Enhancing Stego Image Quality With SIUN Post-Processing of Image Steganography Without Embedding DCGAN Outputs

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ABSTRACT
In digital steganography, hiding information seamlessly within images is key. This study merges Deep Convolutional Generative Adversarial Networks (DCGAN) with Scale-Iterative Upscaling Networks (SIUN) to craft high-quality stego images swiftly and enhance the DCGAN image training period. Eschewing length DCGAN training, SIUN refines post-generation images, ensuring detailed visuals and increased data storage. Using the MNIST dataset, findings show that SIUN not only accelerates the process but also improves the stego image quality, suggesting a significant leap forward for secure communication efficiency. This research found that by using SIUN can enhance the quality of stego images with just 50 epochs of DCGAN training. After this initial training, the images are sent to SIUN for further quality upgrades with more efficient time.

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1. INTRODUCTION
1.1. Background

The increasing need for secure communication in our interconnected world necessitates robust methods for ensuring data privacy and confidentiality. Steganography, the art of concealing information within digital media, has emerged as a critical technique for achieving this goal. Traditional steganographic methods, while effective, often face limitations in balancing payload capacity with the visual quality of the stego image. This trade-off motivates the exploration of advanced techniques that can achieve high levels of security without compromising image fidelity.

Deep learning-based approaches, particularly those leveraging Generative Adversarial Networks, offer a promising avenue for enhancing image steganography. This research focuses on the use of Deep Convolutional Generative Adversarial Networks (DCGAN), known for their ability to generate realistic images, and Scale-Iterative Upscaling Networks (SIUN) to improve the quality of generated stego images.
Deep Convolutional GANs have been explored for steganography, with approaches often focusing on embedding secret information within generated images. However, embedding-based methods can introduce subtle artifacts detectable by steganalysis. This research explores an alternative approach: coverless steganography using DCGANs. This method eliminates the embedding process altogether, thereby increasing security by removing the risk of detectable alterations. Instead of modifying an existing image, this approach leverages DCGANs to generate images conditioned on the secret message. The generated image itself represents the secret information, eliminating the need for embedding and its associated vulnerabilities. This allows for a higher level of undetectability, as the image appears entirely natural, with no telltale signs of modification. Previous research on the use of DCGANs in steganography provides a strong foundation for this work. [1] This research aims to build upon this foundation and further explore the potential of DCGANs for generating high-fidelity stego images.

The selection of DCGANs for this study is justified by their demonstrated effectiveness in generating high-quality images suitable for steganography. Compared to alternatives like Variational Autoencoders, DCGANs offer several advantages, including better image quality and stability during training. DCGANs are effective for generating high-quality images using deep convolutional networks [2], while WGANs improve training stability and convergence through a Wasserstein distance-based loss function [3], and SRGANs specialize in enhancing image resolution by combining GAN principles with a perceptual loss function to produce visually appealing high-resolution images [4].

DCGAN, VidaGAN [5], and HIGAN [6] offer distinct approaches to image steganography using generative adversarial networks. DCGAN, a foundational GAN architecture, excels in generating realistic images and serves as a basis for both coverless and embedding-based steganography. VidaGAN introduces an adaptive steganography method, balancing payload capacity and imperceptibility via a novel convolutional architecture and specialized loss function. HIGAN, conversely, prioritizes secure steganography, emphasizing high capacity and resistance to steganalysis through an encoder-decoder generator coupled with a steganalysis discriminator. These architectures differentiate themselves through their core objectives: DCGAN on image quality, VidaGAN on adaptive capacity-imperceptibility, and HIGAN on robust security.

Similarly, SIUN [7] has been selected for its capability to enhance image resolution and detail while preserving the integrity of the embedded information. In contrast, traditional upscaling methods, such as bicubic interpolation, may introduce artifacts or blurring that can degrade the quality of the stego image and potentially compromise the hidden message. Furthermore, SIUN demonstrates superior performance compared to other deblurring methods, including those proposed by [8] and [9], by effectively reducing blurriness and enhancing image clarity without sacrificing the quality of the embedded information.

This research explores the synergistic combination of DCGANs and SIUN to address the limitations of traditional steganography and create a novel method capable of generating high-fidelity stego images that are visually indistinguishable from their cover images or better known as steganography without embedding. This approach seeks to improve security, robustness, and overall efficiency in image steganography by leveraging the strengths of both deep learning models. This work presents a comprehensive analysis of a novel framework integrating DCGANs and SIUN for image steganography, addressing the current research gap in achieving both high-quality stego images and efficient training period

1.2. Literature Review and Related Work

1.2.1. Image steganography without embedding

Steganography, derived from the Greek words meaning "covered writing," is the practice of concealing information within a non-secret medium to prevent detection by unauthorized parties. This technique has evolved significantly with the advent of digital technology, allowing for the embedding of secret messages within various forms of digital media [10]. Image steganography specifically refers to the concealment of information within digital images, leveraging the properties of image files to hide data without significantly altering the visual appearance of the image [11]. Traditional steganography methods often rely on embedding secret information directly into the cover medium, which can lead to detectable alterations in the host data. In contrast, steganography without embedding, such as coverless steganography, utilizes advanced techniques to synthesize cover images that inherently contain the hidden information, thereby minimizing the risk of detection [12] . This approach not only enhances security but also addresses the limitations of conventional methods, which may introduce artifacts or degrade the quality of the stego image [13]. Furthermore, the integration of generative models, such as those proposed in [14] demonstrates the potential for creating more sophisticated and secure steganographic systems that do not rely on traditional embedding techniques. Overall, the evolution of steganography, particularly in the realm of image data, highlights the ongoing need for innovative methods that enhance both security and data integrity in digital communications.

1.2.2. DCGANs in Image steganography

Generative Adversarial Networks (GANs) are a class of machine learning frameworks designed to generate new data samples that resemble a given dataset. Introduced by Goodfellow et al. in 2014, GANs consist of two neural networks the generator and the discriminator that compete against each other, leading to the generation of high-quality synthetic data [15]. In the context of image steganography, GANs have been employed to enhance the concealment of information within images while maintaining visual fidelity. Various types of GANs, such as Deep Convolutional GANs (DCGANs) and CycleGANs, have been developed to improve the quality and efficiency of image generation [16]. DCGANs, in particular, leverage convolutional layers, making them particularly effective for image-related tasks due to their ability to capture spatial hierarchies and generate high-resolution images [17]. This capability is crucial in steganography, where the goal is to embed information without introducing noticeable artifacts that could reveal the presence of hidden data. Furthermore, the use of GANs in steganography allows for the synthesis of stego-images that are indistinguishable from cover images, thereby enhancing the security of the embedded information [18]. The adaptability of GANs to various applications, including adversarial learning for invertible steganography, highlights their potential in advancing the field of secure communication [19]. Overall, GANs represent a significant advancement in image steganography, providing innovative solutions for embedding information securely and effectively.

Deep DCGANs have emerged as a powerful variant of GANs, specifically designed to improve image generation quality through the use of convolutional layers. Unlike traditional GANs, which may struggle with stability and image fidelity, DCGANs leverage deep learning techniques to produce more realistic images and maintain spatial hierarchies [20]. Additionally, DCGANs are more effective in handling complex datasets, making them preferable for applications such as malware image generation and aesthetic decision-making in automotive design [21], [22]. Their architecture not only enhances the quality of generated images but also facilitates better training stability compared to other GAN variants [16].

1.2.3. Comparison of Networks

The SIUN [7] exhibits superior performance in image upscaling and deblurring compared to traditional networks such as the Deep Multi-Scale Convolutional Neural Network (DMSCNN) and the Scale-Recurrent Network (SRN). SIUN's architecture leverages iterative processing, which allows it to effectively enhance image details while minimizing artifacts, a critical factor for applications in image steganography. In contrast, the DMSCNN, as discussed in [23] focuses on multi-scale features but may not achieve the same level of detail preservation as SIUN. Similarly, the SRN, highlighted in [24]," employs a recurrent approach but can struggle with maintaining image quality during the upscaling process. SIUN's ability to maintain the integrity of embedded information makes it particularly advantageous for supporting DCGAN-based image steganography without embedding, as it ensures that the stego images remain visually indistinguishable from the original images while effectively concealing the hidden data.

1.2.4. Peak Signal-to-Noise Ratio (PSNR)

Peak Signal-to-Noise Ratio (PSNR) is a widely used metric for assessing the quality of reconstructed images, particularly in image processing and compression applications. It measures the ratio between the maximum possible power of a signal (the original image) and the power of corrupting noise that affects the fidelity of its representation [25]. A higher PSNR value indicates better image quality, as it reflects a lower level of distortion. Generally, PSNR values above 30 dB are considered acceptable for good quality images, while values above 40 dB are regarded as excellent [26], [27]. In the context of steganography, maintaining a high PSNR is crucial to ensure that the embedded information remains undetectable, thereby preserving the integrity of the stego image [28].

2. RESEARCH METHOD

The methodology of this research will be described figure 1.

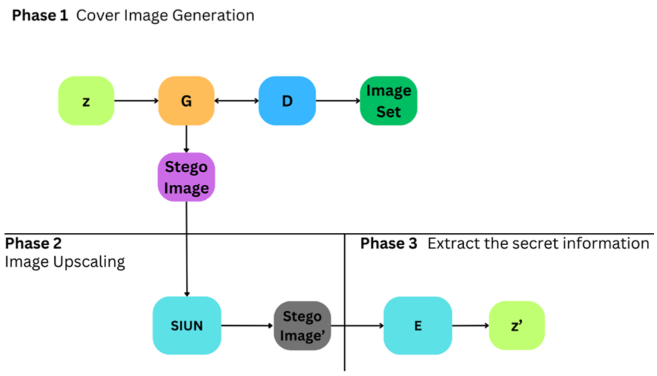

Figure 1. Cover Image Generation

The methodology shown in the Figure 1 consists of several steps such as data preparation, cover image generation, image upscaling, and secret information extraction.

2.1 Data Preparation

1. Obtain the MNIST dataset from a reliable source, such as the official MNIST website or a machine learning library like TensorFlow or PyTorch.
2. Use appropriate libraries or functions to load the MNIST dataset into your Python environment.

3. Convert the dataset into a format suitable for processing by your machine learning models.
4. Organize the preprocessed data into batches or data loaders suitable for training DCGAN and SIUN models.

2.2 Phase 1: Cover Image Generation

1. z: Represents the random noise vector or latent space inputs to the generative model.
2. G (Generator): A part of the Generative Adversarial Network (GAN), specifically the DCGAN in this context, which takes the random noise vector z and generates synthetic images.
3. D (Discriminator): Another component of the DCGAN, the Discriminator evaluates whether the generated images are real (from the dataset) or fake (created by G).
4. Image Set: This is the output from the Discriminator, which consists of images that are considered to be of high enough quality, indistinguishable from real images by D.
5. Stego Image: Among the images generated by G and validated by D, some are designated as stego images.
6. These images contain hidden information embedded within them.

2.3 Phase 2: Image Upscaling

SIUN or Scale-Iterative Upscaling Network, which takes a stego image and enhances its resolution while presumably preserving the hidden information within the image. The output is a higher-resolution version of the input stego image.

The Scale-Iterative Upscaling Network (SIUN) for image deblurring operates in several key steps, processing inputs to generate deblurred images as outputs. Here's a concise outline of the methodological steps, inputs, and outputs based on the document:

1. Blurred Stego Image: The input to the SIUN model is a single blurred image that needs deblurring.
2. Down-sampling and Pyramid Construction: The input image is down-sampled to create a pyramid of images at multiple scales, starting from the original scale down to the smallest scale needed for the iterative process.
3. Iterative Restoration Process: The model starts the restoration from the lowest scale of the pyramid. For each iteration, it takes the output from the previous scale (up-scaled image) and the corresponding down-sampled blurred image as inputs.
4. Upscaling and Detail Restoration: Instead of using a simple upsampling layer, SIUN incorporates a super-resolution structure, specifically a Residual Dense Network (RDN), for upscaling. This approach helps in restoring more details of the image as it is scaled up.
5. Curriculum Learning Strategy: The model applies a curriculum learning strategy both in training and prediction phases. This strategy involves gradually increasing the difficulty of the tasks (i.e., the restoration of more detailed images from higher scales of the pyramid).
6. Repeating the Process: The process is repeated iteratively, with the image being up-scaled and details restored at each step, until the full resolution is achieved.
7. Final Image Restoration: The iterative process continues until the image is restored to its original scale, with each iteration aimed at refining the sharpness and detail of the deblurred image.
8. Outputs: Deblurred Image at Full Resolution: The final output is a sharp, deblurred image restored to its original resolution, with improved sharpness and detail compared to the input blurred image.

This summary encapsulates the SIUN's methodological approach, starting from a single blurred input image through an iterative process involving down-sampling, pyramid construction, iterative restoration with super-resolution upscaling, and employing a curriculum learning strategy, to produce a deblurred image.

2.4 Phase 3: Secret Information Extraction

Stego Image'is the upscaled stego image, which has gone through the enhancement process by SIUN, presumably has better quality and higher resolution while maintaining the embedded secret information. To extract the secret information, there are additional CNN extractors needed, below described outlines of phase 3:

1. E (Extractor): This component is responsible for detecting and extracting the hidden information from the enhanced stego image.
2. z': The output from the Extractor, which is the retrieved secret information or data that was initially hidden within the original stego image.

$$\mathrm{mj} = \frac{(\mathrm{zij}+1)\times 2\sigma-1}{2} \tag{1}$$

3. mj is the mapped value.
4. zij is the extracted bit from the stego image at the ith image and jth bit position
5. σ is the number of bits in each payload segment (in this case, 3)

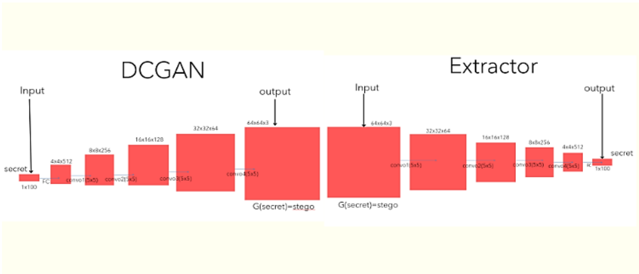

Figure 2. DCGAN Model Architecture

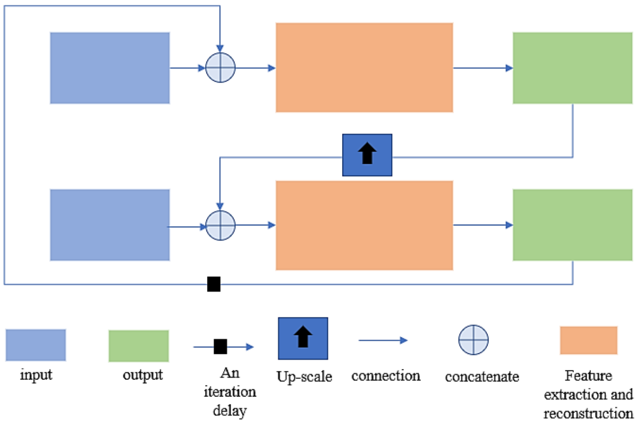

Figure 3. SIUN Model Architecture

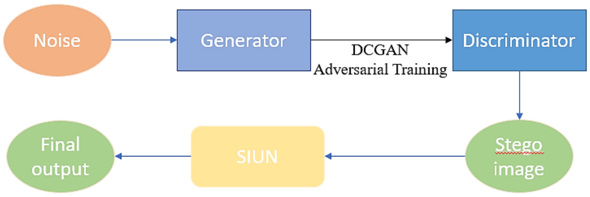

Figure 4. Overall Model Architecture

The provided images (Figure 2,3,4) collectively illustrate the architecture and processes involved in the modified model for steganography using a Deep Convolutional Generative Adversarial Network (DCGAN) and a Scale Iterative Upscaling Network (SIUN). Figure 2 details the layers within the DCGAN, demonstrating how the generator takes a secret input and transforms it through several convolutional layers to produce a stego image. This stego image, which embeds the secret information, is then processed by the Figure 3, which depicts the upscaling process using SIUN. This network enhances the quality and resolution of the stego image, ensuring that the embedded information remains intact and undetectable. Finally, Figure 4 provides an overview of the entire flow, illustrating how the input data is processed through the DCGAN to generate the stego image, which is subsequently upscaled by SIUN. Together, these diagrams offer a comprehensive understanding of the model's architecture and the modifications made, addressing the feedback for a more detailed illustration.

3. RESULTS AND ANALYSIS

In this segment, we display the initial set of 28x28 pixel stego images generated by the DCGAN model, trained on the MNIST dataset for 50 epochs. The learning rate for both the generator and discriminator optimizers was set to 0.0001, a common choice for stabilizing training in GANs, and the Adam optimizer was employed for this models. These foundational results are pivotal, as they establish the benchmark for the subsequent enhancement through SIUN. Observing the model's performance over 50 epochs provides insight into its capacity for generating clear and distinct handwritten digits, essential for the next phase of image upscaling and quality enhancement.

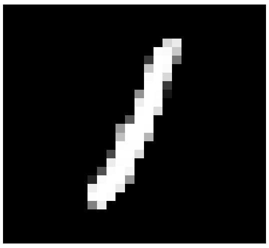

Figure 5. DCGAN Image Generation Results (Stego Image)

In the initial step, we determine the total pixel count for both a 64x64 image, totaling 4096 pixels, and a 28x28 image, totaling 784 pixels. Subsequently, we calculate the pixel ratio between these two image sizes. Second, based on human assessment, the generated stego image looks blurry (Figure 5) and made up of small pixels.

Table 1. DCGAN Research Comparison

Methods	Absolute Capacity	Image Size	Pixels
Previous Research	37.5 bytes	64x64	4096
Our Research	7.1 bytes	28x28	784

Table 1 presents a comparison between our research and previous studies on the performance of the Deep Convolutional Generative Adversarial Network (DCGAN) in terms of absolute capacity, image size, and pixel count. Notably, our research demonstrates a significantly reduced absolute capacity of 7.1 bytes, compared to 37.5 bytes in previous research. This reduction indicates a more efficient encoding of information, allowing for better utilization of resources. Additionally, while the previous research utilized an image size of 64x64 pixels with a total of 4096 pixels, our study employed a smaller image size of 28x28 pixels, resulting in a total of 784 pixels. This suggests that our model not only achieves a lower absolute capacity but also operates effectively with smaller images, highlighting its efficiency and potential for practical applications in steganography.

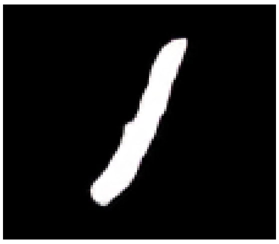

Figure 6. SIUN Image Enhancement Results

Table 2. Comparison of SIUN Enhanced Image Capacity

Methods	Absolute Capacity	Image Size	Pixels
Previous Research (DCGAN)	37.5 bytes	64x64	4096
Our Research (DCGAN)	7.1 bytes	28x28	784
Upscaled	114.84 bytes	112x112	12544

Figure 6 showcases the results of image enhancement using the Scale Iterative Upscaling Network (SIUN), illustrating the improved quality of the generated images. Accompanying this figure, Table 2 provides a detailed comparison of image capacity across different methods. It highlights that our research, utilizing the DCGAN, achieves an absolute capacity of 7.1 bytes with an image size of 28x28 pixels and a total of 784 pixels In contrast, previous research with DCGAN had an absolute capacity of 37.5 bytes for images sized 64x64 pixels and 4096 pixels. Additionally, the upscaled images demonstrate a significant increase in capacity, reaching 114.84 bytes with an image size of 112x112 pixels and 12,544 pixels. This comparison underscores the effectiveness of the SIUN in enhancing image quality while optimizing data capacity.

The PSNR value from the enhanced image is 39db indicates a high level of similarity between the upscaled image and an ideal or original high-resolution image, assuming the PSNR is calculated against such a reference. PSNR is expressed in decibels (dB), and higher values indicate better quality. A PSNR of 39 is considered very good, suggesting that the upscaling method has effectively reduced the appearance of artifacts and noise while retaining or enhancing image features.

By human assessment, the image looks 70% better because it could be generated number images that can be easily recognized. image pixels are also very much so that the texture in the image looks very smooth.

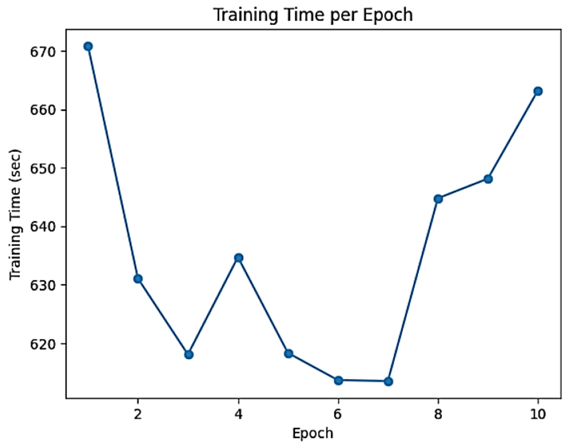

Figure 7. DCGAN Training Time

The plot (Figure 7) shows the training time per epoch for a DCGAN model trained on the MNIST dataset using a regular CPU on Google Colab. From the plot, we can observe that the training time fluctuates significantly across epochs. It starts at its highest at epoch 1, taking almost 670 seconds, then sharply drops by epoch 2. It shows a notable dip to its lowest point around epoch 5, taking just above 620 seconds. Afterward, there is a general upward trend in training time with some fluctuation, reaching nearly 650 seconds by epoch 10.

To produce good enough image need at least 50 epochs, but training a DCGAN on MNIST for 50 epochs using a regular CPU on Google Colab can be quite time-consuming, and given the runtime limitations of the Colab environment, there might be instances where the session ends before reaching the desired 50 epochs. To mitigate this, you could consider saving the model's state after each epoch so you can resume training if interrupted. Another strategy could be to use Google Colab's GPU or TPU runtime, which can provide faster training compared to a CPU.

Our experiments led to several key findings that mark significant advancements in the field of image steganography and enhancement through the use of Deep Convolutional Generative Adversarial Networks (DCGAN) integrated with Super-Image Upscaling Network (SIUN). Firstly, we observed a notable reduction in training time, enabling more efficient generation and processing of images. This efficiency is crucial for applications requiring rapid deployment or iterative development processes. Secondly, the integration approach facilitated the generation of larger stego images. This advancement is particularly important as it enhances the capacity for information concealment within an image, thereby broadening the applicability of our method in secure communications. Lastly, the combined use of DCGAN and SIUN resulted in images that are not only larger but also exhibit a smoother and more refined appearance. This improvement in image quality is vital for maintaining the authenticity and undetectability of steganographic images, making our approach more robust against detection and analysis. These findings collectively signify a forward leap in the capabilities and potential applications of image-based steganography and enhancement technologies.

4. CONCLUSION

In this study, we propose a modified model that integrates the Scale Iterative Upscaling Network (SIUN) with a Deep Convolutional Generative Adversarial Network (DCGAN) to enhance the quality of stego images. Our experiments demonstrate that the proposed method significantly improves image quality compared to previous networks, as evidenced by PSNR. Additionally, the training period was optimized, allowing the model to achieve these results within only 50 epochs using DCGAN, which is more efficient than traditional methods that often require longer training times. This combination of enhanced image quality and reduced training duration positions our method as a competitive alternative to existing approaches in the field of image steganography.

The enhanced performance of our model can be attributed to the effective upscaling capabilities of SIUN, which allows for better detail retention and clarity in the generated stego images. By leveraging iterative upscaling, the model not only produces higher-resolution images but also maintains the integrity of the embedded information. This improvement is crucial in steganography, where the goal is to conceal data without compromising the quality of the host image.

When comparing our results with previous studies, we observe that traditional GAN architectures often struggle with generating high-quality images, particularly in the context of steganography. For instance, earlier works utilizing standard DCGANs produced images that, while visually appealing, often lacked the necessary detail for effective data concealment. In contrast, our approach demonstrates a marked improvement in both the perceptual quality of the images and the fidelity of the hidden information. This aligns with findings from recent literature that emphasize the importance of advanced upscaling techniques in enhancing image quality.

The implications of our findings are significant for the field of steganography. The ability to generate high-quality stego images not only enhances the effectiveness of data concealment but also broadens the potential applications of steganography in secure communications. However, it is essential to acknowledge the limitations of our study. While the integration of SIUN has shown promising results, the model's performance may vary with different datasets or under varying conditions. Future research should explore the adaptability of this approach across diverse image types and resolutions.

Based on our findings, we recommend further exploration into hybrid models that combine SIUN with other advanced neural network architectures. Additionally, conducting experiments with larger and more diverse datasets could provide deeper insights into the model's robustness and generalizability. Investigating the trade-offs between image quality and computational efficiency will also be crucial for practical applications in real-world scenarios.

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