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# Image Enhancement Techniques under Low-Light Conditions Using GANs - A Review

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Image enhancement in low-light conditions is a critical area of research, and is essential for applications such as autonomous driving, security surveillance, and medical imaging. Low-light environments can significantly degrade image quality, reducing visibility and detail, which impacts the accuracy and reliability of computer vision systems. Traditional image enhancement techniques often struggle to deliver satisfactory results under challenging lighting conditions, leading to the exploration of generative AI methods as a promising solution. This review examines the state-of-the-art approaches in low-light image enhancement utilizing generative adversarial networks (GANs), convolutional neural networks (CNNs), and other machine learning techniques. We synthesize advancements in GAN-based low-light image enhancement, focusing on methods like Retinex-based illumination decomposition, multi-scale feature extraction, attention mechanisms, and visible-infrared fusion. Key methodologies, such as decomposing images into illumination and reflectance components, attention-guided feature prioritization, and adaptive loss functions, are highlighted for their ability to improve both global brightness and local detail retention. Experimental results from recent studies indicate that these techniques enhance visibility, maintain natural colors, and reduce artifacts across varied low-light scenarios. The paper concludes by identifying future research directions, including real-time optimization, lightweight architectures for edge devices, and the integration of multi-modal data for more robust low-light enhancement.
**Keywords:** Image enhancement, Generative AI, GANs, CNNs.

## 1. Introduction

Low-light image enhancement has emerged as a critical area of research in computer vision, driven by the increasing demand for reliable image processing solutions in diverse applications such as surveillance, autonomous driving, medical imaging, and photography. Conventional enhancement methods, while foundational, often struggle to address the complexities of modern imaging challenges, such as non-uniform illumination, noise, and color distortion. In response, deep learning-based approaches, particularly Generative Adversarial Networks (GANs), have revolutionized the field by offering robust solutions that leverage their unique adversarial training mechanisms. GANs, introduced by Ian Goodfellow in 2014, consist of two neural networks—a generator and a discriminator—that compete to improve image quality iteratively. This framework has given rise to various advanced architectures such as

CycleGAN, EnlightenGAN, and RetinexGAN, each tailored to address specific challenges in low-light scenarios.

Recent studies have demonstrated significant advancements in GAN-based methodologies, integrating physics-informed principles, attention mechanisms, and multi-scale processing to enhance low-light image quality. By leveraging state-of-the-art datasets and innovative loss functions, these models achieve remarkable improvements in image clarity, brightness, and realism while addressing domain-specific challenges. Despite these advancements, the field continues to grapple with issues such as computational complexity, the scarcity of high-quality datasets, and the need for better generalization across diverse real-world conditions. This review aims to explore the progression of low-light image enhancement techniques, analyze the strengths and limitations of existing methods, and provide insights into future research directions.

## 2. Generative Adversarial Networks

Theoretical Framework

Generative Adversarial Networks (GANs) are deep learning models consisting of a generator and a discriminator trained in an adversarial manner. They offer powerful tools for unsupervised and semi-supervised learning, and have applications in various fields like image synthesis, medical diagnostics, and 3D modeling. GANs address challenges in data representation and synthesis, particularly in high-dimensional spaces. Advanced variants like Conditional GANs and Wasserstein GANs address training instability and mode collapse. (Creswell et al., 2017).

GAN architecture is a deep learning system that uses specialized neural networks to transform dark, low-quality images into brighter, clearer versions. GANs consist of two main components: the Generator and the Discriminator. The Generator enhances dim, underexposed images by adding appropriate lighting, reducing noise, and improving details. The Discriminator acts as a quality inspector, learning to distinguish between naturally well-lit images and artificially enhanced ones. The Generator continually improves its enhancement techniques, while the Discriminator becomes better at detecting artificial enhancements. Eventually, the Generator becomes so skilled that the Discriminator struggles to differentiate between natural and enhanced images. GANs have transformed low-light photography, enabling automatic enhancement of night-time photos and security camera footage under challenging lighting conditions. The generator model creates synthetic data that mimics real data distribution, using random noise or latent variables as input. The generator fine-tunes its parameters using back propagation to produce enhanced images that closely resemble well-lit, high-quality versions of the input. The goal is to create visually realistic images that can deceive the discriminator, and the generator minimizes its loss function to create realistic low-light enhanced images. The loss function is defined as:

$$J_G = -\frac{1}{m}\sum_{i=1}^{m} \log D(G(z_i)) \qquad (1)$$

Where, $J_G$: Measures how effectively the generator fools the discriminator and $\log D(G(z_i))$:

The log probability that the discriminator classifies the generated image as real.

The Discriminator Model is a binary classifier that distinguishes between real and enhanced images, with convolutional layers for image data. It improves over time through training and minimizes the negative log-likelihood of correctly classifying both images. The loss function is defined as:

$$J_D = -\frac{1}{m}\sum_{i=1}^{m}\log D(x_i) - \frac{1}{m}\sum_{i=1}^{m}\log(1 - D(G(z_i))) \qquad (2)$$

Where, $J_D$: Evaluates the discriminator's ability to classify real and generated images, $\log D(x_i)$: Log-likelihood of correctly classifying real images and $\log(1-D(G(z_i)))$: Log-likelihood of correctly classifying generated images as fake.

Minimax Loss is a key feature in adversarial training in GANs, ensuring iterative improvement of the generator and discriminator, resulting in realistic and detailed low-light images. Loss function is

$$\min_G \max_D (G, D) = \mathbb{E}_{x\sim p_{\text{data}}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1 - D(G(z)))] \qquad (3)$$

Where, G: The generator network, D: The discriminator network, $p_{data}(x)$: True data distribution for well-lit images, $p_z(z)$: Prior noise distribution (e.g., normal or uniform), D(x): Probability that the discriminator classifies real data as authentic and D(G(z)): Probability that the discriminator classifies generated data as authentic.

Working of GAN

GANs are a revolutionary approach in generative modeling that operates through a sophisticated adversarial training mechanism between two neural networks. The process begins with the establishment of two distinct neural networks: a Generator (G) and a Discriminator (D). The Generator transforms random noise vectors into synthetic data samples, while the Discriminator evaluates the authenticity of data samples. The system's core functionality lies in its adversarial training dynamic, where the Discriminator successfully identifies real data and synthetic data, providing appropriate feedback. The Generator's parameters are updated based on the Discriminator's evaluations, and the Discriminator's adaptation is continuous. As training progresses, the system aims to reach a state of equilibrium where the Generator produces high-quality synthetic samples, and the Discriminator achieves only random chance accuracy in distinguishing between real and generated data. This interplay between the Generator and Discriminator represents a unique approach to unsupervised learning, enabling the system to capture complex data distributions without explicit probability density estimation. GANs have demonstrated significant potential in advancing the field of generative modelling in various applications, such as image synthesis and data augmentation.

TABLE I. TYPES OF GENERATIVE ADVERSARIAL NETWORKS

| Type of GAN | Key Features | Advantages for Low-Light Image Enhancement | Limitations |
|---|---|---|---|
| Vanilla GAN | Basic architecture with multi-layer perceptrons. Uses stochastic gradient descent. | Simple to implement. Provides a baseline for generative tasks. | Limited capacity to capture complex spatial features. Not specialized for low-light conditions. |
| Conditional GAN (CGAN) | Adds conditional parameters to the Generator and Discriminator. Labels guide data generation. | Enables targeted enhancements (e.g., brightness adjustments). Improves control over the enhancement process. | Requires labeled data. Complexity increases with the addition of conditions. |
| Deep Convolutional GAN (DCGAN) | Uses ConvNets with strided convolutions. Excludes max pooling and fully connected layers. | Captures spatial features effectively. Suitable for improving details in low-light images. | May struggle with global consistency in very challenging lighting conditions. |
| Laplacian Pyramid GAN(LAPGAN) | Multi-scale representation with Laplacian pyramids. Multiple Generators and Discriminators for refinement. | Produces high-quality, detailed results. Progressive image refinement addresses noise and artifacts in low-light images. | Computationally intensive. Requires careful tuning to maintain balance between scales. |
| Super-Resolution GAN (SRGAN) | Combines deep neural networks with adversarial loss. Optimized for high-resolution output. | Enhances resolution and details. Ideal for recovering textures and brightness in low-light images. | Focused on resolution; may need adaptation for more specific low-light enhancement requirements. |

## 3. Low-Light Image Enhancement Methods

This section discusses the progress in enhancing low-light images (LLI) using traditional methods, machine learning, and deep learning. Traditional methods use algorithms to modify visual properties, but they can introduce artifacts or fail to preserve details in complex lighting conditions. Machine learning automates the enhancement process, using statistical models and feature extraction techniques to recognize patterns in data. This allows for adaptive and context-aware image processing, offering a balance between computational efficiency and performance. Deep learning, the latest evolution, uses advanced neural network architectures like Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) to enhance low-light images. However, they require extensive datasets and computational resources, making them less accessible for some applications.

Traditional Low-Light Image Enhancement (LLIE) methods are mathematical and algorithmic techniques used to improve image quality and perception in various fields such as transportation, healthcare, and business. These methods can be categorized into three main types: gray-level transformation, histogram equalization, and Retinex-based methods. Gray-level transformation improves image contrast and brightness by adjusting grayscale values through functions like gamma, logarithmic, piecewise, and linear transformations. Histogram equalization increases the dynamic range and improves the brightness and contrast of low-light images by modifying gray levels through the Cumulative Distribution Function (CDF). Advanced methods like Brightness Preserving Bi-Histogram Equalization (BBHE), Dualistic Sub-Image Histogram Equalization (DSIHE), and Recursive Mean Separate Histogram Equalization (RMSHE) focus on preserving image brightness while enhancing contrast.

Retinex-based methods address illumination and reflectance separation to enhance brightness, contrast, and color consistency in images. Early approaches like Single-Scale Retinex (SSR), Multi-Scale Retinex (MSR), and MSR with Color Restoration (MSRCR) focused on dynamic range compression and edge enhancement. Innovations like Illumination Map Estimation (LIME) improved computational efficiency, kernel-based Retinex models minimized complexity, and methods like sigmoid MSR tackled color distortion and noise in low-light conditions. Retinex-based approaches continue to evolve, offering robust solutions for low-light image enhancement.

Machine learning (ML) has significantly improved low-light image enhancement (LLIE) by addressing the limitations of traditional methods like histogram equalization and Retinex algorithms. ML techniques leverage large datasets to optimize enhancement processes, offering adaptive and advanced solutions. ML-based LLIE methods, such as color estimation models and fuzzy rule-based algorithms, enable models to adjust automatically to varying lighting conditions, enhancing image quality effectively. The process generally involves image pre-processing, feature extraction, and dividing data into training and testing sets. ML techniques for LLIE have shown significant promise by synthesizing traditional and advanced methodologies. Examples include sparse representation techniques, fuzzy rule image enhancement algorithms, Color Estimation Models (CEM), sparse imaging principles, and advanced computational strategies like modified U-Net architectures, Recurrent Residual Convolutional Units (RRCU), and Dilated Convolutions.

Machine learning's capability to enhance image quality extends beyond aesthetics to feature retrieval for computer vision applications. Convolutional Neural Networks (CNNs) are used to generate reference data from luminance characteristics under low-light conditions, which are then employed in Gaussian Process models to enhance image features in real-time. The TreEnhance method, which combines Monte Carlo Tree Search with deep reinforcement learning, enhances image resolution and provides transparency in the enhancement process. The transition to deep learning further enhances this process, employing neural networks to capture complex visual attributes and deliver superior results.

Deep learning, a subset of AI, has significantly improved low-light image enhancement (LLIE) by extracting complex features from vast datasets. Techniques like Generative Adversarial Networks (GANs) and Deep Convolutional Neural Networks (CNNs) significantly improve image quality and visibility. LLIE methods, categorized into supervised, unsupervised, and zero-shot learning paradigms, enable systematic investigations tailored to specific conditions. These methods involve pre-processing, data division, training, and evaluation using metrics like SSIM and PSNR. Despite technical complexities, they outperform traditional approaches, delivering enhanced image clarity and facilitating advancements in image processing and computer vision. Supervised learning methods, such as GANs and CNNs, are widely used in LLIE, relying on paired datasets to train models that adjust brightness, contrast, and color balance. However, their reliance on specific training datasets limits adaptability to unstructured, dynamic lighting conditions. Unsupervised learning methods, such as EnlightenGAN and Exposure Correction Network (ExCNet), address issues like over fitting and poor generalization by balancing global and local enhancement and minimizing feature discrepancies between input and enhanced images.

## 4. Literature Review

The reviewed studies employ a diverse range of methods to address the challenges of low-light image enhancement, demonstrating innovations in GAN architectures and training paradigms.

Zero-DCE (Zero-Reference Deep Curve Estimation) is a novel zero-reference learning framework for low-light image enhancement, using a curve estimation network trained without reference images to estimate pixel-wise light adjustment curves. This method enhances image brightness and clarity, especially in scenarios where ground-truth images are unavailable. Zero-DCE uses self-supervised learning to estimate light curves, eliminating the need for paired datasets. It uses LPIPS (Learned Perceptual Image Patch Similarity) in TensorFlow and trains on SICE, LOL, and LIME datasets. The framework can be further enhanced using contrastive learning and domain adaptation strategies to improve robustness and generalizability. Integrating physics-informed approaches also enhances interpretability. (Guo et al., 2020)

EnlightenGAN is a generative adversarial network designed for light enhancement using unpaired learning to handle datasets without paired low-light and normal-light images. It employs a U-Net with attention mechanisms and a self-feature-preserving discriminator to preserve critical image features. EnlightenGAN incorporates adversarial loss and perceptual loss, improving subjective quality metrics like NIQE and user satisfaction. It uses unpaired datasets and is validated on LOL and LIME datasets. EnlightenGAN uses PyTorch and NIQE and BRISQUE to evaluate naturalness. Its application in surveillance, autonomous vehicles, and medical imaging has expanded. (Jiang et al., 2021).

The Cycle-LLIE (Cycle-Consistent GAN for Low-Light Image Enhancement) is a specialized version of CycleGAN designed for bidirectional transformations between low-light and normal-light images. It uses dual discriminators and cycle-consistent generators for reversible mappings. . It is particularly effective for surveillance systems where image quality and contextual integrity are crucial.

Cycle-LLIE uses cycle consistency loss to maintain reversible mappings, along with adversarial and identity losses for added stability. It is trained on unpaired images and tested on surveillance-specific datasets and LOL. However, it is insufficient for capturing real-world scene variability. (Kim et al., 2021)

RetinexGAN, inspired by Retinex theory, uses a dual-stream generator and multi-scale discriminators to separate images into illumination and reflectance components. This decomposition improves image visibility while preserving natural reflectance and col or balance. It also incorporates reconstruction loss and perceptual loss to enhance details, especially in low-light conditions. RetinexGAN uses LOL and SICE for training and evaluates on LIME, MEF, and NPE datasets. However, it faces limitations when applied to real-world images with unpredictable lighting variations and balancing enhancement and noise reduction. (Chen et al., 2022).

TABLE II OVERVIEW OF LOW-LIGHT IMAGE ENHANCEMENT METHODS USING GAN

| Year | Paper Title | Authors | Method | Learning Method | Network Structure | Loss Function | Dataset | Evaluation Metrics | Platform |
|---|---|---|---|---|---|---|---|---|---|
| 2018 | Deep Photo Enhancer: Unpaired Learning for Image Enhancement from Photographs with GANs | Yu-Sheng Chen, Yu-Ching Wang, et al. | Two-Way GAN with Global U-Net | Unsupervised | U-Net with global feature fusion | Wasserstein Loss, Adaptive Weighting | **MIT-Adobe 5K:** 2,250 (training source), 2,250 (target), 500 (testing) | PSNR, SSIM | PyTorch, Nvidia GTX 1080Ti |
| 2020 | Zero-DCE: Zero-Reference Deep Curve Estimation for Low-Light Image Enhancement | Guo et al. | Zero-DCE | Zero-reference learning | • Light-curve estimation network• Curve estimation modules• Non-reference architecture | • Spatial consistency loss<br>• Exposure control loss<br>• Color constancy loss<br>• Illumination smoothness loss | Training: Multiple exposure dataset, SICE<br>Testing: LOL, LIME, NPE, DICM | PSNR, SSIM, LPIPS | TensorFlow |
| 2021 | EnlightenGAN: Deep Light Enhancement without Paired Supervision | Jiang et al. | EnlightenGAN | Unpaired learning | • U-Net with attention• Self-feature preserving discriminator• Unpaired training strategy | • Adversarial loss<br>• Self-feature preserving loss<br>• Perceptual loss | Training: Unpaired low/normal light images, LOL<br>Testing: LOL, NPE, LIME, MEF | PSNR, SSIM, NIQE, User study | PyTorch |
| 2021 | Low-Light Image Enhancement for Surveillance Systems Using Cycle-Consistent GAN | Kim et al. | Cycle-LLIE | Cycle-consistent learning | • Cycle-consistent generator<br>• Dual discriminators<br>• Bidirectional enhancement | • Cycle consistency loss<br>• Adversarial loss<br>• Identity loss | Training: Unpaired low/normal light<br>Testing: Surveillance datasets, LOL | PSNR, SSIM, FID, User study | PyTorch |
| 2022 | RetinexGAN: Retinex-Based Low-Light Enhancement Using Improved GAN | Chen et al. | RetinexGAN | Retinex-based supervised learning | • Dual-stream generator<br>• Multi-scale discriminator<br>• Retinex-based decomposition | • Retinex loss<br>• Adversarial loss<br>• Reconstruction loss<br>• Perceptual loss | Training: LOL, SICE<br>Testing: LOL, LIME, MEF, NPE | PSNR, SSIM, NIQE, BRISQUE | PyTorch |
| 2022 | Efficient Lane Detection under Low-Light Conditions Using GAN | Thangarajah Akilan, Hrishikesh Vachhani, et al. | Style Transfer + YOLO | Deep Learning | GAN for enhancement + YOLO | BCE, Anchor Loss | **DIML, Caltech, KITTI:** 70% (training), 30% (testing) | F1 Score, mAP, Recall, Precision | Google Colab (NVIDIA GTX1080Ti) |
| 2023 | Low-Light Image Enhancement with Wavelet-Based GAN and Dual Discriminators | Zhang et al. | WaveletGAN | Supervised learning with wavelet decomposition | • Wavelet-based generator<br>• Dual discriminators<br>• Multi-resolution processing | • Wavelet reconstruction loss<br>• Adversarial loss<br>• Feature matching loss | Training: LOL, SICE, Dark Face<br>Testing: LOL, DICE, NPE | PSNR, SSIM, LPIPS, NIQE | PyTorch |
| 2023 | Physics-Guided Low-Light Image Enhancement Using GANs | Park et al. | Physics-GAN | Physics-guided learning | • Physics-guided generator<br>• Multi-scale discriminator<br>• Light estimation branch | • Physics consistency loss<br>• Adversarial loss<br>• Reconstruction loss | Training: Custom physics-based dataset, LOL<br>Testing: LOL, Real low-light images | PSNR, SSIM, LPIPS, Physics metrics | TensorFlow |
| 2023 | Multi-Scale Attention Generative Adversarial Network for Medical Image Enhancement | Guojin Zhong, Weiping Ding, Long Chen, Yingxu Wang, Yu-Feng Yu | MAGAN (Multi-Scale Attention GAN) | Unsupervised | Res-U-Net with attention gates and FPN | Adversarial, Cycle, Perceptual, Smoothing Loss | **CORN-2:** 340 (low-quality training), 288 (high-quality training), 60 (low-quality testing) | PSNR, SSIM, Entropy, AVG, BRISQUE, NIQE, PIQE | Ubuntu 18.04 with Nvidia RTX 3090 |
| 2023 | DEGAN: Decompose-Enhance-GAN Network for Simultaneous Low-Light Image Lightening and Denoising | Jialiang Zhang, Ruiwen Ji, Jingwen Wang, Hongcheng Sun, Mingye Ju | DEGAN | Supervised | Decom-Net, Enhance-Net, GAN | Adversarial, MSE, BCE, SSIM, Perceptual Loss | **LOL, LSRW, LIME, NPE, MEF, DICM, VV:** Combined datasets with paired and unpaired low-light images | PSNR, SSIM, NIQE, FSIM, NLIEE, MAE | PyTorch on Nvidia GTX3080Ti |
| 2023 | Enhancement of Images Under Low-Light Conditions Using Artificial Intelligence | Mazhara Marzook, Madhawa Herath, et al. | Autoencoder and GAN comparison | Supervised | CNN Encoder-Decoder | MSE | **LOL:** 450 pairs (training), 50 pairs (testing); Custom DSLR data: 30 pairs (training/testing unspecified) | SSIM, PSNR | Google Colab |
| 2023 | Unleashing the Power of GANs: A Novel Machine Learning Approach for Vehicle Detection and Localization in the Dark | Md Saif Hassan Onim, Hussain Nyeem, et al. | Pix2PixGAN + CycleGAN | Supervised, Unsupervised | CycleGAN, U-Net | L1 Loss, Adversarial Loss | **PKUdata, Stanford-Cars, Caltech-Cars:** Combined 80% (training), 20% (testing) | IoU, Detection Accuracy | TensorFlow on Nvidia RTX 2080Ti |
| 2024 | Low-Resolution Image Enhancement using Generative Adversarial Networks | Melvin Ajuluchukwu, Atef Shalan, et al. | SRGAN | Supervised | Residual learning, up-sampling, CNN | Binary Cross-Entropy, Perceptual Loss | **Kaggle dataset:** 500 images preprocessed to 256x256 pixels (training/testing split not specified) | PSNR, SSIM | Google Colab (TensorFlow) |
| 2024 | Modified Perceptual Cycle Generative Adversarial Network-Based Image Enhancement for Improving Accuracy of Low-Light Image Segmentation | S.W. Cho, N.R. Baek, et al. | Modified Perceptual CycleGAN | Supervised | CycleGAN with PSPNet | L1 Loss, Cycle Consistency, Perceptual | **CamVid:** 351 (training), 350 (testing); **KITTI:** 222 (training), 223 (testing) | PSNR, SSIM, IOU, Pixel Acc | TensorFlow, Nvidia GTX 1080 |
| 2024 | LEGAN: A Low-Light Image Enhancement Generative Adversarial Network for Industrial Internet of Smart Cameras | Jing Tao, Junliang Wang, et al. | LEGAN | Supervised | Dual-channel encoder-decoder with Harr Wavelet | Adversarial, MSE, VGG Loss | **Industrial Dataset:** 900 images (training), 100 images (testing) | PSNR, SSIM, NIQE, Detail Recovery Metrics | TensorFlow on Nvidia RTX 3060 |

Acknowledgment (Heading 5)

WaveletGAN is a multi-resolution image processing algorithm that uses wavelet decomposition and dual discriminators to enhance global and local image features. It uses wavelet reconstruction loss, adversarial loss, and feature matching loss to achieve fine-grained enhancements, especially for high-frequency image details. WaveletGAN uses LOL, SICE, and Dark Face datasets for training and validation, employing LPIPS to gauge perceptual similarity. It uses PyTorch for processing high-noise environments. (Zhang et al., 2023).

Physics-Guided GAN (Physics-GAN) is a physics-based generator that uses domain-specific knowledge of light behavior to enhance images. It uses multi-scale discriminators and a light estimation branch to align the output with physical models of light and reflectance. This method is useful in scientific and engineering applications where theoretical accuracy is crucial. It incorporates physics-guided learning and self-supervised learning to improve enhancement accuracy. Physics-GAN uses a custom physics-based dataset and LPIPS to gauge perceptual similarity. It shows promise for domain-specific tasks but relies heavily on physics-based assumptions' accuracy. Future research could explore hybrid frameworks combining data-driven methods with theoretical principles. (Park et al., 2023)

The DEGAN (Decompose-Enhance GAN) framework, developed by Zhang et al., combines two sub-networks, Decom-Net and Enhance-Net, to enhance light and reduce noise simultaneously. It uses adversarial, MSE, SSIM, and perceptual losses to improve visibility and denoising. DEGAN is versatile, processing both paired and unpaired datasets, making it ideal for industrial and smart camera applications. However, achieving the optimal balance remains a challenge. (Zhang et al., 2023).

LEGAN (Low-Light Image Enhancement GAN) is a dual-channel encoder-decoder architecture designed for industrial imaging systems, specifically smart camera systems. It combines MSE loss, VGG loss, and adversarial loss to enhance brightness and reduce noise. The architecture is implemented in TensorFlow and uses a custom dataset of 900 low-light images for training and 100 for testing. The architecture uses VGG-based perceptual metrics to evaluate structural integrity in high-resolution outputs. However, broader adoption requires diverse, large-scale datasets. (Tao et al., 2024)

Super-Resolution GAN (SRGAN) is a deep learning model used for super-resolution tasks, generating high-quality images from low-resolution inputs. It uses residual learning and up-sampling layers to preserve natural textures and details. SRGAN is commonly used in applications like medical imaging and satellite imagery, and can be optimized for constrained environments using techniques like neural architecture search and model pruning. (Ajuluchukwu et al., 2024).

The Modified Perceptual CycleGAN (Cho and Baek, 2024) integrates perceptual loss and segmentation networks like PSPNet, enhancing image quality and segmentation accuracy. This makes it suitable for low-light urban scene analysis, combining enhancement and segmentation tasks. (Cho and Baek, 2024)

Pix2PixGAN + CycleGAN is a hybrid approach that combines paired learning from Pix2PixGAN with unpaired learning from CycleGAN, making it effective for tasks like vehicle detection and localization in low-light traffic scenarios. This approach leverages L1 loss and adversarial loss to ensure contextual integrity and visual realism. It combines

PKUdata, Stanford-Cars, and Caltech-Cars for vehicle detection and enhancement tasks, enhancing adaptability and reducing computational resources for real-time applications on resource-constrained devices. (Hassan Onim et al., 2023).

Deep Photo Enhancer uses a two-way GAN architecture and global U-Net-based feature fusion to improve photographic images in unpaired settings. It balances local and global features using Wasserstein loss and adaptive weighting. The model uses MIT-Adobe 5K for training and testing, but requires significant computational resources, making it limited for real-time applications. (Chen et al., 2018)

MAGAN, a multi-scale attention learning technique, enhances performance in high-dimensional tasks like medical imaging by focusing on relevant features across multiple scales. (Zhong et al., 2023).

Efficient Lane Detection using GAN combines style transfer with YOLO for robust low-light lane detection. It uses binary cross-entropy and anchor loss, using DIML, Caltech, and KITTI datasets. F1 score, recall, and precision are critical. However, generalization struggles under diverse conditions. Techniques like neural architecture search and model pruning could improve performance. (Akilan et al., 2022)

Marzook et al. (Marzook Onim et al., 2023), highlight the need for perceptual metrics that align with human visual preferences in user studies. They suggest using novel evaluation methods to ensure better acceptance and usability of enhanced images. Google Colab is used for image enhancement under low-light conditions, demonstrating the accessibility of cloud-based platforms for experimentation.

Domain-specific applications like medical imaging, surveillance, and autonomous driving require low-light enhancement methods that can be complex. Multi-Scale Attention GAN, for example, targets medical images, allowing models to focus on essential features. Expanding these mechanisms to dynamically adapt enhancement strategies based on scene context could significantly improve real-world performance. (Zhong, Ming et al., 2023)

The review of low-light image enhancement studies focuses on various learning methods, including supervised and unsupervised techniques, loss functions, datasets, evaluation metrics, and platforms. Challenges include diverse illumination conditions, noise amplifying, data limitations, and computational complexity. Future directions include advancing self-supervised and unsupervised learning, multi-task learning, large-scale real-world datasets, crowd-sourced datasets, context-aware and attention-based models, lightweight and energy-efficient architectures, user-centric evaluations, and perceptual metrics. The focus should also be on improving cross-domain generalization, allowing models to perform effectively across multiple applications without retraining. Techniques like transfer learning and meta-learning could further enhance the versatility of low-light image enhancement models, enabling their application in various fields.

## 5. Conclusions

The advancements in low-light image enhancement through GAN-based approaches represent a significant leap in image processing capabilities, addressing longstanding challenges of illumination inconsistencies, noise amplification, and structural degradation. Furthermore, the adoption of advanced datasets, innovative loss functions, and hybrid frameworks has expanded the applicability of these methods to diverse fields, including surveillance, autonomous vehicles, and medical imaging.

However, persistent challenges such as the high computational demands of GAN training, the need for scalable and diverse datasets, and limited generalizability across domains highlight the ongoing gaps in this field. Future research must focus on developing lightweight architectures, enhancing cross-domain learning capabilities, and incorporating human-centric evaluation metrics to improve real-world applicability. By addressing these challenges, low-light image enhancement can further evolve to meet the demands of emerging technologies and practical applications. This review underscores the transformative potential of GAN-based methods while paving the way for innovative solutions to the remaining challenges in this dynamic area of research.

## References

1. Creswell, T., White, V., Dumoulin, K., Arulkumaran, B., Sengupta, B., & Bharath, A. A. (2018). Generative adversarial networks: An overview. IEEE Signal Processing Magazine, 35(1), 53–65. https://doi.org/10.1109/MSP.2017.2765202
2. Ajuluchukwu, M., Shalan, A., & Ibrahim, S. D. (2024). Low-resolution image enhancement using generative adversarial networks. Journal of Visual Communication and Image Representation, 91, 103099.
3. Akilan, T., Vachhani, H., & Sastry, P. S. (2022). Efficient lane detection under low-light conditions using GAN. IEEE Transactions on Intelligent Transportation Systems, 23(9), 15312–15321.
4. Bertalmío, M., Caselles, V., & Provenzi, E. (2009). Issues about Retinex theory and contrast enhancement. International Journal of Computer Vision, 83(1), 101–119. https://doi.org/10.1007/s11263-009-0221-5
5. Cai, Y., & Kintak, U. (2019). Low-light image enhancement based on modified U-Net. 2019 International Conference on Wavelet Analysis and Pattern Recognition (ICWAPR), IEEE.
6. Cepeda-Negrete, J., & Sanchez-Yanez, R. E. (2015). Automatic selection of color constancy algorithms for dark image enhancement by fuzzy rule-based reasoning. Applied Soft Computing, 28, 1–10.
7. Chang, H., Ng, M. K., & Wang, W. (2015). Retinex image enhancement via a learned dictionary. Optical Engineering, 54(1), 013107.
8. Chen, L., Zhao, L., Zhong, T., & Wu, C. (2022). RetinexGAN: Retinex-based low-light enhancement using improved GAN. Applied Optics, 61(6), 1334–1344.
9. Chen, Y. S., Wang, Y. C., Kao, M. H., & Chuang, Y. Y. (2018). Deep photo enhancer: Unpaired learning for image enhancement from photographs with GANs. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR).
10. Cho, S. W., & Baek, N. R. (2024). Modified perceptual cycle generative adversarial network-based image enhancement for improving accuracy of low-light image segmentation. Image and Vision Computing, 122, 104513.
11. Cotogni, M., & Cusano, C. (2023). TreEnhance: A tree search method for low-light image enhancement. Pattern Recognition, 136, 109249.
12. Fotiadou, K., Tsagkatakis, G., & Tsakalides, P. (2014). Low-light image enhancement via sparse representations. Image Analysis and Recognition: 11th International Conference, ICIAR 2014. Springer.
13. Fu, H., Ma, H., & Wu, S. (2012). Night removal by color estimation and sparse representation. Proceedings of the 21st International Conference on Pattern Recognition (ICPR2012), IEEE.
14. Fu, X. Y., Zeng, D. L., Huang, Y., et al. (2016). A weighted variational model for simultaneous reflectance and illumination estimation. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Seattle, WA.
15. Guo, C., Li, C., Guo, J., Loy, C. C., & Hou, J. (2020). Zero-DCE: Zero-reference deep curve estimation for low-light image enhancement. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern

Recognition (CVPR).
16. Haris, M., Yusoff, Y., & Zain, A. M. (2024). Breaking down multi-view clustering: A comprehensive review of multi-view approaches for complex data structures. Engineering Applications of Artificial Intelligence, 132, 107857.
17. Hassan Onim, M. S., Nyeem, H., & Sarker, I. H. (2023). Unleashing the power of GANs: A novel machine learning approach for vehicle detection and localization in the dark. Cognitive Computation and Systems, 5(2), 122–137.
18. Hussain, S. F., & Haris, M. (2019). A k-means based co-clustering (kCC) algorithm for sparse, high-dimensional data. Expert Systems with Applications, 118, 20–34.
19. Jiang, Y. F., Gong, X. Y., Liu, D., et al. (2021). EnlightenGAN: Deep light enhancement without paired supervision. IEEE Transactions on Image Processing, 30, 2340–2349. https://doi.org/10.1109/TIP.2021.3051462
20. Jiang, Y., Wang, Z., Ren, S., Chen, C., Jin, X., & Yan, S. (2021). EnlightenGAN: Deep light enhancement without paired supervision. Pattern Recognition, 117, 107012.
21. Kim, Y., Choi, J., Yoon, J., & Kim, S. (2021). Low-light image enhancement for surveillance systems using cycle-consistent GAN. Sensors, 21(5), 1784.
22. Li, J., Feng, X., & Hua, Z. (2021). Low-light image enhancement via progressive-recursive network. IEEE Transactions on Circuits and Systems for Video Technology, 31(11), 4227–4240.
23. Loh, Y. P., Liang, X., & Chan, C. S. (2019). Low-light image enhancement using Gaussian process for features retrieval. Signal Processing: Image Communication, 74, 175–190.
24. Marzook, M., Herath, M., & Weerakoon, B. (2023). Enhancement of images under low-light conditions using artificial intelligence. Multimedia Tools and Applications, 82, 2587–2605.
25. Park, J., Lee, J. Y., Yoo, D., et al. (2018). Distort-and-recover: Color enhancement using deep reinforcement learning.
26. Park, S., Kim, S. H., Lee, D. G., & Jung, Y. M. (2023). Physics-guided low-light image enhancement using GANs. IEEE Transactions on Computational Imaging, 9, 547–559.
27. Ren, X. T., Yang, W. H., Cheng, W. H., et al. (2020). LR3M: Robust low-light enhancement via low-rank regularized Retinex model. IEEE Transactions on Image Processing, 29, 5862–5876. https://doi.org/10.1109/TIP.2020.2984098
28. Tao, J., Wang, J., & Li, X. (2024). LEGAN: A low-light image enhancement generative adversarial network for smart cameras. IEEE Access, 12, 15203–15215.
29. Yang, Q., Wu, Y., Cao, D., et al. (2021). A low-light image enhancement method learning from both paired and unpaired data by adversarial training. Neurocomputing, 433, 83–95.
30. Zhang, J., Goh, E. S., & Sunar, M. S. (2024). Low-light image enhancement: A comprehensive review on methods, datasets, and evaluation metrics. Journal of King Saud University - Computer and Information Sciences, 36, 102234. https://doi.org/10.1016/j.jksuci.2024.102234
31. Zhang, J., Ji, R., Wang, J., Sun, H., & Ju, M. (2023). DEGAN: Decompose-enhance-GAN network for simultaneous low-light image lightening and denoising. Pattern Recognition Letters, 172, 123–130.
32. Zhang, M., Du, X., & Zhang, J. (2023). Low-light image enhancement with wavelet-based GAN and dual discriminators. IEEE Transactions on Multimedia, 25, 401–413.
33. Zhang, Y., Zhang, J., & Guo, X. (2019). Kindling the darkness: A practical low-light image enhancer. Proceedings of the 27th ACM International Conference on Multimedia.
34. Zhong, G., Ding, W., Chen, L., Wang, Y., & Yu, Y. F. (2023). Multi-scale attention generative adversarial network for medical image enhancement. Computers in Biology and Medicine, 152, 106487.