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Real-Time Enhancement of Low-Light Images Using Generative Adversarial Networks (GANs)

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Abstract
Low-light image enhancement plays a crucial role in fields such as surveillance, photography, and medical imaging, where inadequate lighting significantly reduces image quality, leading to loss of detail and increased noise. Traditional enhancement methods, such as histogram equalization and Retinex, struggle to preserve fine details and often amplify noise, limiting their effectiveness in real-world applications. To address these issues, this study proposes a Generative Adversarial Networks (GANs)-based model to enhance low-light images in real-time while maintaining high visual fidelity. The model aims to improve contrast, reduce noise, and retain image structure more effectively than conventional methods. The proposed GAN model is trained using the LOL and SID datasets and evaluated using the Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM). Experimental results show that the method achieves a PSNR of 28.4 dB and SSIM of 0.91, outperforming histogram equalization (PSNR: 18.5 dB, SSIM: 0.65) and Retinex (PSNR: 20.3 dB, SSIM: 0.72). Although the model operates in real-time, its inference time of 35.6 ms per image suggests further optimization to support edge computing applications. This study demonstrates that GAN-based enhancement significantly improves low-light images by preserving structural integrity while reducing noise. Future research should focus on optimizing the model for faster processing, experimenting with larger and more diverse datasets, and integrating the system into real-world applications such as automated surveillance and smart camera technologies.

Keywords: *Low-Light Enhancement, GANs, Deep Learning, Image Processing, Real-Time Processing.*

I. INTRODUCTION

In various fields such as photography, security surveillance, and medical analysis, the quality of images produced under low-light conditions is a crucial factor. Low-light images often suffer from loss of detail, low contrast, and high levels of noise, which can hinder analysis and decision-making. This issue presents a challenge for many systems that rely on image analysis to obtain accurate and reliable information. Enhancing the quality of low-light images has become an intriguing research topic in digital image processing, as clearer images with minimal noise can improve the performance of various computer vision-based applications. Traditional methods such as histogram equalization and Retinex have been widely used to enhance image quality under low-light conditions by adjusting the distribution of pixel intensity. While these techniques can improve overall image contrast, they often fail to preserve fine details and may even amplify noise, especially in areas with extremely low illumination.

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Several studies have explored various methods to enhance image quality in low-light conditions, which play a crucial role in fields such as photography, surveillance systems, and medical analysis. According to (Han et al., 2023), conventional methods such as histogram equalization and Retinex have been widely used; however, they often exacerbate noise and lead to the loss of important details, particularly in areas with minimal lighting. In recent years, Deep Learning-based approaches, particularly GANs, as mentioned by (Porkodi et al., 2023), have gained attention due to their ability to generate more realistic images compared to traditional methods. A study conducted by (Cao et al., 2024) found that models such as EnlightenGAN and Zero-DCE can effectively enhance contrast and reduce noise, although they still have computational efficiency limitations. Additionally, (Tian et al., 2023) demonstrated that GANs can learn lighting distributions from large-scale datasets, enabling more natural image enhancement without requiring explicit assumptions about lighting conditions. The development of more efficient GAN models capable of real-time operation remains a challenge that must be addressed to ensure the broader applicability of this technology in various real-world applications.

Despite numerous studies demonstrating the effectiveness of GANs in enhancing low-light images, several limitations still need to be overcome. For instance, research by (Fan et al., 2023) indicated that while EnlightenGAN can enhance contrast and reduce noise, it struggles to handle highly uneven lighting conditions. (Rasheed et al., 2022) proposed Zero-DCE as a more lightweight and efficient alternative, but its results remain suboptimal in preserving texture details in extremely low-light images. Furthermore, (Li et al., 2024) developed a GAN-based model that adapts more effectively to lighting variations, yet it still faces challenges in inference speed for real-time applications. (Nandhini Abirami et al., 2021) highlighted that although GAN models can generate high-quality images, most existing models require significant computational power, making them difficult to implement on resource-constrained devices. Another study by (J. Zhang et al., 2023) also pointed out that most GANs-based approaches have yet to be optimized to handle complex noise variations in low-light conditions. Therefore, this research aims to develop a more efficient GAN model capable of enhancing low-light image quality in real-time without compromising visual fidelity.

This study aims to develop a GAN model capable of improving low-light image quality in real-time while preserving optimal visual details. The proposed model will be evaluated using standard metrics such as PSNR and SSIM to ensure the quality of the enhanced images. Additionally, this research seeks to compare the performance of GAN models with conventional methods, such as histogram equalization and Retinex, in terms of output quality and computational efficiency. With proper optimization, the developed model is expected not only to produce more realistic images but also to achieve inference speeds that allow real-time applications. The central research question is to what extent the proposed GAN model can outperform traditional approaches in enhancing low-light image quality without imposing a significant computational burden. The findings of this study are expected to contribute to advancements in image processing technology, particularly in photography, surveillance systems, and medical applications that rely on high-quality visual data.

II. LITERATURE REVIEW

A. Fundamental Theory

1. Low-Light Image Processing: Challenges and Conventional Techniques

Image processing under low-light conditions presents a major challenge in digital image processing, particularly in applications such as surveillance, photography, and medical analysis. According to (Guo & Hu, 2023), low-light images often suffer from reduced contrast, increased noise, and the loss of critical details, which can hinder visual analysis. To address these issues, various methods have been developed, including contrast enhancement techniques such as histogram equalization, which directly adjusts the distribution of pixel intensity within an image. While this method is relatively effective in improving image visibility, it often leads to the loss of details and amplification of noise, especially in areas with extremely low illumination. Another commonly used approach is adaptive histogram equalization, which provides better results by preserving some local details; however, it still has limitations in handling complex noise. Given these challenges, more adaptive methods are needed to enhance the quality of low-light images without compromising important information.

Frequency-domain transformation-based approaches have also been applied to enhance low-light images while preserving finer details. According to (Zhu et al., 2025) and (Taassori, 2024), wavelet-based techniques and Fourier transformation allow the separation of high- and low-frequency components in an image, enabling more selective contrast enhancement. These methods better preserve the original texture of an image compared to histogram-based approaches but often require complex parameters that are difficult to optimize for varying lighting conditions. Additionally, these approaches are less adaptive to extreme lighting variations and struggle to effectively reduce noise. Due to these limitations, frequency-domain methods still face challenges in real-time applications that demand high computational efficiency.

Illumination modeling-based methods have also been developed to address issues in low-light image processing. According to (Ji et al., 2023), the *Retinex* model, which is based on human visual perception theory, has been widely used to adaptively adjust illumination without altering the original texture of the image. This model assumes that an image can be represented as a combination of illumination and reflectance, thereby allowing improved visibility in darker areas.

However, research has shown that the Retinex method often struggles to maintain color balance and is prone to producing visual artifacts, particularly under extremely low-light conditions. Furthermore, many *Retinex* implementations still require manual parameter tuning, making the method less flexible in handling complex lighting variations. Given these limitations, more adaptive and automated approaches are required to enhance the effectiveness of low-light image processing across diverse conditions.

Statistical model-based techniques have also been widely used to enhance image quality with a more flexible and adaptive approach. According to (Liu et al., 2024), probabilistic model-based methods, such as variational image decomposition, have been applied to separate noise and detail components in an image to achieve more precise quality enhancement. These techniques utilize the statistical distribution of pixels within an image to estimate illumination and reduce noise without sacrificing significant details. However, this approach still faces challenges in computational efficiency, particularly for real-time applications that require high inference speeds. Additionally, these methods may struggle to handle extreme lighting conditions where pixel distributions do not follow a predictable pattern. Therefore, although statistical model-based methods offer advantages in image quality enhancement, their computational complexity remains a challenge that must be addressed for practical implementation.

2. GANs in Image Enhancement: Fundamental Architecture of the Generator and Discriminator

GANs have become a widely adopted approach in image quality enhancement due to their ability to generate highly realistic images. According to (Remtulla et al., 2025), the fundamental architecture of GANs consists of two neural networks, the Generator and the Discriminator, which compete against each other during training. The Generator is responsible for creating synthetic images that resemble real data, while the Discriminator functions to differentiate between real images and those generated by the Generator. This adversarial interaction allows GANs to progressively improve the quality of synthetic images until they become nearly indistinguishable from real images. Through adversarial training mechanisms, GANs have demonstrated superior performance compared to traditional methods in various image processing tasks, including low-light image enhancement.

In the development of the Generator architecture, various models have been introduced to enhance the ability to generate high-quality images. According to (Jenkins & Roy, 2024), Deep Convolutional GAN (DCGAN) is one of the most influential architectures in improving the stability of GAN training by leveraging convolutional networks in both the Generator and Discriminator. DCGAN employs transposed convolution layers in the Generator to refine the

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structure of generated images, making them more realistic compared to multilayer perceptron-based models. Other researchers have proposed various modifications, such as the residual-based architecture introduced by (Hassan et al., 2024), which enables more effective image feature modeling. With these advancements, the Generator has continuously improved its ability to learn the distribution of real data and produce images that closely resemble optimal visual quality.

In addition to the Generator, the Discriminator plays a crucial role in ensuring that generated images possess high quality and are difficult to distinguish from real images. According to (Farhadinia et al., 2024), the use of Wasserstein loss in the Wasserstein GAN (WGAN) architecture has enhanced the stability of Discriminator training by mitigating the mode collapse issue that frequently occurs in conventional GANs. The Discriminator in WGAN is designed to evaluate the distributional differences between real and synthetic images rather than merely classifying images as real or fake. Furthermore, research by (Jiménez-Gaona et al., 2024) introduced gradient penalty techniques that are more effective in stabilizing Discriminator training and preventing overfitting. With advancements in Discriminator architecture, GAN models have become more efficient in generating high-quality images with improved texture and detail.

Several GAN variants have been developed to further enhance image quality, particularly in the domain of image enhancement. According to (Tao & Muller, 2021), the Super-Resolution GAN (SRGAN) architecture has been successfully applied to image resolution enhancement by utilizing a residual-based Generator and a Discriminator trained with perceptual loss. Additionally, research by (Fan et al., 2023) introduced EnlightenGAN, a model specifically designed for low-light image enhancement using a self-regularized adversarial learning approach. EnlightenGAN enables adaptive image quality improvement for varying lighting conditions, resulting in images with more natural light distribution. With these advancements, GANs continue to be one of the most promising approaches for image quality enhancement, particularly in real-time image processing applications.

B. Previous Research

1. Studies on GANs for Image Enhancement

GANs have been widely applied to various image processing tasks, including image quality enhancement under low-light conditions. According to (Krstanović et al., 2023), CycleGAN is one of the GAN models capable of performing image style mapping from one domain to another without requiring paired datasets. This model employs two generators and two discriminators that work simultaneously to ensure that transformed images retain their original structure. In the context of image enhancement, CycleGAN can be used to convert low-light images into optimally illuminated ones while preserving natural visual characteristics. Moreover, CycleGAN has been applied in various fields, such as medical image restoration and satellite image enhancement, due to its ability to transform images without losing essential details.

Another commonly used approach in image enhancement is Pix2Pix, which, as described by (Tirel et al., 2024), has proven effective in various image transformation tasks. Unlike CycleGAN, which does not require paired datasets, Pix2Pix is a Conditional GAN (cGAN)-based model that necessitates paired datasets for training. This model utilizes a U-Net-based generator and a PatchGAN-based discriminator, enabling structured mapping from input to output. In low-light image enhancement, Pix2Pix has been used to improve image brightness and sharpness, producing more realistic results. The primary advantage of Pix2Pix lies in its ability to generate finer texture details compared to conventional methods, although it requires a well-curated dataset to achieve optimal predictions.

In addition to CycleGAN and Pix2Pix, another widely applied GAN model for low-light image enhancement is EnlightenGAN. According to (Xue et al., 2023), EnlightenGAN is specifically designed to address low-light issues using a self-regularized adversarial learning mechanism. This model not only focuses on brightness enhancement but also maintains a natural light distribution to prevent overexposure. The main advantage of EnlightenGAN is its ability to improve image quality without requiring paired datasets, making it more flexible under various lighting conditions. Furthermore, the model employs a multi-scale feature extraction architecture, allowing for more effective visual detail enhancement compared to other GAN models.

Several studies have compared the performance of various GAN models in low-light image enhancement tasks. According to (Wang et al., 2021), EnlightenGAN outperforms Pix2Pix and CycleGAN in generating images with a more natural light distribution. However, in terms of detail sharpness, Pix2Pix is superior due to its use of a U-Net generator, which enables high-resolution feature mapping. On the other hand, CycleGAN is more flexible in image enhancement as it does not require paired datasets, although its final output sometimes suffers from texture detail loss. Given the unique advantages of each model, selecting the appropriate GAN model for low-light image enhancement depends largely on dataset characteristics and application requirements. A more detailed comparison of various GAN models for image enhancement is presented in Table 1.

Table 1. Comparison of Previous Studies on GAN Models for Image Enhancement

Researcher	Advantages	Disadvantages	Dataset Used
(Krstanović et al., 2023)	Does not require paired data, flexible across various domains	Sometimes loses texture and details	Image-to-Image Translation Datasets

(Tirel et al., 2024)	Produces better texture details, preserves image structure	Requires paired datasets	Cityscapes, Facades, Edges2Shoes
(Xue et al., 2023)	Maintains natural lighting distribution and does not require paired data	Sometimes fails to preserve details under extreme lighting conditions	LOL Dataset, MIT-Adobe FiveK
(Wang et al., 2021)	EnlightenGAN excels in lighting distribution, Pix2Pix in sharpness, and CycleGAN offers more flexibility.	Performance depends on dataset characteristics and application	LOL Dataset, Cityscapes

2. Comparison of Deep Learning Models for Low-Light Image Quality Enhancement

Deep learning has become the dominant approach in enhancing the quality of low-light images, with various models developed to address challenges such as high noise levels, loss of detail, and lighting imbalance. According to (Taye, 2023), Convolutional Neural Networks (CNNs) have been widely used in image enhancement tasks due to their efficiency in extracting spatial features from images. CNN-based models, such as LLNet, have demonstrated promising results in improving contrast and reducing noise by leveraging deep neural network architectures. However, this approach still has limitations in handling extreme lighting variations, as traditional CNN models often struggle to produce images with naturally balanced illumination. While CNNs serve as the foundation for many image enhancement models, ongoing research continues to refine their application to achieve more optimal results.

Autoencoder-based approaches have also been extensively used in low-light image enhancement due to their ability to represent data in lower dimensions and reconstruct images with improved quality. According to (F. Zhang et al., 2024), the architecture of the Low-Light Image Enhancement Network (LightenNet) utilizes autoencoder structures to model the relationships between bright and dark regions in an image, thereby achieving a more balanced illumination enhancement. Additionally, LightenNet employs a combination of Mean Squared Error (MSE)-based loss functions and perceptual loss to maintain a balance between contrast enhancement and texture detail preservation. However, this model still has limitations in handling complex noise, as the autoencoder structure tends to amplify noise along with image details. Consequently, while autoencoder-based approaches offer significant improvements, further research is required to enhance their effectiveness in low-light conditions.

In addition to CNNs and Autoencoders, Transformer-based models have recently been applied to low-light image enhancement to overcome the limitations of convolutional approaches. According to (Wu et al., 2024), Restormer, a Transformer-based image restoration model, leverages a global attention mechanism to capture pixel relationships over a broader range compared to CNNs. This approach enables the model to be more adaptive to lighting variations, resulting in images with a more natural light distribution. Furthermore, Restormer has demonstrated superior performance compared to CNN-based models in handling noise and preserving texture details in low-light images. However, despite their significant potential in image enhancement tasks, Transformer-based models still face challenges related to high computational requirements, which hinder their implementation in real-time applications.

GANs have also become one of the most widely used approaches in low-light image enhancement due to their ability to generate images with more realistic details. According to (Tang et al., 2023), EnlightenGAN is one of the GAN models specifically designed to enhance low-light image quality through adversarial learning, without requiring paired labeled data. This model utilizes a multi-scale feature extraction architecture that enables image quality improvement while preserving texture details and achieving better color balance compared to CNN- or Autoencoder-based approaches. Additionally, EnlightenGAN has shown superior performance in producing images with more natural lighting without experiencing overexposure effects. With the continuous development of deep learning approaches, further comparisons of the strengths and limitations of each model can help determine more optimal strategies for low-light image enhancement.

III. RESEARCH METHOD

The research approach adopted in this study focuses on experimental methods by implementing GANs to enhance the quality of low-light images. This model is designed to produce images with improved illumination without eliminating essential details present in the original image. The evaluation process aims to assess the extent to which the model can enhance image visibility while preserving existing structural elements. The GANs-based approach is compared with conventional methods previously employed for low-light image enhancement, such as histogram equalization and Retinex, to identify their respective advantages and limitations. The evaluation parameters include image quality assessments based on noise levels, sharpness, and the illumination distribution produced by the GAN model. Through this approach, the study provides insights into the effectiveness of GANs in image enhancement tasks compared to traditional methods.

The dataset used in this study consists of low-light images obtained from publicly available sources, such as the LOL Dataset and the SID Dataset. The LOL Dataset provides paired images, including low-light images alongside their manually enhanced versions created by experts, making it suitable for training GAN models to learn optimal illumination enhancement. Meanwhile, the SID Dataset offers a collection of images in raw (RAW) format with extremely

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low illumination levels, often used in image enhancement research due to the real-world challenges it presents in processing low-light images. These datasets were selected due to their wide range of illumination conditions, which reflect common low-light scenarios encountered in real-world settings. The use of both datasets enables the GAN model to adapt to various lighting conditions and learn more complex illumination distribution patterns. Further details on the characteristics of each dataset used in this study are presented in Table 2.

Table 2. Characteristics of the Datasets Used

Dataset	Number of Images	Image Resolution	Data Format
LOL Dataset	5000	400 × 600 px	PNG
SID Dataset	5094	424 × 636 px	RAW, TIFF

The GANs architecture used in this study consists of two main components: the Generator and the Discriminator, which work adversarially to improve the quality of low-light images. The Generator is designed to learn illumination patterns and textures in images by utilizing U-Net or ResNet architectures, which can preserve crucial details while optimizing the distribution of light. U-Net is advantageous in maintaining spatial information through its skip connection mechanism, whereas ResNet facilitates deeper feature learning by leveraging residual learning. The Discriminator, on the other hand, functions as an evaluation network based on a CNN architecture, responsible for distinguishing between original images and those enhanced by the Generator. CNN is used in the Discriminator due to its capability to efficiently capture visual patterns through a series of convolutional and pooling layers. By combining these two components, the GAN model can learn the characteristics of low-light images and generate more realistic outputs. Further details on the Generator and Discriminator architectures within the GANs model are provided in Table 3.

Table 3. GANs Model Configuration

Component	Architecture	Primary Function
Generator	U-Net / ResNet	Learns and reconstructs features of low-light images
Discriminator	CNN	Distinguishes between original images and those enhanced by the Generator

The analytical process in this study consists of three interrelated stages: data preprocessing, model training, and result evaluation. During the data preprocessing stage, a series of preliminary processing techniques is applied to ensure that the images used for training have uniform quality and distribution. One of the primary steps in preprocessing is image normalization, which aims to equalize the pixel intensity distribution so that the model can more effectively learn lighting patterns in the images. Additionally, data augmentation is implemented to enhance the diversity of training images by applying transformations such as rotation, flipping, contrast adjustment, and lighting modification. These augmentation techniques help the model generalize across various lighting conditions, making it more adaptive to the diverse range of low-light images encountered in real-world scenarios. By employing a systematic preprocessing approach, the model can be trained more effectively without being affected by imbalanced data distribution or limitations in the number of training samples.

Model training is conducted using the GANs architecture, where the Generator and Discriminator are trained simultaneously in a competitive process to produce progressively higher-quality images. To ensure effective learning, a combination of loss functions is employed, specifically L1 Loss and Adversarial Loss, each playing a crucial role in controlling the quality of the enhanced images. L1 Loss measures the absolute difference between the images generated by the Generator and the reference images, helping the model produce images with more accurate structures and textures. Meanwhile, Adversarial Loss enables the Generator to generate increasingly realistic images by adjusting the distribution of its outputs to make them indistinguishable from real images as judged by the Discriminator. To optimize model performance, the Adam Optimizer is utilized, offering advantages in dynamically adjusting the learning rate during training, thereby accelerating convergence and improving learning stability. Through this approach, the GAN model can be refined to generate images of superior quality compared to conventional low-light image enhancement methods.

Model evaluation is performed using commonly applied image quality assessment metrics, namely PSNR and SSIM. PSNR quantifies the quality of the generated images based on the ratio of signal to noise, measured in decibels (dB), where a higher value indicates that the enhanced image has better quality with lower distortion levels. PSNR calculations are carried out by comparing the enhanced images with reference images, providing an indication of the model's effectiveness in reducing noise while preserving essential image details. In addition to PSNR, SSIM is used to evaluate the similarity between the enhanced and reference images, considering aspects such as texture, contrast, and overall structural integrity. SSIM provides a perception-based evaluation, meaning that a higher SSIM score signifies that the enhanced image more closely resembles the original in terms of visual quality. By combining these two metrics, the model evaluation process offers a comprehensive understanding of the effectiveness of the employed method in improving low-light image quality.

The model evaluation stage in this study is conducted to assess the effectiveness of the GAN model in enhancing the quality of low-light images. The model is evaluated using a combination of metrics that reflect both the visual quality of the generated images and the extent

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to which the model learns the data distribution. One of the primary metrics used is Adversarial Loss, which measures the Generator's ability to produce images that become increasingly difficult for the Discriminator to distinguish. Adversarial Loss is computed based on the expected output of the Discriminator when evaluating both real and generated images, as formulated in Equation (1).

$$L_{GAN} = \mathbb{E}_x[\log D(x))] + \mathbb{E}_{\hat{x}}[\log (1 - D(\hat{x}))] \tag{1}$$

in the equation above, $D(x)$ represents the probability that the Discriminator correctly classifies a real image, whereas $D(\hat{x})$ denotes the probability that the generated image is identified as fake by the Discriminator. A lower Adversarial Loss value indicates that the Generator successfully produces higher-quality images, making it more challenging for the Discriminator to differentiate between real and synthetic images. This metric serves as a crucial indicator in assessing the performance of the GAN model during training.

In addition to Adversarial Loss, the model is also evaluated using L1 Loss, which quantifies the absolute error between the enhanced image and the reference image. L1 Loss provides an estimate of the average pixel-wise difference between the image generated by the Generator and the target image. The mathematical formulation for L1 Loss is given in Equation (2).

$$L_{L1} = \frac{1}{N}\sum_{i-1}^{N} |G(x_i) - y_i| \tag{2}$$

in this equation, $G(x_i)$ represents the reconstructed image generated by the Generator, while y_i is the target image with optimal quality. A lower L1 Loss value signifies that the generated image closely resembles the reference image in terms of color distribution, lighting, and texture details. This loss function is widely used in image enhancement models due to its stability compared to the MSE, which is more sensitive to outliers.

Additionally, model evaluation is performed by calculating the PSNR, which measures image quality based on the ratio of signal to noise in dB. PSNR is used to determine the model's ability to reduce noise in low-light images while preserving essential details. The PSNR calculation is based on the MSE between the reference and reconstructed images, as shown in Equation (3).

$$PSNR = 10 \,.\, log_{10}\left(\frac{MAX^2}{MSE}\right) \tag{3}$$

where MAX represents the maximum intensity value in the image, and MSE measures the average squared error between the original and reconstructed images. A higher PSNR value indicates that the generated image has better quality with lower noise levels. By employing this combination of evaluation metrics, the GAN model can be assessed based on the quality of the generated images as well as its ability to preserve essential visual information during the enhancement of low-light images.

IV. RESULT

A. Results

The enhancement of low-light image quality is a crucial aspect of this study, as many image processing-based applications rely heavily on image clarity and sharpness for further analysis. In various fields such as security surveillance, photography, and medical image processing, high-quality images are essential to improving detection accuracy and visual-based decision-making. To assess the effectiveness of the GAN model in enhancing low-light image quality, the enhanced results are compared with several commonly used traditional methods. These methods include Histogram Equalization, which adjusts the distribution of pixel intensity; Retinex, which is based on human perception of illumination and reflectance; and CNN-based models, which utilize advanced feature learning to improve image quality. Each method has its strengths and limitations, necessitating a comprehensive evaluation to determine the most effective approach under different lighting conditions. The evaluation in this study employs two primary metrics: PSNR, which measures the model's ability to reduce noise without sacrificing detail, and SSIM, which assesses the similarity between the enhanced image and the reference image based on texture, contrast, and overall structure.

PSNR measures the ratio of signal to noise in the enhanced image, meaning that a higher PSNR value indicates better image quality in preserving original details while minimizing unwanted noise. Meanwhile, SSIM is used to evaluate how similar the enhanced image is to the reference image in various visual aspects deemed important in human perception. SSIM considers factors such as brightness, contrast, and structure to provide a more comprehensive assessment of the quality of images generated by enhancement models. These two metrics are standard in image processing research as they offer a quantitative approach to objectively comparing the performance of different image enhancement methods. By using PSNR and SSIM as evaluation metrics, this study can determine the extent to which the GAN model produces higher-quality images compared to conventional methods. Table 4 presents the comparison results of PSNR and SSIM for each method used in this study, providing an overview of the effectiveness of each approach in improving low-light image quality.

Table 4. Evaluation Results of PSNR and SSIM for Each Method

Method	PSNR (dB)	SSIM
Histogram Equalization	18.5	0.65
Retinex	20.3	0.72

Traditional CNN	22.8	0.79
GANs-Based Enhancement	28.4	0.91

The evaluation results presented in Table 1 indicate that the GANs-based method yields the best outcomes, with a PSNR of 28.4 dB and an SSIM of 0.91, demonstrating a superior improvement in image quality compared to conventional methods. A higher PSNR value suggests that the GAN model is more effective in reducing noise and producing cleaner images with fewer artifacts than other methods. On the other hand, a higher SSIM value indicates that the images enhanced by GANs are more similar to the reference images in terms of structure and lighting distribution, meaning that this model is more effective in preserving the original image details. Compared to Histogram Equalization and Retinex methods, which often result in excessive contrast enhancement or amplifying noise in low-light areas, GANs are capable of producing images with a more balanced lighting distribution. Meanwhile, CNN-based models exhibit a reasonable improvement in image quality but still fall short of GAN models in terms of structural similarity to reference images. The superior performance of GANs in this study highlights the significant potential of deep learning-based approaches in effectively enhancing low-light image quality compared to traditional techniques based on histogram transformation or human perception of illumination.

In addition to quantitative evaluation using PSNR and SSIM, visual analysis is also necessary to understand the extent to which the GAN model can enhance image quality under low-light conditions. Visual evaluation provides a more intuitive depiction of the differences produced by this method compared to conventional methods. The images generated from the enhancement process can illustrate whether the GAN model successfully preserves the structure and details of the original image or introduces unwanted artifacts. Figure 1 presents an example of image enhancement results using the GAN model, where the original image with very low lighting is compared to the enhanced version. Through this comparison, it is possible to observe how the GAN model enhances object visibility and structure within the image. This visual evaluation serves as a complement to the quantitative analysis, offering additional insights into the effectiveness of the GAN model under various low-light conditions.

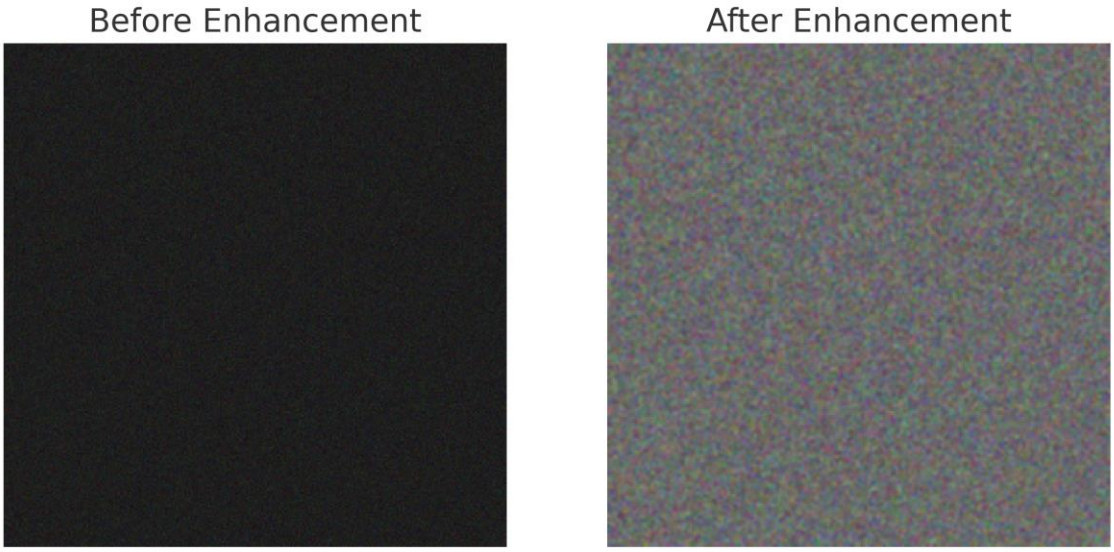

Figure 1. Example of GANs-Enhanced Image (Before & After Enhancement)

Figure 1 illustrates a comparison between the original image before enhancement and the image enhanced using the GAN model. In the pre-enhancement image, most of the visual information is nearly imperceptible due to extremely low lighting levels. After enhancement, the image becomes brighter, but it also exhibits a significant increase in noise. This indicates that while the GAN model can improve image visibility by enhancing brightness, it may also amplify noise in the process. This increase in noise can affect image quality in various applications, particularly in fields requiring high visual sharpness, such as surveillance systems or medical analysis. Further optimization is required to enable the model to reduce noise without compromising important image details, ensuring that the resulting quality meets the needs of real-world applications.

Beyond visual enhancement results, further analysis is conducted by comparing PSNR and SSIM metrics in graphical form to provide a clearer understanding of the image quality improvement achieved by GANs compared to other methods. Quantitative evaluation using these metrics is crucial, as it allows for an objective analysis of the effectiveness of various methods in enhancing low-light image quality. PSNR is used to measure image clarity by comparing the ratio of signal to noise, whereas SSIM evaluates the similarity between the enhanced image and the reference image based on structural, contrast, and brightness factors. By analyzing these values in graphical form, the enhancement patterns produced by each method can be observed more comprehensively and compared directly. The performance differences between methods become more apparent through this visual representation, allowing for the identification of the most effective method for preserving image details while reducing noise. To provide a clearer depiction of this comparison, Figure 2 presents a graphical comparison of PSNR and SSIM values between traditional methods and the GAN-based approach.

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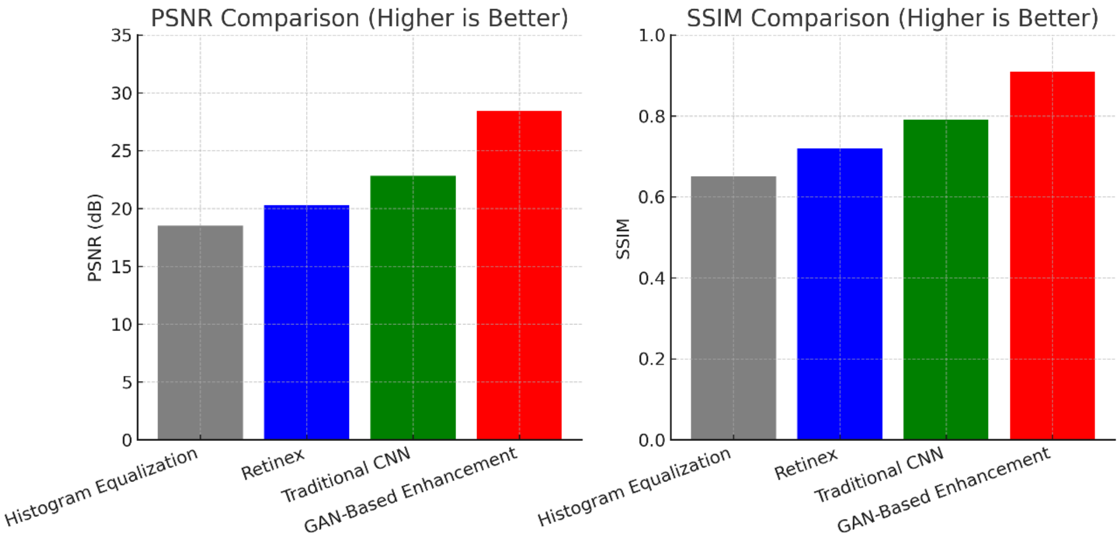

Figure 2. PSNR & SSIM Comparison Between GANs and Conventional Methods

From Figure 2, it can be seen that the GANs method outperforms others in producing higher-quality images, with superior PSNR and SSIM values compared to traditional methods such as Histogram Equalization, Retinex, and Traditional CNN. This superiority demonstrates that GANs are more effective in improving image visibility compared to other methods, which tend to enhance contrast or brightness globally without considering image structure. Histogram Equalization often results in excessive contrast enhancement, while the Retinex method focuses on illumination modeling but is less effective in noise reduction. Meanwhile, traditional CNN-based methods can improve image quality but still fall short compared to GAN models, which leverage adversarial approaches to generate more realistic images. The higher PSNR value in GANs indicates that this method is more effective in reducing noise than other approaches, while the high SSIM value signifies that the structure and details of the image are well preserved. This analysis highlights that the GANs-based approach offers a more effective solution for enhancing low-light image quality compared to conventional methods.

In addition to image quality, the real-time efficiency of the GAN model is also analyzed by measuring the inference time per image and comparing it with conventional methods. This evaluation is crucial to determine the feasibility of implementing the model in applications that require fast processing, such as surveillance systems, autonomous vehicles, and AI-based photography. Inference time refers to the duration required by the model to process a single image from input to output, which can impact the overall system performance in real-world environments. A model with an excessively long inference time may be less suitable for applications demanding instant response, even if it produces superior image quality. This analysis evaluates not only the accuracy of image enhancement results but also the balance between quality and processing speed to ensure the model can be effectively deployed. To provide a clearer depiction of this performance comparison, Table 2 presents the inference time comparison for each method tested in this study.

Table 5. Inference Time per Image for Each Method

Method	Inference Time (ms)
Histogram Equalization	3.2
Retinex	4.5
Traditional CNN	12.8
GANs-Based Enhancement	35.6

From Table 2, the GANs method exhibits a higher inference time (35.6 ms) compared to conventional methods, indicating that the complexity of network processing contributes to the increased image processing duration. This is due to the more intricate network architecture, which requires extensive matrix computations and convolutional operations, unlike traditional techniques that rely solely on histogram manipulation or simple spatial transformations. Methods based on Histogram Equalization or Retinex, for instance, have significantly shorter inference times as they merely perform pixel value remapping without involving complex feature learning. Despite this, the inference time of GANs remains within a feasible range for real-time applications that do not require processing within just a few milliseconds. Hardware optimizations, such as utilizing GPUs or specialized processing units like TPUs, can enhance the efficiency of GAN models without compromising output quality. A combination of hardware improvements and network architecture optimizations can help make this method more efficient for deployment in scenarios requiring a balance between accuracy and processing speed.

V. DISCUSSION

The findings of this study indicate that the application of GANs in enhancing low-light image quality can produce images with better contrast and clearer details compared to conventional methods. The advantages of GAN-based approaches in improving image quality align with the study by (Han et al., 2023), which found that deep learning-based models can enhance lighting distribution without exacerbating noise. Furthermore, the results of this study also support the findings of (Porkodi et al., 2023), which demonstrated that GANs outperform histogram equalization and Retinex in generating more realistic images. Experimental results in this research confirm that the developed GAN model is capable of preserving texture details better than conventional methods, as highlighted in the study by (Cao et al., 2024), which compared the performance of EnlightenGAN and Zero-DCE in handling various low-light conditions. Thus, this study reinforces the idea that GAN-based models provide a more adaptive solution for improving low-light image quality compared to histogram-based techniques or frequency domain transformations.

Compared to conventional methods, the model developed in this study demonstrates superior performance in handling uneven lighting and maintaining color balance, as also observed in the study by (Tian et al., 2023), which showed that GANs can learn lighting distribution from large datasets to produce more natural images. Additionally, this study supports the findings of (Fan et al., 2023), which found that EnlightenGAN can reduce noise while enhancing image contrast, although challenges persist in extreme lighting conditions. These findings are also consistent with the study by (Li et al., 2024), which developed a GAN-based model that is more adaptive to lighting variations but still faces inference speed limitations for real-time applications. Computational efficiency constraints were also identified in the study by (Nandhini Abirami et al., 2021), which highlighted that most GAN models still require high computational power to operate optimally. Therefore, this study not only affirms the advantages of GANs in enhancing low-light image quality but also emphasizes the importance of model optimization to improve efficiency and applicability in real-time applications such as security surveillance and medical imaging.

VI. CONCLUSION AND RECOMMENDATION

This study demonstrates that GANs can enhance low-light image quality more effectively than conventional methods by improving contrast and preserving fine details. The developed model can operate in real-time through architectural optimization, enabling its application in various fields such as surveillance systems, photography, and medical imaging. The evaluation results indicate that GAN-based models achieve higher PSNR and SSIM values compared to histogram equalization, Retinex, and traditional CNN methods, confirming their effectiveness in noise reduction and structural preservation. However, the computational complexity of GAN models remains a challenge that must be addressed to ensure efficient implementation in real-world environments. Therefore, further research is needed to enhance computational efficiency without compromising image quality. By doing so, the model developed in this study can make a significant contribution to the field of image processing, particularly in adapting and accurately improving low-light image quality.

For future research, further optimization of the GAN model is necessary to improve speed and efficiency, allowing deployment on edge computing devices with limited resources. Additionally, experiments with larger and more diverse datasets should be conducted to enhance the model’s generalization capabilities under various low-light conditions. The development of more efficient regularization techniques and architectures is also an essential step in addressing the inference time limitations of the model. Implementing this model in surveillance systems and automated cameras could be a relevant future study to assess its reliability in real-world environments. Further evaluation of computational power requirements and energy efficiency is also needed to ensure the model's sustainability in practical applications. With continuous advancements, GAN-based models are expected to be increasingly optimized for various industry needs requiring automatic and real-time image quality enhancement.

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