ADVANCEMENTS IN LOW-LIGHT IMAGE ENHANCEMENT: A REVIEW OF DEEP LEARNING TECHNIQUES

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Abstract:. Low-light image enhancement (LLIE) is a crucial task in computer vision, with applications ranging from surveillance, autonomous driving, medical imaging, and photography. Traditional enhancement methods, such as histogram equalization and Retinex-based methods, often struggle with artifacts, loss of intricate details, and the adaptability limitation when exposed to diverse lighting conditions. Recent advancements in deep learning have introduced multi-scale feature extraction and attention mechanisms, thereby significantly improving the enhancement quality by capturing the fine-grained details and dynamically prioritizing image regions based on the level of illumination. This paper presents a systematic review of the state-of-the-art deep learning-based LLIE techniques, while explicitly following the PRISMA methodology to ensure a structured survey process. The existing approaches are categorized into supervised, unsupervised, and semi-supervised methods, highlighting their strengths and limitations. Additionally, the key performance metrics, including PSNR (Peak Signal-to-Noise-Ratio), SSIM (Structural Similarity Index Measure), NIQE (Natural Image Quality Evaluator), and computational efficiency, are analyzed while also addressing the dataset biases and real-world applicability. A comparative analysis of multi-scale feature extraction and attention-based models is provided to illustrate their impact on LLIE. Finally, computational cost, generalization, and dataset limitations, as challenges, and the future research directions for more efficient and robust LLIE solutions are proposed.

Index terms: Low-Light Image Enhancement, Deep Learning, Multi-Scale Learning, Attention Mechanisms, Adversarial Training

I. INTRODUCTION

Low-light image enhancement (LLIE) is a fundamental problem in computer vision with applications in autonomous driving, surveillance, semantic segmentation, medical imaging, and computational photography [1], [2], [3]. In such scenarios, the degraded images that are captured under insufficient lighting conditions suffer from inadequate visibility, low contrast, noise, and color distortions, which makes it difficult for both human observers and deep learning models to extract meaningful and intricate information [2], [4]. Therefore, enhancing these images is crucial for improving the performance of downstream vision tasks such as object detection, face recognition, and medical diagnostics [5].

A. Limitation of Traditional LLIE Methods

Classical LLIE approaches, as histogram equalization (HE), Retinex-based methods, and image fusion techniques, have been used widely to enhance these degraded low-light images. However, these methods suffer from a selection of identified drawbacks [3].

Histogram Equalization (HE) -based methods adjust the contrast globally but can introduce overexposure effects in the regions of the image and unnatural brightness levels [3], [6]. Retinex-based methods, which are inspired by the Human Visual System (HVS) models, estimate the illumination and reflectance components but do introduce unexpected artifacts and demonstrate inadequacy in enhancement in extremely dark regions of the images [6]. Image fusion techniques proceed with merging multiple enhanced versions of low-light images, but this technique requires multiple exposures or well-calibrated multi-frame inputs of the same degraded image sample, which thereby limits real-world applicability [3], [7].

These traditional methods often struggle to generalize the enhancement process in different and distinct lighting conditions, which leads to loss of fine details, thereby leading to an unnatural enhancement with color distortions [5], [8].

B. Deep Learning-based LLIE Methods Over Traditional Methods

With the advancements of deep learning, LLIE methods have evolved to the state of addressing the shortcoming of the traditional techniques through learning complex mapping from low light to well-lit images [1], [9], [10]. Deep learning-based LLIE models are identified to be advantageous in situation such as learning from large datasets, enabling them to generalize across diverse lighting conditions, Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) showing capabilities of preserving intricate and fine details, edges, and textures more effectively [9], [11], and also the Vision Transformer (ViTs) based models and attention mechanism being able to selectively enhance the darker regions while preventing overexposure effect [12], [13], [14].

These advancements enable deep learning methods to adaptively enhance the low-light degraded images in diverse ranges of lighting conditions, which does not require explicit handcrafted rules, which makes them superior to classical LLIE methods.

This paper provides a comprehensive review of deep learning-based LLIE techniques by categorizing existing approaches and benchmarking their performance. In comparison to the previous surveys, our work specifically focuses on:

- Categorization of LLIE techniques into supervised, unsupervised, and hybrid learning approaches, targeting a clear taxonomy of existing solutions.
- Comparison of Multi-Scale and Attention-based LLIE models, thereby highlighting how the multi-scale feature extraction utilization leads to improved detail preservation and how the attention mechanisms selectively enhance critical regions that require enhancement.
- Discussion on the datasets and evaluation metrics, identifying the challenges of real-world LLIE datasets while focusing on the key performance metrics used for model evaluations.

II. CATEGORIZATION OF LLIE TECHNIQUES

Deep learning techniques, as mentioned previously, have made remarkable progress in the LLIE space, and these methods can be broadly categorized based on the learning paradigm followed and the data requirements. This section will outline the key characteristics of supervised, unsupervised, and semi-supervised/hybrid LLIE techniques.

A. Supervised Learning Methods

Supervised learning methods form a significant portion of the methods based on deep learning techniques in the LLIE domain. These approaches rely on paired datasets consisting of low-light input images and their corresponding well-lit, normal-light ground truth images [1].

CNNs are frequently employed in supervised LLIE. Architectures such as encoder-decoder structures, which are exemplified by U-Net [2], are common, and they accompany skip connections to preserve intricate details. Residual learning, as seen in networks that incorporate ResNet blocks, is also utilized, thereby enabling the network to learn the residual between the low-light input and the desired enhancement result [16]. The concept of network learning complex non-linear mappings for image transformation is central to supervised LLIE [17]. For instance, a network can be designed to estimate global illumination and reconstruct details based on their estimation [13].

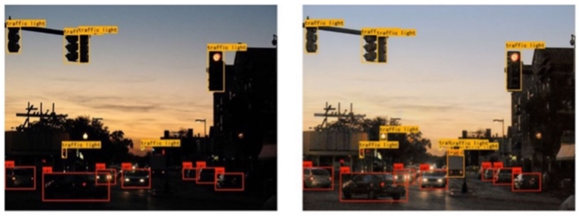

Figure 1: Sample Image from the ExDark dataset with YOLOv4 object detection results on the low-light and enhanced image, improving detection accuracy.

GANs have also been adapted for supervised LLIE. While EnlightenGAN [6] is an unsupervised method, the general GAN framework, which involves the generator that produces enhanced fake images and a discriminator that distinguishes between enhanced and real normal-light images, is used with paired data by adjusting the respective loss functions [12]. Zero-DCE and its variations are generally formulated as unsupervised or zero-shot methods, where the method focuses on curve estimation rather than directly mapping the paired data [13]. Similarly, the Retinex theory, which decomposes the image into reflectance and illumination components, is often integrated into the supervised paradigm of deep learning [3], [6]. These methods tend to utilize the CNNs to estimate the reflectance and illumination maps and then enhance the image based on the components [3], [13], [17]. Hybrid Transformer-CNN architectures are a more recent trend in various vision tasks, which includes LLIE [19]. These architectures are aiming to leverage the strengths of both CNNs (local feature extraction) and Transformers (global context modeling). By combining these, the networks can potentially capture both fine-grained details and long-range dependencies in low-light images, thereby producing a more effective enhancement [2].

A typical supervised LLIE pipeline would involve a low-light image as input to a deep neural network, such as a CNN or a Transformer-based network. The network trained on paired low-light and normal-light images produces an enhancement. The training process involves comparing the produced enhancement with the corresponding ground-truth normal-light image, updating the weights of the network based on the calculated loss.

B. Unsupervised Learning-Based LLIE

Unsupervised learning methods for LLIE gained increased attention due to the difficulty and the cost that is associated with the acquisition of large, perfectly aligned paired datasets [6]. These methods operated on unpaired datasets, with both low-light and normal-light images, learning the underlying distributions of each domain, even with non-correspondence, directly [12]. CycleGAN [20] is a prominent technique in unsupervised image-to-image translations, including LLIE. It employs two generators and two discriminators to learn the mapping between the low-light and normal-light domains in a cycle-consistent manner [21]. This ensures that the translation of the low-light image to the normal-light image and back to the low-light image should resemble the expected original low-light image [4]. Contrastive Learning (CL) can be used in unsupervised LLIE, which is through training the network to learn representations that group the enhancement closer to normal-light images while also pushing them away from other low-light images [9]. This can be achieved through various loss functions, which encourage the closest resemblance within the desired domain and least resemblance across other domains. Self-supervised learning techniques for LLIE aim to leverage inherent properties of the degraded image or large unlabeled datasets to learn useful image data representations without explicit supervision [12]. Methods like Zero-DCE [22] that learn the curve estimations that are specific to the image for enhancement can also be called self-supervised, as they do not rely on paired or unpaired sets of images but rather learn from the input image itself [13]. EnlightenGAN [18] uses a global-local discriminator and self-feature retention loss and is also a member of this category [6]. A key advantage of unsupervised methods is the flexibility enabled for handling diverse and complex scenarios without the strict requirement of paired data [12]. However, they come along with limited capabilities in fine-tuning the model when compared to the supervised methods, while their performance can also be sensitive to the network architecture choices that proceed alongside the loss functions [3]. Detail recovery and noise handling can also be a major challenge in the absence of direct supervision from paired normal images [12].

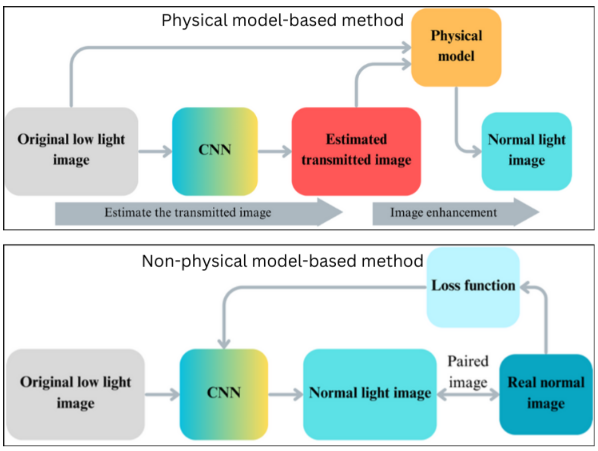

Figure 2: Comparison of non-physical and physical model-based methods in LLIE.

C. Semi-Supervised and Hybrid LLIE

Semi-supervised LLIE methods seek to bridge the gap between the supervised and unsupervised learning paradigms by leveraging a combination of labeled and unlabeled data [6]. These approaches can be particularly useful when the acquisition of a large amount of paired data is low, but a larger amount of unpaired data is available [5].

Contrastive Pre-training on large unlabeled datasets followed by fine-tuning on a smaller labeled dataset is a strategy commonly followed in semi-supervised learning [9]. The pre-training phase helps the network to learn generalizable features that can then be adapted for the specific LLIE task using the labeled data.

Hybrid LLIE can also refer to architectures that combine different learning paradigms or network components within a single framework [16]. As an example, a network can use a supervised branch for the initial enhancement and an unsupervised branch with a GAN loss for refining the perceptual quality [13]. Another hybrid approach is to involve the combination of traditional model-based methods, such as Retinex theory in a deep learning architecture, where the deep learning component is to predict parameters for the model or learn the decompositions and enhancement steps [3].

Semi-supervised and hybrid methods aim to harness the benefits of both labeled and unlabeled data, which leads to improved performance and generalization compared to purely supervised or unsupervised approaches, moreover with a data scarcity [5]. In conclusion, LLIE techniques based on deep learning can be effectively categorized into supervised, unsupervised, and semi-supervised (hybrid) methods. Supervised learning relies on the paired data, demonstrating a strong performance, but can be limited by the data availability. Unsupervised learning offers flexibility by using unpaired data, yet often leads to challenges in fine and intricate details restoration. Semi-supervised (hybrid) approaches strive to combine the strengths of both paradigms to achieve a robust and effective low-light image enhancement.

III. MULTI-SCALE LEARNING AND ATTENTION MECHANISMS

Multi-scale learning and attention mechanisms are crucial for effectively enhancing low-light images, as it enables the networks to understand the context at various levels and focus on the most important image features information [14]. In the multi-scale learning space, spatial domain and frequency domain are key feature distributions. For spatial domain feature extractions, techniques such as U-Net architectures, with the contracting and expanding kernel paths, process the information at different image resolutions, fusing the multi-scale features for texture and detail preservation [10], [14]. ResNet-based networks also incorporate the multi-scale modules using the varying kernel sizes to capture details at different levels [10]. For instance, the multi-scale window division scheme can further refine self-attention computation at the pixel level [3]. Frequency domain distributions, on the other hand, are used for analysis and enhancement of images based on their frequency components using transforms like wavelets [19] or the Fourier Transform [2]. This allows for targeted noise suppression and brightness adjustment in different frequency bands, such as high-level frequency and low-level frequency information [10]. For example, WMANet uses deep wavelet transform for separate processing of low and high frequencies [19].

Different techniques are used to determine attention mechanisms. With self-attention, Transformers and Vision Transformers (ViTs) capture long-range dependencies and global content that is vital for understanding overall illumination distribution in an image [3]. MSATr uses a global transformer branch for brightness perception [3]. Channel and Spatial Attention Mechanisms, such as those used in CBAM and SE-Net, reweight feature maps along channel and spatial dimensions to highlight important information and suppress noise [13]. These can be integrated into various network blocks, such as SE-Res2block [10]. A brightness attention mechanism can guide the network to focus on underexposed prominent regions [15].

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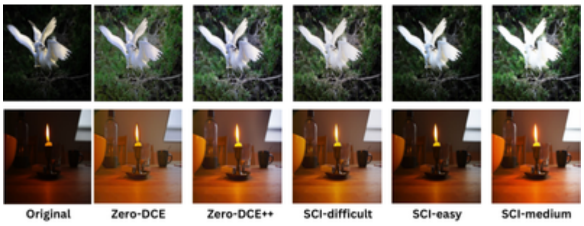

Figure 3: Qualitative performance of different methods.

Hybrid attention models combine different attention mechanism techniques, integrating them into architectures like GANs (Attention-GANs) and U-Nets, thereby further refining the enhancement process [6], [8]. These hybrid approaches leverage the strengths of different attention mechanisms for better feature selection and fusion [6]. As an example, MSCAM integrates multi-scale context spatial and channel attention to selectively refine feature maps [6]. The synergy of processing this image information at multiple scales and selectively focusing on the crucial features through attention allows LLIE models to achieve better brightness, details-texture recovery, and noise reduction [2], [3], [23]. For instance, MSATr combines multi-scale local attention in a global transformer to balance the illumination and preserve details [3]. Similarly, GARN [24] embeds a module for global attention within a Retinex-based network to extract much richer features

Table 1: Performance in PSNR and SSIM Across Datasets

Method	Zero-DCE	Zero-DCE++	SCI-Difficult	SCI-Easy	SCI-Medium
PSNR Scores					
NPE	14.51	13.96	13.99	18.89	12.19
MEF	11.80	11.84	11.84	18.70	10.28
VV	15.61	13.98	14.02	17.46	11.48
SSIM Scores					
NPE	0.322	0.323	0.325	0.678	0.267
MEF	0.428	0.439	0.432	0.790	0.418
VV	0.500	0.581	0.582	0.795	0.533

IV. PERFORMANCE BENCHMARKING AND CHALLENGES

A. Common LLIE Benchmark Datasets

Performance benchmarking is crucial in the field of LLIE to evaluate and compare different methods. Deep learning-based LLIE relies on extensive training data, marking the significance of the choice of benchmark datasets [9].

Common LLIE benchmark datasets include the publicly available datasets with varying sizes and diverse scenarios that are used for training and evaluating LLIE models [9]. Some of the most frequently mentioned datasets include the Low-Light Dataset (LOL) [3], MIT-Adobe FiveK [6], and SICE [7]. Other datasets used for evaluation include naturalness preserved enhancement (NPE) [9], Vasileios Vonikakis (VV) [3], multi-exposure image fusion (MEF) [9], Exdark [7], DICM [1], LSRW [25], UHD-LL [26], DarkFace [26], Brightening [27], and VE-LOL-L [5]. Furthermore, examples of different datasets can be found in Figure 4.

Figure 4: Image Samples from Different Datasets

Researchers utilize these datasets to train and evaluate the low-light image enhancement models, which provides a diverse range to suit different research requirements [9]. While some datasets contain paired low-/normal-light images, others are unpaired [3].

B. Evaluation Metrics

To evaluate and analyze different LLIE methods, both quantitative and qualitative evaluations are conducted [9]. Reference-based metrics chosen for datasets containing ground-truth normal-light images (i.e., LOL, SICE) are the full-reference metrics such as Peak-Signal-to-Noise Ratio (PSNR) and Structural Similarity (SSIM) for quantitative analysis [9]. PSNR measures the pixel-wise difference between the enhanced image and the ground truth image, while SSIM assesses the structural similarity in terms of factors such as brightness, contrast, and structure [2]. A higher PSNR and SSIM generally indicate a better enhancement quality [6]. Learned Perceptual Image Patch Similarity (LPIPS) is another reference-based metric utilized to calculate the perceptual similarity using the features extracted from the pre-trained networks, whereas smaller LPIPS values indicate higher perceptual similarity [28]. Other reference metrics include Pixel-based visual information fidelity (VIF), Universal quality image index (UQI), Multi-scale structural similarity index (MS-SSIM), Spatial correlation coefficient (SCC), Spectral angle mapper (SAM) [17], and Delta-E (ΔE) [19].

Non-reference-based metrics are chosen for datasets lacking the ground truth counterpart image (i.e., NPE, LIME, MEF, VV, ExDark, DICM), where the non-reference image quality evaluation (NR-IQA) metrics are used [6]. A lower NIQE score typically suggests a better perceptual quality [1]. Other non-reference metrics include Blind Image Quality Indices (BIQI), CIE2000 Color Difference (CD), Pearson Correlation Coefficient [11], Lightness Order Error (LOE) [5], Image Entropy (IE), No-Reference Image Quality Evaluation (NIQE) [25], Blind/Referenceless Image Quality Evaluator (BRISQUE), and IL-NIQE [27]. Qualitative evaluation involves the perception of the human visual system (HVS) for the enhanced images [9]. Additionally, user studies employing Mean Option Scores (MOS) are also conducted [6].

V. CHALLENGES IN CURRENT LLIE APPROACHES

A. Dataset Biases and Real-World Generalization

Deep learning methods heavily rely on substantial training data, and the performance of a model is significantly impacted by the dataset size [9]. The selection of the dataset needs careful consideration to ensure it represents a wide range of scenarios and categories while adding complexities to the training process [9]. The majority of the datasets are captured under specific indoor or synthetic conditions (i.e., LOL), and models trained on these datasets tend to suffer from dataset biases and exhibit limited generalizability to diverse real-world low-light conditions [24]. Acquiring paired low-/normal-light image datasets under real-world conditions and across all possible lighting scenarios is impractical [1]. This domain gap between the training data and real-world images leads to a higher tendency to produce suboptimal performance [25]. Some methods are evaluated on real-world datasets to test their generalization performance [3], [6].

B. Computational Complexity in Balancing Enhancement Quality and Efficiency

An ideal enhancement algorithm should produce excellent enhancement results while having low computational complexity [6], [13]. Many high-performing deep learning models have large network structures with a large number of parameters and high FLOPs (floating-point operations), resulting in longer running times and making them less applicable for usage and deployment on resource-constrained devices such as mobile terminals [13], [16], [23]. There is often a trade-off between the enhancement quality and computational efficiency [16]. To date, efforts are being made to develop lightweight networks with fewer parameters and shorter training times while achieving high-quality results [13]. The run time for enhancing an image varies significantly across different methods and hardware platforms [6].

C. Overfitting and Lack of Adaptability to Diverse Low-Light Conditions.

Some existing deep learning methods primarily focus on improving model performance on specific benchmark datasets, potentially overlooking the practicality and generalizability of the results [9]. Models trained on limited datasets can be overfit to the training data and are unable to adapt effectively to complex low-light conditions in real-world scenarios [13]. This can lead to issues like under-enhancement, over-enhancement, noise, colour distortion, and loss of finer details [25]. There is a need for methods that can adaptively adjust the illumination and local contrast with image context, especially with both dark and bright regions [13]. Furthermore, distinguishing complex noise and details remains a challenge [14].

CONCLUSION

This survey reviews the advancements in LLIE using deep learning through the categorization of existing approaches into supervised, unsupervised, and hybrid methods. The integration of multi-scale feature extraction has improved detail preservation, while attention mechanisms have enabled adaptive brightness correction, thereby reducing overexposure and artifacts. Comparative benchmarking demonstrated that deep learning-based LLIE models outperform traditional methods in terms of perceptual quality, structure, and adaptability to diverse lighting conditions. Despite these advancements, several challenges persist. Existing models often suffer from overfitting, high computational costs, and biases in benchmark datasets, limiting their real-world generalization. Additionally, the lack of diverse, high-quality training data affects the robustness of the LLIE models with varying illumination conditions. **Future research** should focus on transformer-based architectures for enhanced feature extraction and contextual illumination correction, self-supervised learning to minimize the data dependencies, and finally, the development of more diverse, unbiased LLIE datasets to improve generalization.

REFERENCES

[1] J. Hai, Y. Hao, F. Zou, F. Lin, and S. Han, "Advanced RetinexNet: A fully convolutional network for low-light image enhancement," *Signal Process. Commun*, vol. 112, no. 116916, p. 116916, 2023, doi: 10.1016/j.image.2022.116916.

[2] K. Shang, M. Shao, Y. Qiao, and H. Liu, “Frequency-aware network for low-light image enhancement,” *Comput. Graph.*, vol. 118, no. Journal Article, pp. 210–219, 2024, doi: 10.1016/j.cag.2023.12.014.
[3] X. Fang *et al.*, “A non-uniform low-light image enhancement method with multi-scale attention transformer and luminance consistency loss,” *Vis. Comput.*, no. Journal Article, 2024, doi: 10.1007/s00371-024-03452-w.
[4] G. Han, Y. Zhou, and F. Zeng, “Unsupervised learning based dual-branch fusion low-light image enhancement,” *Multimed. Tools Appl.*, vol. 82, no. 24, pp. 37593–37614, 2023, doi: 10.1007/s11042-023-15147-w.
[5] H. Tang, H. Zhu, L. Fei, T. Wang, Y. Cao, and C. Xie, “Low-Illumination Image Enhancement Based on Deep Learning Techniques: A Brief Review,” *Photonics*, vol. 10, no. 2, p. 198, 2023, doi: 10.3390/photonics10020198.
[6] S. Hu, J. Yan, and D. Deng, “Contextual Information Aided Generative Adversarial Network for Low-Light Image Enhancement,” *Electronics*, vol. 11, no. 1, p. 32, 2022, doi: 10.3390/electronics11010032.
[7] Z. Yao, J.-N. Su, G. Fan, M. Gan, and C. L. P. Chen, “GACA: A Gradient-Aware and Contrastive-Adaptive Learning Framework for Low-Light Image Enhancement,” *IEEE Trans. Instrum. Meas.*, vol. 73, no. Journal Article, pp. 1–14, 2024, doi: 10.1109/TIM.2024.3353285.
[8] H. Jin, Q. Wang, H. Su, and Z. Xiao, “Event-guided low light image enhancement via a dual branch GAN,” *J. Vis. Commun. Image Represent.*, vol. 95, no. Journal Article, p. 103887, 2023, doi: 10.1016/j.jvcir.2023.103887.
[9] Z. Tian *et al.*, “A Survey of Deep Learning-Based Low-Light Image Enhancement,” *Sensors*, vol. 23, no. 18, p. 7763, 2023, doi: 10.3390/s23187763.
[10] G.-D. Fan, B. Fan, M. Gan, G.-Y. Chen, and C. L. P. Chen, “Multiscale low-light image enhancement network with illumination constraint,” *IEEE TransCircuits SystVideo Technol*, vol. 32, no. 11, pp. 7403–7417, 2022, doi: 10.1109/tcsvt.2022.3186880.
[11] X. Wang, Y. Zhai, X. Ma, J. Zeng, and Y. Liang, “Low-light image enhancement based on GAN with attention mechanism and color Constancy,” *MultimedTools Appl*, vol. 83, no. 1, pp. 3133–3151, 2024, doi: 10.1007/s11042-022-13335-8.
[12] J. Tan, T. Zhang, L. Zhao, D. Huang, and Z. Zhang, “Low-light image enhancement with geometrical sparse representation,” *Appl. Intell.*, vol. 53, no. 9, pp. 11019–11033,2023,doi:10.1007/s10489-022-04013-1.
[13] S. Fan, W. Liang, D. Ding, and H. Yu, “LACN: A lightweight attention-guided ConvNeXt network for low-light image enhancement,” *Eng. Appl. Artif. Intell.*, vol. 117, no. Journal Article, p. 105632, 2023, doi: 10.1016/j.engappai.2022.105632.
[14] Z. He *et al.*, “Low-light image enhancement with multi-scale attention and frequency-domain optimization,” *IEEE TransCircuits SystVideo Technol*, vol. 34, no. 4, pp. 2861–2875, 2024, doi: 10.1109/tcsvt.2023.3313348.
[15] Y. Liu, T. Huang, W. Dong, F. Wu, X. Li, and G. Shi, “Low-light image enhancement with multi-stage residue quantization and brightness-aware attention,” *2023 IEEECVF Int. Conf. Comput. Vis. ICCV*, no. Generic, Jul. 2024, doi: 10.1109/iccv51070.2023.01115.
[16] T. Cao, T. Peng, H. Wang, X. Zhu, J. Guo, and Z. Zhang, “Multi-scale adaptive low-light image enhancement based on deep learning,” *J. Electron. Imaging*, vol. 33, no. 4, p. 043033, 2024, doi: 10.1117/1.JEI.33.4.043033.
[17] S. Yang, D. Zhou, J. Cao, and Y. Guo, “LightingNet: An integrated learning method for low-light image enhancement,” *IEEE TransComputImaging*, vol. 9, no. Journal Article, pp. 29–42, 2023, doi: 10.1109/tci.2023.3240087.
[18] Y. Jiang *et al.*, “EnlightenGAN: Deep Light Enhancement Without Paired Supervision,” *IEEE Trans. Image Process.*, vol. 30, no. Journal Article, pp. 2340–2349, 2021, doi: 10.1109/TIP.2021.3051462.
[19] Y. Xiang, G. Hu, M. Chen, and M. Emam, “WMANet: Wavelet-Based Multi-Scale Attention Network for Low-Light Image Enhancement,” *IEEE Access*, vol. 12, no. Journal Article, pp. 105674–105685, 2024, doi: 10.1109/ACCESS.2024.3434531.
[20] G. Tang, J. Ni, Y. Chen, W. Cao, and S. X. Yang, “An improved CycleGAN-based model for low-light image enhancement,” *IEEE SensJ*, vol. 24, no. 14, pp. 21879–21892, 2024, doi: 10.1109/jsen.2023.3296167.
[21] W. Yu, L. Zhao, and T. Zhong, “Unsupervised Low-Light Image Enhancement Based on Generative Adversarial Network,” *Entropy*, vol. 25, no. 6, p. 932, 2023, doi: 10.3390/e25060932.
[22] C. Guo *et al.*, “Zero-Reference Deep Curve Estimation for Low-Light Image Enhancement,” presented at the 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Seattle, WA, USA: IEEE Xplore, Jun. 2020, pp. 1777–1786. doi: 10.1109/CVPR42600.2020.00185.
[23] J. Zhang, J. Huang, M. Yao, M. Zhou, and F. Zhao, “Structure- and texture-aware learning for low-light image enhancement,” *Proc. 30th ACM Int. Conf. Multimed.*, no. Generic, 2022, doi: 10.1145/3503161.3548359.
[24] Y. Wang and Z. Zhang, “Global attention retinex network for low light image enhancement,” *JVisCommunImage Represent*, vol. 92, no. 103795, p. 103795, 2023, doi: 10.1016/j.jvcir.2023.103795.
[25] J. Zhang, R. Ji, J. Wang, H. Sun, and M. Ju, “DEGAN: Decompose-enhance-GAN network for simultaneous low-light image lightening and denoising,” *Electron. Basel*, vol. 12, no. 14, p. 3038, Jul. 2024, doi: 10.3390/electronics12143038.
[26] T. Chobola, Y. Liu, H. Zhang, J. A. Schnabel, and T. Peng, “Fast context-based low-light image enhancement via neural implicit representations,”
[27] S. Yuan, J. Li, L. Ren, and Z. Chen, “Multi-Frequency Field Perception and Sparse Progressive Network for low-light image enhancement,” *J. Vis. Commun. Image Represent.*, vol. 100, no. Journal Article, p. 104133, 2024, doi: 10.1016/j.jvcir.2024.104133.
[28] W. Wang and Z. Jin, “CAPformer: Compression-aware pre-trained transformer for low-light image enhancement,” Jul. 2024.

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