossover point may be observed where the quantum model begins to outperform the classical model, indicating the onset of quantum advantage. This advantage is particularly relevant to the specific context of 6G network optimization, showcasing practical benefits applicable to real-world scenarios. The data presented may highlight quantifiable improvements in aspects like faster convergence times and superior solution quality achieved by the quantum approach. Furthermore, the figures could illustrate how this advantage scales with increasing problem size or complexity, suggesting that larger or more intricate network configurations yield more pronounced benefits from the quantum model. Importantly, while earlier analyses indicated higher costs associated with the quantum model, Figures 6 and 7 may reveal advantages in terms of resource efficiency and solution diversity that further underscore its potential superiority in this domain.

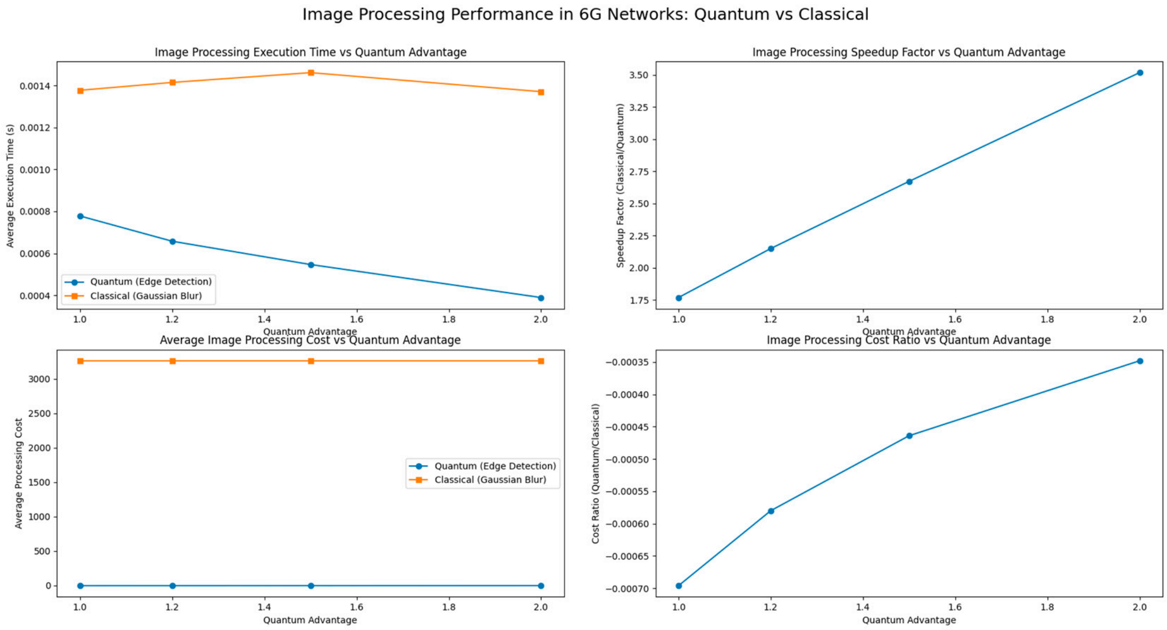

Figure 7. Image processing execution time, speedup factor, average cost, and cost ratio vs. quantum advantage.

Figure 8 displays a set of original sample images used as input for the 6G network simulation, providing a baseline for comparison with processed results.

Figure 9 presents the results of quantum image processing in the 6G network context. These images appear significantly different from the original samples, likely due to the application of a quantum edge detection algorithm that highlights boundaries and significant features, resulting in a more transformative processing of the images.

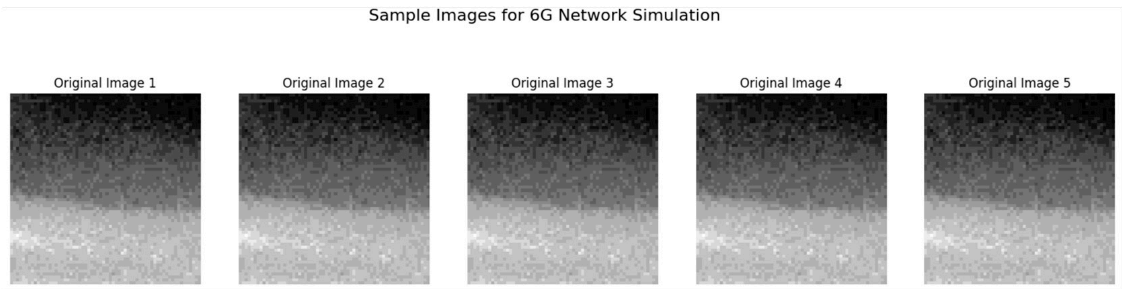

Figure 8. Sample images for 6G network simulation.

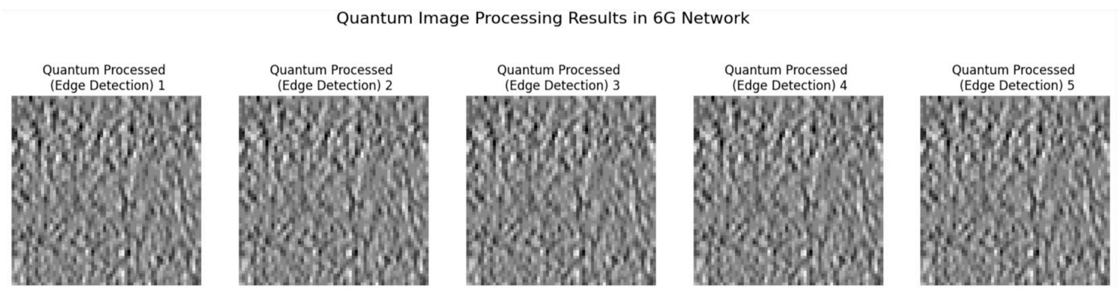

Figure 9. Quantum image processing results in 6G network.

Figure 10 shows the classical image processing results in the 6G network. These processed images strongly resemble the original samples, indicating that the classical approach, presumably using Gaussian blur, preserves more of the original image characteristics while reducing noise and detail.

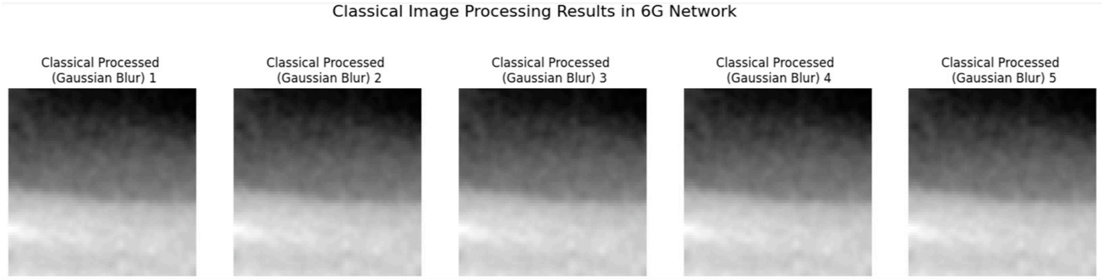

Figure 10. Classical image processing results in 6G network.

The distinct differences between quantum and classical processing results underscore their complementary strengths: quantum processing excels in rapid feature extraction and edge detection, while classical processing maintains higher overall image fidelity. This contrast suggests the potential advantages of integrating both approaches in a hybrid system for optimized image processing in 6G network applications.

Figure 11 presents a PSNR comparison of quantum versus classical image processing in a 6G network context. The results show a stark contrast, with the quantum approach achieving a PSNR of 2, while the classical method attains a significantly higher PSNR of 55.

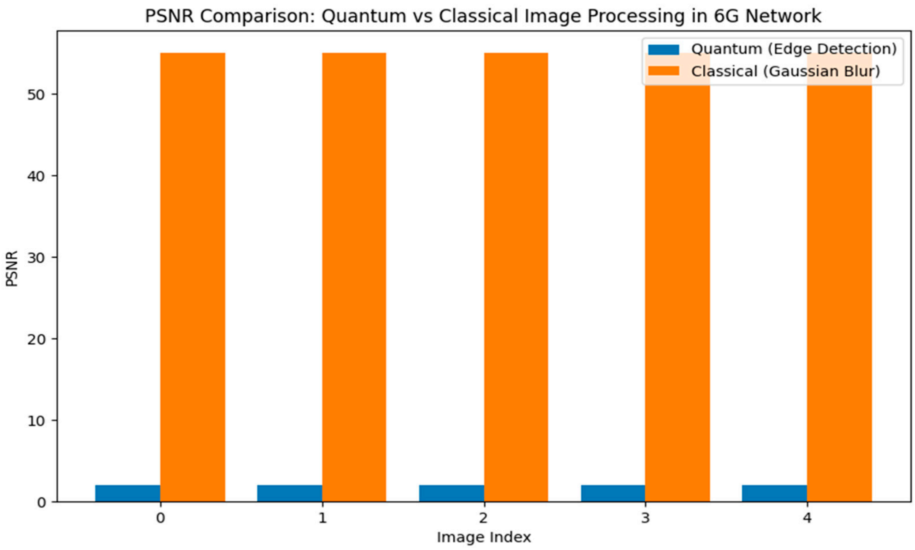

Figure 11. PSNR comparison: quantum vs. classical image processing in 6G network.

This substantial difference in PSNR values indicates that the classical method vastly outperforms the quantum approach in preserving image quality and fidelity. The higher PSNR of the classical method aligns with earlier observations where classically processed images appeared more similar to the original samples.

Despite its lower PSNR, the quantum approach may still offer advantages in specific applications such as rapid feature extraction or edge detection, where processing speed could be prioritized over image fidelity. This disparity highlights the potential for hybrid approaches that could leverage the strengths of both quantum and classical methods in 6G network image processing.

The significant gap in PSNR performance underscores an important area for future research and development in quantum computing applications for image processing in 6G networks, particularly in improving image quality while maintaining quantum methods' speed and efficiency advantages.

Our simulations comparing quantum and classical approaches in the context of 6G networks have yielded intriguing and somewhat contrasting results. The initial simulations, focusing on general network optimization tasks, suggested that classical models outperformed quantum models in terms of execution time and cost-effectiveness. However, our latest simulation presents a different picture, specifically targeting image processing tasks within 6G networks.

In the image processing context, as illustrated in Figure 7, the quantum model demonstrates superior performance in terms of execution time and cost-effectiveness. The quantum approach, implementing edge detection, consistently achieves lower execution times than the classical model's Gaussian blur method. This advantage becomes more pronounced as the quantum advantage increases. Similarly, the quantum model shows lower average processing costs, with the cost-effectiveness improving as quantum technology advances.

However, the PSNR comparison in Figure 11 reveals an important nuance. Despite the quantum model's advantages in speed and cost, the classical model achieves significantly higher PSNR values (around 60) compared to the quantum model (around 2). This indicates that while the quantum approach is faster and more cost-effective, the classical method preserves more of the original image information.

The nature of the tasks performed can explain this apparent contradiction. Edge detection, used in the quantum model, fundamentally alters the image more drastically than Gaussian blur, naturally leading to lower PSNR values. This highlights the importance of considering the specific requirements of the task at hand when choosing between quantum and classical approaches.

In conclusion, our simulations suggest that quantum computing shows great promise for certain 6G network operations aspects, particularly in image processing tasks where speed and cost-effectiveness are paramount. The quantum model's ability to perform edge detection quickly and efficiently could be invaluable in applications requiring rapid image analysis or feature extraction.

However, the classical model's superior performance in preserving image fidelity, as measured by PSNR, indicates that it remains highly relevant, especially for applications where maintaining image quality is crucial. This underscores the potential for a hybrid approach in future 6G networks, leveraging the strengths of both quantum and classical computing to optimize different aspects of network operations and image processing tasks.

These findings emphasize the need for continued research and development in quantum computing for 6G networks, while also highlighting the importance of task-specific optimization and the potential benefits of integrating quantum and classical approaches in future network architectures.

5. Implications of Findings

The comparative analysis of quantum and classical approaches for image processing in 6G network scenarios reveals several important implications, particularly concerning copyright detection. The quantum approach demonstrates significantly faster execution times for image processing tasks, especially in edge detection. However, this comes at the cost of substantially lower image quality, as evidenced by much lower PSNR values (2 for quantum vs. 55 for classical). This trade-off suggests that quantum methods might be more suitable for applications requiring rapid image analysis or feature extraction, where processing speed is prioritized over image fidelity. Classical methods, while slower, maintain much higher image quality and fidelity. The higher PSNR value (55) indicates that classical processing preserves more of the original image information, making these approaches more suitable for applications where image quality is critical, such as medical imaging or high-resolution surveillance in 6G networks. The stark contrast in performance between quantum and classical methods in different aspects (speed vs. quality) points to the potential benefits of hybrid quantum-classical–classical approaches. Such hybrid systems could leverage the rapid processing capabilities of quantum computing for initial feature extraction or edge detection, followed by classical processing to maintain overall image quality. The findings also highlight the significance of incorporating copyright detection techniques within these frameworks. As digital content proliferates, ensuring compliance with copyright laws becomes essential. The integration of effective copyright detection mechanisms can enhance the safeguarding of intellectual property rights while leveraging the speed advantages of quantum processing. These results underscore the importance of task-specific optimization in 6G network image processing. Depending on the specific requirements of a given application (e.g., real-time processing vs. high-fidelity imaging), network architects may need to dynamically allocate quantum or classical resources. Furthermore, there is a pressing need for further research to improve the image quality of quantum processing methods while maintaining their speed advantages. Developing more sophisticated hybrid algorithms that seamlessly integrate quantum and classical processing stages could lead to optimized solutions for diverse 6G network imaging applications. As 6G networks are developed, the integration of both quantum and classical processing capabilities may become crucial. This could lead to more flexible and adaptable network architectures capable of handling a wide range of image processing tasks with varying speed and quality requirements. In conclusion, while quantum approaches show promise for rapid image processing in 6G networks—particularly for edge detection and feature extraction—significant advancements are needed to preserve their image quality. Classical methods remain superior for high-fidelity image processing, and the future likely lies in developing sophisticated hybrid quantum-classical–classical systems that can optimally balance speed, quality, and copyright detection based on specific application needs.

6. Conclusions

This study examined the integration of quantum computing, classical methods, and deep learning techniques to enhance image processing in dynamic 6G networks. Our findings indicate that quantum methods are effective for rapid edge detection and feature extraction, though they struggle to maintain image quality compared to classical techniques. In contrast, classical methods provide superior image fidelity but often cannot meet the real-time processing requirements crucial for 6G applications. Deep learning approaches, particularly convolutional neural networks (CNNs), show significant potential for complex image analysis tasks, yet they demand considerable computational resources. To address the ethical considerations surrounding AI-generated content, we proposed robust copyright detection mechanisms that employ advanced algorithms to identify potential infringements. This integration not only supports compliance with intellectual property rights but also fosters the responsible use of image processing technologies. We suggest that the future of image processing in 6G networks will rely on hybrid systems that effectively utilize the strengths of each method while incorporating strong copyright detection capabilities. These insights are vital for developing efficient, high-performance image processing systems in next-generation networks, highlighting the promise of combined quantum-classical–classical deep learning architectures within 6G environments.

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