

Deep Learning-Based Low-Light Image Enhancement: A Review

Pengyun Shi*

School of Software, Henan Polytechnic University, Jiaozuo, 454000, Henan, PR China.

* Corresponding author: Pengyun Shi

Abstract: With the rapid development of deep learning in the field of computer vision, low-light image enhancement (LLIE) has shifted from traditional handcrafted prior-based methods to data-driven learning paradigms. Deep models can automatically learn the complex non-linear mapping between low-light and normal-exposure images through end-to-end training, showing remarkable advantages in brightness improvement, detail restoration, and noise suppression. According to the dependence on labeled data and the form of supervision signals during training, existing deep learning-based LLIE methods are mainly divided into five categories: supervised, reinforcement, unsupervised, zero-shot, and semi-supervised learning. Among them, supervised learning is the most mature and mainstream technical route, which has evolved from convolutional neural networks and Retinex decomposition to Transformer and state-space models (e.g., Mamba), achieving accurate recovery of illumination, texture, and color with stable performance. Reinforcement learning formulates LLIE as a sequential decision-making problem but is still in the exploratory stage due to low learning efficiency and high sensitivity to reward function design. Unsupervised and zero-shot learning methods solve the problem of difficult data annotation in real scenarios by designing unpaired, no-reference, or self-supervised mechanisms, respectively. Semi-supervised learning balances data acquisition cost and enhancement performance by combining a small amount of labeled data with a large number of unlabeled data. This paper summarizes the core principles, representative works, advantages, and existing challenges of various methods, pointing out that supervised learning dominates LLIE due to its stability and precision, while other methods provide effective supplements in data-scarce or complex scenarios. Future research should focus on improving the adaptability of models to different signal-to-noise ratio regions and balancing global illumination consistency and high-frequency detail preservation.

Keywords: Low-light image; Image enhancement; Deep learning; Supervised Learning; Unsupervised Learning;

1. Introduction

Low-Light Image Enhancement (LLIE) is an important research direction in the field of computer vision, mainly addressing problems such as insufficient brightness, blurred details, and obvious noise of images in low-light environments. Its technological development directly promotes the improvement of visual quality in many practical application scenarios, including intelligent monitoring, autonomous driving, medical imaging, and mine monitoring. With the rapid penetration of deep learning technology in the field of computer vision, LLIE technology has completed the transformation from traditional handcrafted prior-dependent methods to data-driven learning paradigms. Through end-to-end training, deep models can automatically explore the complex non-linear mapping between low-light images and normal-exposure images, showing incomparable advantages over traditional methods in brightness improvement, detail restoration, and noise suppression.

According to the differences in the degree of dependence on labeled data and the form of supervision signals during training, existing deep learning-based LLIE methods are mainly divided into five categories: supervised learning, reinforcement learning, unsupervised learning, zero-shot learning, and semi-supervised learning. Among them, supervised learning, as the most mature and mainstream technical route, has experienced iterative evolution from convolutional neural networks and Retinex decomposition to Transformer architecture and Mamba state-space model, which can achieve accurate recovery of illumination, texture, and color with stable performance and easy optimization;

reinforcement learning formulates the image enhancement process as a sequential decision-making problem, learning enhancement strategies through the interaction between the agent and the environment, but it is still in the exploratory stage, limited by learning efficiency and reward function design; unsupervised learning and zero-shot learning do not rely on paired labeled data, and effectively solve the pain point of difficult acquisition of labeled data in real scenarios through unpaired constraints, zero-reference mechanisms, or self-supervised strategies respectively; semi-supervised learning combines a small amount of labeled data with a large number of unlabeled data, balancing enhancement performance while reducing data acquisition costs, and has become an important research direction with both practicality and generalization ability.

Focusing on various deep learning-based LLIE methods, this paper systematically sorts out their core principles, representative research achievements, technical advantages, and existing challenges, clarifies the dominant position of supervised learning in this field, as well as the supplementary role of the other four types of methods in special scenarios such as scarce data and complex scenes. It also points out that future research needs to focus on breaking through the adaptability of models to different signal-to-noise ratio regions, balancing global illumination consistency and high-frequency detail protection, so as to provide reference for the further optimization and practical application of LLIE technology. In summary, the main contributions of this paper are as follows: first, this paper systematically classifies and combs the existing deep learning-based LLIE methods, clarifies the evolution context, core principles and technical

characteristics of five major categories of methods (supervised, reinforcement, unsupervised, zero-shot and semi-supervised learning), and establishes a clear framework for the research field of low-light image enhancement; second, it summarizes the representative research works and technical bottlenecks of each type of method, especially focusing on the iterative evolution of supervised learning from convolutional neural networks to Transformer and Mamba models, and objectively evaluates the advantages and application scenarios of various methods, providing a comprehensive reference for subsequent researchers; third, based on the analysis of existing challenges, this paper points out the key directions of future research on LLIE, which helps to guide the follow-up optimization of models and the expansion of practical applications, and promotes the further development of low-light image enhancement technology.

2. Overview of low-light image enhancement methods

With the wide application of deep learning in computer vision, low-light image enhancement has gradually shifted from traditional methods relying on handcrafted priors to data-driven learning paradigms. Through end-to-end training, deep models can automatically learn the complex non-linear mapping between low-light images and normal-exposure images, showing significant advantages in brightness improvement, detail restoration, and noise suppression. According to whether labeled data is used and the form of supervision signals during training, existing deep learning-based low-light image enhancement methods can be mainly categorized into supervised learning, reinforcement learning,

unsupervised learning, zero-shot learning, and semi-supervised learning.

To clearly present the differences among the five categories of methods, Figure 1 illustrates the evolution process of deep learning-based low-light image enhancement methods, intuitively showing the transition from traditional handcrafted prior-based methods to data-driven paradigms and the iterative development of the five categories of methods. Meanwhile, Table 1 provides a detailed comparison of these five categories of methods, covering four key aspects: training data requirements (the type and quantity of data needed for model training), representative approaches (typical models and algorithms of each category), advantages (core strengths in low-light image enhancement), and limitations (existing bottlenecks and deficiencies). This figure and table together enable a concise and intuitive understanding of the characteristics and evolution of each method, laying a foundation for the subsequent detailed introduction of each category.

2.1. Supervised Learning-Based Methods

Supervised learning-based low-light image enhancement represents the most mature technical route in current research. Such methods rely on paired low-light and normal-exposure images to construct pixel-level or feature-level supervision signals, guiding the network to learn the mapping from the low-light domain to the normal-light domain. Due to clear training objectives and stable optimization, supervised methods generally achieve promising performance in brightness recovery, structure preservation, and color consistency, becoming one of the mainstream directions in low-light image enhancement.

Table 1. Comparison of different deep learning-based low-light image enhancement methods, including training data requirements, representative approaches, advantages, and limitations.

Method Type	Training Data Requirement	Representative Methods	Advantages	Limitations
Supervised Learning	Paired low-light and normal-light images	LLNet, KinD, Restormer, LLFormer, Retinexformer, MambaLLIE	High enhancement quality, stable training, accurate illumination recovery	Requires large paired datasets
Reinforcement Learning	No paired data required	ReLLIE	Adaptive enhancement strategy, interpretable operations	Low training efficiency, sensitive to reward design
Unsupervised Learning	Unpaired datasets	EnlightenGAN, LightenDiffusion	Avoids expensive annotation, good generalization	Training instability, limited structural fidelity
Zero-Shot Learning	No training pairs or labels	Zero-DCE, Zero-DCE++, WZD	No dataset dependence, fast deployment	Limited performance in complex scenes
Semi-Supervised Learning	Few paired + many unlabeled images	DRBN, Mean-Teacher framework	Balances performance and data cost	Training complexity, pseudo-label reliability issues

Early supervised methods mainly built end-to-end enhancement models based on convolutional neural networks (CNNs), gradually restoring brightness and details through multi-layer convolutions. The pioneering LLNet [1] model achieved image contrast enhancement and noise suppression via deeply stacked sparse denoising autoencoders, laying the foundation for deep learning-based low-light image enhancement (LLIE). Although these methods improve overall visibility to a certain extent, the local receptive field of convolutions limits their ability to model complex illumination distributions and long-range illumination dependencies.

With further research, scholars have recognized the physical differences between illumination and details in low-

light images and begun to introduce imaging priors to constrain network structures. Against this background, Retinex theory-based supervised methods have attracted extensive attention. Chen et al. [2] constructed a model including Decom-Net and Enhance-Net modules, improving the clarity of low-light images through decomposition, adjustment, and reconstruction. The KinD [3] method explicitly decomposes an image into illumination and reflectance components via the network and models them separately, effectively preserving texture and color consistency while boosting brightness. Its improved version, KinD++ [4], further reduces visual degradation artifacts. Bai et al. [5] proposed the DRWKV model, combining global edge Retinex theory with an improved WKV attention

mechanism, which effectively preserves edges and fine structures while enhancing realistic brightness and color rendition in low-light images.

In recent years, Transformer architectures have been introduced into low-light image enhancement to improve global modeling capability. Xu et al. [6] proposed SNR-Net, a signal-to-noise ratio (SNR)-aware low-light image enhancement network, which adopts SNR-aware feature weighting and hierarchical enhancement to alleviate detail blurring and excessive noise amplification caused by SNR imbalance in low-light scenes. Zamir et al. [7] presented Restormer, an efficient Transformer for high-resolution image restoration, which uses a lightweight Transformer with multi-head window attention and gating feedback mechanisms to address high computational complexity, large memory consumption, and the difficulty of balancing accuracy and efficiency when traditional Transformers process high-resolution images. Wang et al. [8] proposed LLFormer, a Transformer for ultra-high-definition low-light image enhancement, along with a matching UHD low-light benchmark dataset. It uses axial multi-head self-attention and cross-layer feature fusion to improve the efficiency of long-range dependency modeling and the sufficiency of local texture recovery in ultra-high-definition tasks. Cai et al. [10] proposed Retinexformer, a single-stage Retinex-based low-light enhancement Transformer, which deeply integrates Retinex illumination-reflectance decomposition with Transformer self-attention, solving problems such as incomplete decoupling of illumination and reflectance, color distortion, and uneven brightness caused by multi-stage processing in conventional Retinex-based methods. Despite the advantages of Transformers in global modeling, their computational complexity grows quadratically with image resolution, leading to efficiency bottlenecks in high-resolution or real-time applications.

To improve efficiency while maintaining modeling power, state-space models (SSMs) have been gradually introduced into supervised low-light image enhancement. The Mamba model, with linear complexity and strong long-range dependency modeling, provides a new solution for efficient global illumination modeling. Li et al. [10] proposed MambaLLIE, the first attempt to apply the Mamba state-space model to low-light image enhancement, which strengthens modeling of global illumination variations via sequence modeling and improves brightness consistency while maintaining efficiency. Bai et al. [11] proposed RetinexMamba, combining Retinex decomposition with Mamba to model the illumination component in a long-range manner, thereby improving brightness recovery under complex lighting. Wang et al. [12] presented ResVMUNetX, which uses an error regression mechanism and a DenoiseCNN module to effectively enhance brightness and detail restoration while suppressing noise artifacts. Zou et al. proposed Wave-Mamba [13], which integrates wavelet transform into the architecture to refine feature matching and calibration by enhancing low-frequency information, avoiding texture distortion and information loss while achieving superior performance and efficiency in illumination enhancement and denoising.

These methods further demonstrate the clear advantages of Mamba in global illumination modeling. However, existing Mamba-based supervised methods mostly focus on overall illumination distribution modeling, with limited attention to SNR variations across regions and the vulnerability of high-

frequency details to noise interference during enhancement. Furthermore, several works fuse Mamba and Transformer architectures. For instance, Deng et al. [14] proposed CodeMTNet, which integrates a Mamba-Transformer structure and codebook knowledge to solve multi-dimensional degradation, feature domain mismatch, and codebook retrieval structure loss in low-light image enhancement.

Overall, supervised low-light image enhancement methods have evolved from CNNs and Retinex decomposition to Transformers and state-space models. Although recent Mamba-based methods show remarkable advantages in global modeling efficiency, further research is needed to improve their adaptability to regions with different SNRs and effectively constrain high-frequency details while ensuring illumination consistency.



Figure 1. Timeline of deep learning-based low-light image enhancement methods evolution

2.2. Reinforcement Learning-Based Methods

Unlike supervised methods that rely on paired data for direct mapping, reinforcement learning (RL)-based methods formulate image enhancement as a sequential decision-making problem, where an agent gradually learns an enhancement policy through interaction with the environment. Such methods usually do not directly predict the enhanced result but optimize visual quality by learning a sequence of image adjustment operations (e.g., brightness, contrast, or curve parameter tuning).

However, compared with the widespread use of supervised learning in low-light enhancement, RL-based methods are still in the exploratory stage with limited related studies, mostly focusing on parameter-level or strategy-level adjustment.

One early representative work is by Park et al. [15], who modeled image color enhancement as a Markov decision process and introduced deep reinforcement learning to learn a series of interpretable global color adjustment operations, gradually optimizing the image color distribution. Nevertheless, this method mainly targets overall color and style restoration without specific consideration of local brightness recovery, noise suppression, and detail enhancement in low-light scenes. Zhang et al. [16] proposed ReLLIE, which uses deep reinforcement learning to enable the agent to adaptively adjust brightness and contrast according to local image features, achieving customized low-light image enhancement.

In low-light image enhancement, RL can alleviate the difficulty of unifying enhancement policies across different scenes to a certain extent. However, it suffers from low learning efficiency in high-dimensional pixel spaces and high sensitivity to reward function and action space design, making its performance and stability still inferior to mature supervised methods in practical applications. Therefore, reinforcement learning currently serves more as an auxiliary or exploratory technique rather than a systematic or

mainstream solution.

2.3. Unsupervised Learning-Based Methods

Unsupervised learning-based low-light image enhancement methods learn strategies for improving brightness, contrast, and details without paired low-light/normal-light supervision by designing unpaired or no-reference loss functions, representing an important direction to address the difficulty of data annotation in real-world scenarios.

Jiang et al. [17] proposed EnlightenGAN, an unsupervised low-light enhancement method that achieves brightness and contrast improvement without paired training data via generative adversarial network (GAN) design and customized constraints. Ni et al. [18] introduced a cyclic interactive GAN framework that establishes an unsupervised mapping between enhancement and degradation, maintaining detail and brightness consistency across various low-light scenarios. Jiang et al. [19] proposed LightenDiffusion, which combines latent-space Retinex decomposition with diffusion models for unsupervised enhancement, improving visual quality under complex illumination. Lin et al. [20] proposed AGLLDiff, an attribute-guided training-free diffusion model for low-light enhancement, which explicitly constrains the exposure, structure, and color attributes of normal-light images to guide the diffusion process for real-scene low-light enhancement without paired data, showing strong robustness under complex degradations. Wei et al. [21] proposed a two-stage method that decouples illumination and reflectance via regularized Retinex variational game decomposition and achieves balanced enhancement of non-uniform low-light images using dual-layer adaptive vector gamma correction.

2.4. Zero-Shot Learning-Based Methods

Zero-shot learning-based methods perform brightness improvement and detail restoration without any paired low-light/normal-exposure supervision by designing self-supervised, prior-constrained, or generative mechanisms. Guo et al. [22] first proposed Zero-DCE, a zero-reference deep curve estimation method that reformulates low-light enhancement as predicting high-order mapping curves for specific pixels via a deep network and gradually adjusting pixel values to achieve enhancement without any paired labels. Subsequently, Li et al. [23] proposed Zero-DCE++, an accelerated and lightweight version of Zero-DCE, further improving efficiency and real-time performance while maintaining favorable enhancement quality. To address uneven exposure and detail loss in low-light images, Pan et al. [24] proposed a zero-reference generative exposure correction and adaptive fusion method. Based on Retinex theory, it introduces an intensity compensation prior to jointly model under- and over-exposed regions and achieves balanced brightness and natural recovery of details and colors without external training data via adaptive exposure fusion. On this basis, Peng et al. [25] proposed the Wavelet-Guided Zero-Reference Diffusion (WZD) framework, which combines pre-trained diffusion model priors with discrete wavelet multi-scale decomposition to collaboratively optimize illumination recovery, detail preservation, and noise suppression under zero-reference conditions, achieving superior performance on multiple public datasets.

2.5. Semi-Supervised Learning-Based Methods

Semi-supervised learning achieves a favorable balance

between data acquisition cost and enhancement performance by jointly using a small amount of paired labeled data and a large number of unlabeled or unpaired images, gradually becoming an important research direction in low-light image enhancement. Yang et al. [26] first proposed a semi-supervised low-light enhancement framework, constructing the Deep Recursive Band Network (DRBN). In the first stage, signal fidelity recovery is performed using paired low-light/normal-light images; in the second stage, unpaired high-quality images are introduced to further optimize visual quality through perception-driven adversarial learning, achieving collaborative optimization of structural detail reconstruction and perceptual quality. Later, Yang et al. [27] further developed the band representation modeling idea in a journal extension, enhancing the balance between structure recovery and perceptual consistency via more systematic band recursive learning and recombination.

In recent years, semi-supervised low-light enhancement has gradually adopted more stable training strategies. Jiang et al. [28] proposed a quality-oriented pseudo-label generation mechanism based on the Mean-Teacher framework combined with contrastive regularization. High-quality pseudo-labels selected via no-reference image quality assessment guide the student network, effectively improving stability, detail recovery, and color consistency in real and synthetic complex low-light scenarios. Overall, semi-supervised methods alleviate annotation dependence while balancing effectiveness and generalization by fusing signal fidelity constraints and perceptual quality modeling, providing a practically promising research path for low-light image enhancement.

Deep learning-based low-light image enhancement methods exhibit significant advantages in brightness improvement, detail restoration, and noise suppression, among which supervised learning is the dominant research and application paradigm. Supervised methods construct pixel-level or feature-level constraints from paired low-light/normal-light images to achieve accurate recovery of illumination, texture, and color with stable performance and easy optimization. In contrast, reinforcement learning models enhance as sequential decision-making for adaptive exposure and contrast adjustment, mainly focusing on local policy optimization. Unsupervised methods enable brightness and detail enhancement without labeled data using unpaired or zero-reference constraints. Zero-shot learning accomplishes enhancement via deep curve estimation or generative self-supervision. Semi-supervised methods combine limited labels with abundant unpaired data to improve generalization via pseudo-labeling or contrastive learning. In summary, supervised learning dominates low-light enhancement due to its stability and precision, while other methods provide effective supplements in data-scarce or complex scenarios.

3. Conclusion

This paper reviews deep learning-based low-light image enhancement (LLIE) methods. LLIE has shifted from handcrafted prior-based methods to data-driven paradigms, with deep models effectively addressing low-light image defects. Existing LLIE methods are divided into five categories: supervised learning (mainstream, evolved to Transformer/Mamba models), reinforcement learning (exploratory), unsupervised/zero-shot learning (solving annotation difficulties), and semi-supervised learning

(balancing cost and performance). Key challenges include improving model adaptability to different SNR regions and balancing illumination consistency with detail preservation. Future research focuses on model optimization, and this paper provides a reference for subsequent studies.

References

- [1] Lore K G, Akintayo A, Sarkar S. LLNet: A deep autoencoder approach to natural low-light image enhancement[J]. *Pattern Recognition*, 2017, 61: 650-662.
- [2] Wei C, Wang W, Yang W, et al. Deep retinex decomposition for low-light enhancement[J]. *arXiv preprint arXiv:1808.04560*, 2018.
- [3] Kind Zhang Y, Zhang J, Guo X. Kindling the darkness: A practical low-light image enhancer[C]//*Proceedings of the 27th ACM international conference on multimedia*. 2019: 1632-1640.
- [4] Zhang Y, Guo X, Ma J, et al. Beyond brightening low-light images[J]. *International Journal of Computer Vision*, 2021, 129: 1013-1037.
- [5] Bai X, Wang Y, Hu B, et al. DRWKV: Focusing on Object Edges for Low-Light Image Enhancement[C]//*Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*. 2026: 1554-1564.
- [6] Xu X, Wang R, Fu C W, et al. Snr-aware low-light image enhancement[C]//*Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2022: 17714-17724.
- [7] Zamir S W, Arora A, Khan S, et al. Restormer: Efficient transformer for high-resolution image restoration[C]//*Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2022: 5728-5739.
- [8] Wang T, Zhang K, Shen T, et al. Ultra-high-definition low-light image enhancement: A benchmark and transformer-based method[C]//*Proceedings of the AAAI conference on artificial intelligence*. 2023, 37(3): 2654-2662.
- [9] Cai Y, Bian H, Lin J, et al. Retinexformer: One-stage retinex-based transformer for low-light image enhancement[C]//*Proceedings of the IEEE/CVF international conference on computer vision*. 2023: 12504-12513.
- [10] Weng J, Yan Z, Tai Y, et al. Mamballie: Implicit retinex-aware low light enhancement with global-then-local state space[J]. *arXiv preprint arXiv:2405.16105*, 2024.
- [11] Bai J, Yin Y, He Q, et al. Retinexmamba: Retinex-based mamba for low-light image enhancement[C]//*International conference on neural information processing*. Singapore: Springer Nature Singapore, 2024: 427-442.
- [12] Wang S, Tao Q, Tang Z. RESVMUNetX: A Low-Light Enhancement Network Based on VMamba[J]. *arXiv e-prints*, 2024: arXiv: 2407.09553.
- [13] Zou W, Gao H, Yang W, et al. Wave-mamba: Wavelet state space model for ultra-high-definition low-light image enhancement[C]//*Proceedings of the 32nd ACM International Conference on Multimedia*. 2024: 1534-1543.
- [14] Deng R, Jiang A, Peng L, et al. Codebook Knowledge with Mamba-Transformer For Low-Light Image Enhancement[C]//*Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*. 2026: 3720-3729.
- [15] Park J, Lee J Y, Yoo D, et al. Distort-and-recover: Color enhancement using deep reinforcement learning[C]//*Proceedings of the IEEE conference on computer vision and pattern recognition*. 2018: 5928-5936.
- [16] Zhang R, Guo L, Huang S, et al. Rellie: Deep reinforcement learning for customized low-light image enhancement[C]//*Proceedings of the 29th ACM international*
- [17] Jiang Y, Gong X, Liu D, et al. Enlightengan: Deep light enhancement without paired supervision[J]. *IEEE transactions on image processing*, 2021, 30: 2340-2349.
- [18] Ni Z, Yang W, Wang H, et al. Cycle-interactive generative adversarial network for robust unsupervised low-light enhancement[C]//*Proceedings of the 30th ACM International Conference on Multimedia*. 2022: 1484-1492.
- [19] Jiang H, Luo A, Liu X, et al. Lightendiffusion: Unsupervised low-light image enhancement with latent-retinex diffusion models[C]//*European Conference on Computer Vision*. Cham: Springer Nature Switzerland, 2024: 161-179.
- [20] Lin Y, Ye T, Chen S, et al. Aglldiff: Guiding diffusion models towards unsupervised training-free Real-world low-light image enhancement[C]//*Proceedings of the AAAI Conference on Artificial Intelligence*. 2025, 39(5): 5307-5315.
- [21] Wei W, Feng X, Song W, et al. Nonuniform low-light image enhancement based on game-retinex variational and adaptive vector-valued gamma correction[J]. *Information Sciences*, 2026: 123063.
- [22] Chunle Guo, Chongyi Li, Jichang Guo, Chen Change Loy, Junhui Hou, Sam Kwong, and Runmin Cong. Zero-reference deep curve estimation for low-light image enhancement. In *CVPR*, pages 1777–1786, 2020
- [23] Li C, Guo C, Loy C C. Learning to enhance low-light image via zero-reference deep curve estimation[J]. *IEEE transactions on pattern analysis and machine intelligence*, 2021, 44(8): 4225-4238.
- [24] Pan Q, Zhang Z, Tian N. Zero-Reference Generative Exposure Correction and Adaptive Fusion for Low-Light Image Enhancement *J. Neurocomputing*, 2025, 636: 129992
- [25] Peng Y, Guo X, Xu M, et al. Wavelet-Guided Zero-Reference Diffusion for Unsupervised Low-Light Image Enhancement *J. Electronics*, 2025, 14(22): 4460
- [26] Yang W, Wang S, Fang Y, et al. From fidelity to perceptual quality: A semi-supervised approach for low-light image enhancement[C]//*Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2020: 3063-3072.]
- [27] Yang W, Wang S, Fang Y, et al. Band representation-based semi-supervised low-light image enhancement: Bridging the gap between signal fidelity and perceptual quality[J]. *IEEE Transactions on Image Processing*, 2021, 30: 3461-3473.
- [28] Jiang N, Cao Y, Zhang X Y, et al. Low-light image enhancement with quality-oriented pseudo labels via semi-supervised contrastive learning[J]. *Expert Systems with Applications*, 2025, 276: 127106.