Deep Learning for Low-Light Image Enhancement: A Review of Techniques and Challenges

Pansilu Wijesiri
Department of Computer Science and Engineering
University of Westminster
London, UK
pansiluwijesiri@gmail.com

Guhanathan Poravi
School of Computing
Informatics Institute of Technology
Colombo, Sri Lanka
guhanathan.p@iit.ac.lk

***Abstract*—Low-light image enhancement is a crucial task in computer vision, which aims to improve the visibility and the overall quality of images captured in dimly lit environments. While the traditional methods have been identified to have limitations in handling complex low-light scenarios, deep learning has brought to light the potential for tackling these challenges. This paper presents a comprehensive survey of deep learning techniques for low-light image enhancement and the limitations of existing methods. Furthermore, it expands on the various deep learning approaches while being categorized into supervised, unsupervised, and other emerging candidate technologies, alongside an analysis of the architectural distinctions and their characteristics. The paper then expands to a discussion on the commonly used datasets and evaluation metrics, emphasizing the importance of utilizing diverse datasets and evaluation metrics in deep learning. Finally, the challenges and future direction of the research area are outlined, enabling the advancements in this rapidly evolving field.**

***Index Terms*—Low-light image enhancement, deep learning, convolutional neural networks, generative adversarial networks, image processing.**

I. Introduction

Images captured in low-light environments often suffer from poor visibility, noise, and reduced contrast, thereby hindering the performance of downstream computer vision tasks such as surveillance, autonomous driving, image segmentation, and object detection [1]. Low-light image enhancement (LLIE) aims to improve the quality of such degradation-undergone images, making them more visually appealing and informative for both the human visual system (HVS) and computer vision algorithms that utilize the image [2]. The demand for effective LLIE techniques is based on their utilization in various applications across diverse environments within separate domains.

Traditional methods for LLIE, such as histogram equalization and gamma correction, often accompany reliance on the pixel intensities. While they can improve the overall brightness factor of the image, at times they often struggle in handling complex lighting scenes due to non-uniformity of light distribution while also introducing unwelcome artifacts, such as noise and color distortions [2]. Retinex-based methods, which are inspired by the HVS's ability to perceive colors consistently despite the illumination distribution, attempt to decompose the image into reflectance and illumination components [3]. However, these methods depend on handcrafted priors and assumptions, which limits the ability to generalize to diverse low-light scenarios [4].

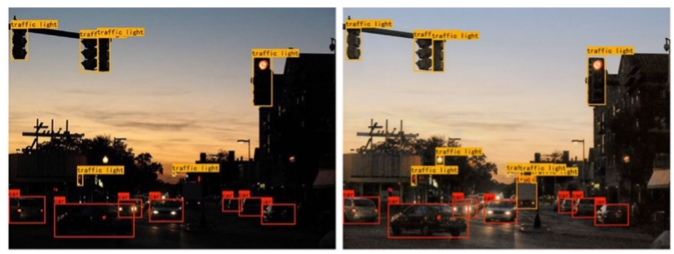

Fig. 1. A sample test image from the ExDark dataset, with YOLOv4 object detection results on the original and enhanced image by a commonly used general LLIE technique. This demonstrates the impact of LLIE on improving object detection accuracy.

With the intervention of deep learning and its revolutionization in the field of LLIE, a more powerful and adaptable solution is produced compared to the traditional approaches [5]. Deep learning models, particularly the involvement of convolutional neural networks (CNNs), have shown great capabilities in learning intricate patterns and representations from degraded images [2], [6]. They can effectively extract features at multiple scales, capture the global and local image contexts, and generalize comparatively well to diverse low-light scenarios [7].

TABLE I
Types of Persistent Low-Light Settings [5]

Low-Light Type	Description
Nighttime Scenes	Naturally dark environments, such as urban streets or rural roads at night.
Indoor Low-Light	Dimly lit rooms with insufficient artificial lighting.
Shadowed Regions	Low-light areas due to occlusions, such as tunnels or under bridges.
Underwater Low-Light	Reduced visibility in deep water due to limited natural light penetration.
Adverse Weather	Fog, rain, or dust storms that decrease ambient light.

The development of deep learning techniques specifically tailored for LLIE has led to significant advancements in enhancements focused on quality, restoring intricate details, and improving visual perception [7]. With these capabilities of deep learning, researchers are consistently pushing the limits of possibilities in LLIE, thereby paving the way for a wider range of applications in downstream vision tasks, which rely on high-quality images for better reliability and accuracy of such systems.

In this paper, a comprehensive survey of the latest advancements in deep learning-based low-light image enhancement techniques and their long-term progression is presented. Specifically, this survey expands on the supervised, unsupervised, and semi-supervised paradigms for the task in hand, alongside an analysis of their strengths, weaknesses, and their applications. The rest of the paper is structured as follows: Section II provides a detailed overview of the deep learning-based low-light image enhancement methodologies, categorized into the paradigms of supervised, unsupervised, and semi-supervised techniques. Section III describes the commonly utilized datasets, which are used in the training and evaluation phases of these models, thereby emphasizing their respective characteristics and relevancy. Section IV expands on the evaluation metrics, both quantitative and qualitative measures, used to assess the enhancement algorithm on its performance. Section V discusses on the key challenges in handling low-light image enhancement and highlights the areas of future research. Finally, Section VI concludes the paper by summarizing the key findings alongside the contributions of this literature survey.

II. Deep Learning-Based Low-Light Image Enhancement Methods

A. Supervised Deep Learning Techniques

Supervised deep learning techniques for low-light image enhancement heavily rely on paired datasets, including low-light input images and their counterpart normal-light images [8]. These paired datasets are crucial for training models to learn the mapping between the degraded image and its counterpart normal-light image. The training process teaches the model how to transform a low-light image into a visually appealing and informative normal-light image [9]. However, accessibility to large-scale, high-quality paired datasets is very challenging. Creating such paired datasets involves capturing the same scenes in two different scenarios of well-illuminated and low-illuminated conditions, thereby ensuring accurate alignment and consistency, which is considered considerably time-consuming and expensive [10]. Despite the data dependency challenge, supervised learning has shown impressive results in low-light image enhancement. Convolutional Neural Networks (CNNs), well-known for their exceptional ability to extract hierarchical features from images, have proven particularly effective in the LLIE domain [7]. CNNs learn to identify the local patterns, edges, and textures through convolutional layers and downsample spatial dimensions using the pooling layers, thereby gradually building a representation of the image that highlights the important features required to undergo the enhancement process [5]. One notable supervised approach, Retinex-Net [11], takes inspiration from the Retinex theory,

$$I = R \odot L \tag{1}$$

which implies that the image ($I \in \mathbb{R}^{H\times W\times 3}$) can be decomposed into reflectance ($R \in \mathbb{R}^{H\times W\times 3}$) and illumination ($L \in \mathbb{R}^{H\times W\times 3}$) components, as in Equation (1). Retinex-Net [11] uses a CNN to estimate the illumination map of low-light images and then applies the adjustments to brighten the image while preserving the essential details. The success of Retinex-Net highlights the effectiveness of integrating traditional concepts with deep learning architectures. Furthermore, MBLLEN [12] uses a multi-branch architecture where each branch focuses on enhancing specific aspects of the image. Such extracted features from diverse levels are processed by separate sub-networks and then combined to produce a comprehensively enhanced output. Another successful method, LightenNet [13], concentrates on learning a mapping from the low-light input to its corresponding illumination map. This learned map, with conjunctive measures with the Retinex-theory-based model, guides the final enhanced image's enhancement process. Transformers [5], initially successful in natural language processing, have also demonstrated promising results in LLIE. The particular strength is in the capacity to capture long-range dependencies within an image using self-attention mechanisms. This allows transformers to learn global contextual relationships crucial for understanding the complex variations in lighting that characterize low-light images [14].

B. Unsupervised Deep Learning Techniques

Unsupervised learning in the image enhancement field addresses the identified challenge of limited paired training data [8]. Collecting paired image data to create a dataset that includes both the low-light input images and their counterpart normal-light images can be time-consuming and considerably expensive [5], [15]. Unsupervised learning allows models to learn from unpaired data, mitigating the reliance on extensive labeled datasets, which are not easily accessible due to scarcity. This approach leverages the inherent patterns and relationships within the images to guide the enhancement process without the paired dataset requirement.

Generative Adversarial Networks (GANs) play a crucial role in many unsupervised LLIE techniques [7], [8], [16]. GANs consist of two neural networks, a generator and a discriminator, working head-to-head in an adversarial training process [7].

$$\begin{aligned}\min_{\mathbf{G}} \max_{\mathbf{D}} V(\mathbf{D}, \mathbf{G}) = \mathbb{E}_{x\sim p_{\text{data}}(x)}[\log \mathbf{D}(x)] + \\ \mathbb{E}_{z\sim p_z(z)}[\log(1 - \mathbf{D}(\mathbf{G}(z)))]\end{aligned} \tag{2}$$

The generator ($\mathbf{G}$) aims to create synthetic (fake) images that resemble real-world images, while the discriminator ($\mathbf{D}$) attempts to distinguish between real and synthetic samples,m as demonstrated in Equation (2). With the proceedings of this adversarial training, the generator learns to produce increasingly realistic images that are hard to differentiate from the real-world well-illuminated image [17].

Cycle consistency is a key concept in unsupervised LLIE, particularly in models like CycleGAN [18]. Cycle consistency ensures that the transformation from a low-light image to a normal-light image and the reverse preserves the original content. This constraint helps prevent the model from drastically altering the image while enhancing its visual coherency [19]. It utilizes two generators and two discriminators to enforce cycle consistency, providing assurance that the transformations are reversible and preserving the content of the original image. Furthermore, EnlightenGAN [20] is another GAN-based approach designed to tackle the unpaired LLIE by incorporating global-local discriminators that account for variations in illumination across the image. Zero-DCE [21] is a method that reframes LLIE as a curve estimation problem that dynamically adjusts image brightness without relying on reference images. This model is known for its computational efficiency and effectiveness in handling diverse low-light scenarios. LE-GAN [22] is a model that incorporates an illumination-aware attention module to improve feature extraction, addressing issues related to noise and color bias. LE-GAN also employs an invariant identity loss to mitigate overexposure problems. MSED [19] is a multi-stream feature modeling network that uses an unsupervised learning strategy based on an attention mechanism to extract and fuse global and local features for enhancement. In addition to these models, researchers have explored various techniques for evaluating the performance of LLIE methods using an unsupervised paradigm. One such approach is to utilize non-reference image quality metrics such as NIQE (Natural Image Quality Evaluator) [7], [18], thereby assessing the quality of the images without relying on a reference image. Another strategy utilized is to employ user studies, where the selective count of participants is given the enhancement for evaluation of the overall visual coherency and quality of the produced image [2], [16]. Unsupervised learning offers a promising hand for LLIE, especially in the scarcity of paired training data. This progress in GANs, cycle consistency, and non-reference image quality assessment has driven significant advancements in the LLIE domain. Continued research in unsupervised LLIE is crucial for developing adaptable and robust methods that can enhance low-light images across diverse contexts.

While supervised and unsupervised learning have made significant strides in LLIE, other techniques are emerging to address the limitations of these methods and further improve performance. Zero-shot learning (ZSL), as its name suggests, aims to enhance low-light images without any prior training examples. This approach relies on transferring knowledge from related tasks or domains to enhance images from unseen environments or with novel degradations [23]. ZSL is particularly beneficial when obtaining paired training data is highly infeasible. For instance, enhancing low-light images from a specific camera model or under unique lighting conditions might require a dedicated dataset, which can be challenging to collect. ZSL methods can potentially overcome this limitation by leveraging knowledge from existing datasets and models trained on different but related tasks [7]. One prominent example of ZSL in LLIE is RRDNet (Retinex-inspired Restoration and Denoising Network) [24]. RRDNet comprises a three-branch CNN that performs denoising and restoration of underexposed images without the need for prior training data samples. This method accompanies Retinex theory and image statistics in guiding the enhancement process.

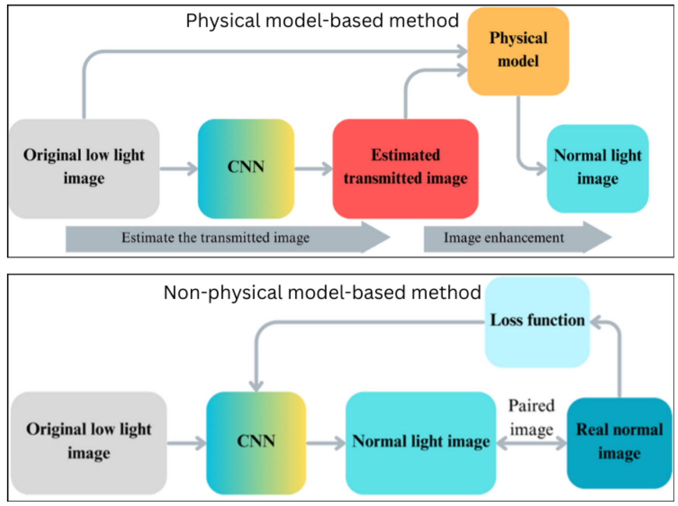

Fig. 2. Comparison between physical model-based methods and non-physical model-based methods for low-light image enhancement [5].

C. Semi-Supervised Deep Learning Techniques

Semi-supervised learning stands in between supervised and unsupervised paradigms. This approach utilizes a lesser amount of labeled data alongside a larger pool of unlabeled data to train the model. The labeled data acts in providing some guidance and supervision, while the unlabeled data contributes to the generalization and robustness capabilities of the model [23]. Semi-supervised learning is particularly advantageous in scenarios where large-scale labeled data is very expensive, but the feasibility of obtaining unlabeled data is relatively possible. DRBN (Deep Recursive Band Network) [25] is an example of a semi-supervised LLIE method. DRBN employs a two-stage training process. In the first stage, the paired low-light and normal-light images are utilized in training the network for initial enhancement. In the second stage, it leverages a GAN trained on unpaired data to further refine the enhancement results. This combination of supervised and unsupervised learning leverages the strengths of both approaches, resulting in better enhancements with considerably preserved image quality [26]. While these areas present high potential, particularly in ZSL and semi-supervised LLIE, researchers are exploring further directions, such as developing more effective knowledge-transferring techniques to enable models to generalize better to unseen low-light conditions and exploring new architectures and loss functions specifically tailored for semi-supervised LLIE, allowing

TABLE II
COMPARISON OF LLIE ALGORITHMS ON PSNR, SSIM, AND NIQE [5].

Method	PSNR ↑	SSIM ↑	NIQE ↓
NPE	17.932	0.729	2.959
MEF	17.537	0.768	3.156
VV	18.006	0.689	2.615
ExDark	17.188	0.702	3.609
Zero-DCE	15.606	0.500	3.145
Zero-DCE++	13.984	0.532	3.211
SCI-Medium	12.185	0.268	3.052
SCI-Easy	18.892	0.790	2.838
SCI-Difficult	13.989	0.326	3.082

models to learn efficiently from limited labeled data, and the integration of domain knowledge and image priors into ZSL and semi-supervised learning paradigms in LLIE, thereby improving performance and catering specific challenges, as noise and color distortion in degraded images [10], [18], [23]. ZSL and semi-supervised learning offer promising solutions to the data dependency challenges in LLIE and provide greater flexibility and adaptability to varied scenes, allowing for the enhancement of low-light images in diverse and challenging scenarios [15], [26]. As research in these areas progresses, the advanced possibilities are brought to light through further advancements in data-efficient and robust LLIE methods [8].

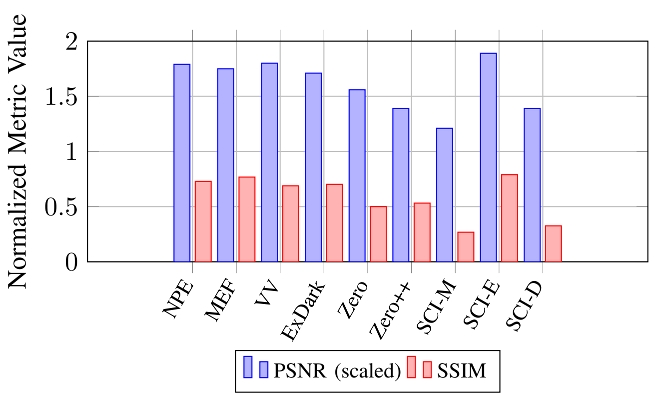

Fig. 3. Comparison of LLIE methods based on PSNR and SSIM [5]. PSNR values are scaled down by a factor of 10 for visualization clarity.

III. DATASETS

Deep learning-based LLIE heavily relies on diverse and comprehensive datasets for training robust enhancement models. The choice of the dataset significantly impacts the overall performance and the generalization factor of the LLIE algorithms. To date, there are several widely used publicly available datasets formed to cater to the specific needs of the LLIE research, which are each bearing its characteristics, strengths, and weaknesses. Upon such, the LOL (Low-Light) dataset [11], SID (See-in-the-Dark) dataset [27], MEF (Multi-Exposure Image Fusion) dataset [28], DICM dataset [29], LIME dataset [30], ExDark (Exclusively Dark) dataset [31] are in the well-known category in the field of LLIE.

TABLE III
COMPARISON OF KEY LOW-LIGHT IMAGE ENHANCEMENT METHODS FROM EACH FEATURE EXTRACTION PARADIGM

Method	Architecture	Key Weaknesses and Improvements
LightingNet [33]	Res2Net + ViT	**Weakness:** Shows tendency to struggle with extreme low-light environments and noise levels. **Improvement:** Global feature extraction for better noise and brightness handling capabilities.
MBLLEN [12]	Multi-Branch CNN	**Weakness:** Presents difficulty in preserving details under varied (non-uniform) low-light environments. **Improvement:** Requires better optimization for real-time performance application.
LE-GAN [22]	GAN with Attention Mechanism	**Weakness:** Real-time processing incabapilities due to model size causing inefficiencies. **Improvement:** Reduced computational complexity.
R2RNet [10]	Real-to-Real Learning	**Weakness:** Demonstrates deficiencies in producing accurate color saturation levels and naturalness which are closer to ground truth. **Improvement:** Improved levels of saturation and tone balancing for naturalness.

LOL dataset, introduced in 2018, contains 500 pairs of low-light and normal-light images, primarily depicting indoor scenes captured with various devices. Its realistic noise representation and diverse low-light conditions make it considerably valuable in training and evaluating LLIE models. The SID dataset focuses on extremely low-light image enhancement. MEF dataset, introduced in 2015, comprises images of multiple low-light scenarios captured under various lighting conditions, including candlelight and daytime and nighttime shots, thereby including diverse scenes and shooting conditions, which make it highly suitable for research, development, and evaluation of image enhancement algorithms. The DICM dataset comprises 69 low-light images and is often used for evaluating the generalization capacity of LLIE models on real-world image samples. The LIME dataset contains 10 low-light images captured in different scenes. It is often used to test and evaluate LLIE algorithms. ExDark dataset contains 7363 low-light images, encompassing various low-light conditions from twilight to very low-light conditions. Its diversity in lighting conditions and real-world scenarios enables it to stand out in the training and evaluation phases of the model. Several other datasets utilized for LLIE tasks are the NPE (Nighttime Photometric Enhancement) dataset [5], [7], [26], [32], [33], LSRW (Large-Scale Real-World) dataset [5], MIT-Adobe FiveK dataset [7], [23], [34], [35], and more. The utilization of diverse datasets for training LLIE models is crucial for ensuring the generalization and robustness of the enhancement models. These trained on limited datasets often struggle to handle images with varying lighting conditions, noise ranges, and scene diversities. A dataset that accompanies various low-light scenarios, cameras, and object types allows the model to learn intricate and comprehensive representations of low-light image characteristics, thereby enabling better reliability when the model is exposed to unseen data.

IV. Evaluation Metrics

Measuring the quality of the produced output of the enhancement model is essential to determine the level of performance of the LLIE algorithm, which includes both subjective and objective metrics. In terms of measuring the subjective sphere, the reliance on the human perception and judgment of the enhanced image for visual quality is followed. Although it targets the ultimate requirement of producing enhancements with improved human perception, these subjective evaluation measures undergo bias and inconsistency. Therefore, alongside objective evaluation metrics, accompanying quantitative metrics to measure specific aspects of image quality are utilized. Such commonly considered metrics are PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index Measure), LPIPS (Learned Perceptual Image Patch Similarity), NIQE (Natural Image Quality Evaluator), and many other metrics.

PSNR measures the ratio between the maximum possible signal and the noise level, where a higher PSNR score generally indicates a better image quality [5], [16]. The SSIM metric measures the similarity between two images based on luminance, contrast, and structure, where a higher SSIM score indicates greater similarity, which, in turn, speaks for its better image quality [5]. LPIPS metrics, particularly, compare images based on their perceptual similarity, where a lower LPIPS score indicates a closer perceptual resemblance. NIQE, which is a non-reference-based qualitative metric, assesses the image quality by comparing its statistical features to a model of natural image statistics, where a lower NIQE score indicates a better perceptual quality [15]. Other than these commonly used qualitative metrics, BRSQUE [9], LOE [16], VIF [36], IE [34], and many more can be utilized to determine the specific assessment requirement of the deep learning model [2], [4], [16]. While objective metrics provide quantitative assessment, they do not perfectly align with the human visual perception [4]. Some enhanced images may achieve high scores on the quantitative objective metrics while still presenting unnatural, less pleasing results. This common discrepancy highlights the requirement for further research to develop a more perceptually aligned evaluation metric that satisfies human perception while relying on quantitative outcomes in assessments.

TABLE IV
Mathematical Equations for LLIE Evaluation Metrics

Metric	Equation
PSNR [5]	$$\text{PSNR} = 10\log_{10}\left(\frac{MAX_I^2}{MSE}\right)$$ MAX_I = max pixel intensity, MSE = mean squared error.
SSIM [5]	$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$ μ_x, μ_y = means, σ_x, σ_y = variances, σ_{xy} = covariance, C_1, C_2 = stability constants.
LPIPS [5]	$$d(x,y) = \sum_l w_l \|F_l(x) - F_l(y)\|_2^2$$ $F_l(x), F_l(y)$ = deep feature activations, w_l = weights.
NIQE [15]	$$NIQE = D(\mu_f, \Sigma_f, \mu_r, \Sigma_r)$$ D = Mahalanobis distance, μ_f, Σ_f = test image stats, μ_r, Σ_r = reference image stats.
LOE [16]	$$LOE = \sum_{i=1}^{N}\sum_{j=1}^{N} \lvert O(i,j) - O'(i,j)\rvert$$ $O(i,j)$ = lightness order in original image, $O'(i,j)$ = lightness order in enhanced image.
VIF [36]	$$VIF = \frac{\sum_s I_s(X_s, Y_s)}{\sum_s I_s(X_s, X_s + V_s)}$$ I_s = mutual information, X_s = reference image, Y_s = distorted image, V_s = noise component.
IE [34]	$$IE = -\sum_{i=1}^{N} p_i \log_2(p_i)$$ p_i = probability score for pixel intensity values.

V. Challenges and Future Research Directions

Low-light image enhancement using deep learning has progressed significantly, but several unforeseen challenges remain. Such challenges are handling noise, color distortion, and detail preservation, more specifically in the context of dealing with complex lighting scenarios [1]. A key issue is a heavy reliance on the extensive training data, which can be expensive and time-consuming to acquire and process as required, and the challenge of ensuring diversity upon collection of data samples, which highly influence the model training phase targeted generalization capabilities, with the introduction of a wide range of lighting conditions, camera types, and scene compositions [5]. Future research should focus on exploring more efficient and accurate deep-learning models for superior image enhancement. Thereby addressing the prevailing generalization issues through the enhancement of the adaptability of the model in diverse scenes and image characteristics. This requirement can be explored with the intervention of techniques such as transfer learning, domain adaptation, and development techniques to enable robust and multi-scale feature representations. Improving the speed and efficiency of deep learning models for real-time or near-real-time processing is also a considerable priority.

VI. Conclusion

Deep learning has significantly evolved over the past years and has led to being impactful in the field of low-light image enhancement, thereby offering promising techniques to enhance under-illuminated scenes and improve the overall visual coherency. While researchers are actively developing more efficient and accurate deep-learning models with a target to achieve identified challenges of noise, color fidelity, and generalization, it has been in active exploration of new approaches, such as integrating models from different tasks, improving generalization capabilities, and enhancing processing speed, which is towards achieving superior image enhancement effects. These advancements hold immense potential for downstream task applicability, including nighttime photography, surveillance, and computer vision tasks in complex and challenging lighting conditions.

REFERENCES

[1] R. Khan, A. Mehmood, F. Shahid, Z. Zheng, and M. M. Ibrahim, "Lit me up: A reference free adaptive low light image enhancement for in-the-wild conditions," Pattern Recognit., vol. 153, no. Journal Article, p. 110490, 2024, doi: 10.1016/j.patcog.2024.110490.

[2] S. Lin, F. Tang, W. Dong, X. Pan, and C. Xu, "SMNet: Synchronous Multi-Scale Low Light Enhancement Network With Local and Global Concern," IEEE Trans. Multimed., vol. 25, no. Journal Article, pp. 9506–9517, 2023, doi: 10.1109/TMM.2023.3254141.

[3] 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.

[4] K. Singh and A. S. Parihar, "Illumination estimation for nature preserving low-light image enhancement," Vis. Comput., vol. 40, no. 1, pp. 121–136, 2024, doi: 10.1007/s00371-023-02770-9.

[5] 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.

[6] 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.

[7] 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.

[8] 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.

[9] Q. Li, B. Jiang, X. Bo, C. Yang, and X. Wu, "Effective low-light image enhancement with multiscale and context learning network," Multimed. Tools Appl., vol. 82, no. 10, pp. 15271–15286, 2023, doi: 10.1007/s11042-022-13830-y.

[10] J. Hai et al., "R2RNet: Low-light image enhancement via Real-low to Real-normal Network," JVisCommunImage Represent, vol. 90, no. 103712, p. 103712, 2023, doi: 10.1016/j.jvcir.2022.103712.

[11] C. Wei, W. Wang, W. Yang, and J. Liu, "Deep Retinex Decomposition for Low-Light Enhancement," ArXiv, no. Journal Article, 2018, [Online]. Available: https://www.semanticscholar.org/paper/Deep-Retinex-Decomposition-for-Low-Light-Wei-Wang/c7798bbbcd2e85593a2b2d37b92dabac63420cd8.

[12] F. Lv, F. Lu, J. Wu, and C. Lim, "MBLLEN: Low-Light Image/Video Enhancement Using CNNs," presented at the British Machine Vision Conference, Sementic Scholar, 2018. [Online]. Available: https://www.semanticscholar.org/paper/MBLLEN

[13] C. Li, J. Guo, F. Porikli, and Y. Pang, "LightenNet: A Convolutional Neural Network for weakly illuminated image enhancement," Pattern Recognit. Lett., vol. 104, no. Journal Article, pp. 15–22, 2018, doi: 10.1016/j.patrec.2018.01.010.

[14] Y. Cai, H. Bian, J. Lin, H. Wang, R. Timofte, and Y. Zhang, "Retinexformer: One-stage Retinex-based Transformer for Low-light Image Enhancement," in CVF International Conference on Computer Vision (ICCV), CVF Conference on Computer Vision and Pattern Recognition (CVPR): ARXIV, Oct. 2023, pp. 12504–12513. [Online]. Available: http://arxiv.org/abs/2303.06705

[15] 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.

[16] N. YU, J. LI, and Z. HUA, "FLA-Net: multi-stage modular network for low-light image enhancement," Vis. Comput., vol. 39, no. 4, pp. 1251–1270, 2023, doi: 10.1007/s00371-022-02402-8.

[17] J. Wang et al., "N-LoLiGan: Unsupervised low-light enhancement GAN with an N-Net for low-light tunnel images," Digit. Process, vol. 143, no. 104259, p. 104259, 2023, doi: 10.1016/j.dsp.2023.104259.

[18] 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.

[19] G. Han, Y. Wang, J. Liu, and F. Zeng, "Low-light images enhancement and denoising network based on unsupervised learning multi-stream feature modeling," J. Vis. Commun. Image Represent., vol. 96, no. Journal Article, p. 103932, 2023, doi: 10.1016/j.jvcir.2023.103932.

[20] 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.

[21] 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.

[22] Y. Fu, Y. Hong, L. Chen, and S. You, "LE-GAN: Unsupervised low-light image enhancement network using attention module and identity invariant loss," Knowl.-Based Syst., vol. 240, no. Journal Article, p. 108010, 2022, doi: 10.1016/j.knosys.2021.108010.

[23] 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.

[24] A. Zhu, L. Zhang, Y. Shen, Y. Ma, S. Zhao, and Y. Zhou, "Zero-Shot Restoration of Underexposed Images via Robust Retinex Decomposition," in 2020 IEEE International Conference on Multimedia and Expo (ICME), Jul. 2020, pp. 1–6. doi: 10.1109/ICME46284.2020.9102962.

[25] W. Yang, S. Wang, Y. Fang, Y. Wang, and J. Liu, "From Fidelity to Perceptual Quality: A Semi-Supervised Approach for Low-Light Image Enhancement," in 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Jun. 2020, pp. 3060–3069. doi: 10.1109/CVPR42600.2020.00313.

[26] 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.

[27] C. Chen, Q. Chen, M. Do, and V. Koltun, "Seeing Motion in the Dark," in 2019 IEEE/CVF International Conference on Computer Vision (ICCV), Seoul, Korea (South): IEEE, Oct. 2019, pp. 3184–3193. doi: 10.1109/ICCV.2019.00328.

[28] K. Ma, K. Zeng, and Z. Wang, "Perceptual Quality Assessment for Multi-Exposure Image Fusion," IEEE Trans. Image Process., vol. 24, no. 11, pp. 3345–3356, Nov. 2015, doi: 10.1109/TIP.2015.2442920.

[29] C. Lee, C. Lee, and C.-S. Kim, "Contrast enhancement based on layered difference representation," presented at the 2012 19th IEEE International Conference on Image Processing, Orlando, FL, USA: IEEE Xplore, Sep. 2012, pp. 965–968. doi: 10.1109/ICIP.2012.6467022.

[30] X. Guo, Y. Li, and H. Ling, "LIME: Low-Light Image Enhancement via Illumination Map Estimation," IEEE Trans. Image Process., vol. 26, no. 2, pp. 982–993, 2017, doi: 10.1109/TIP.2016.2639450.

[31] Y. P. Loh and C. S. Chan, "Getting to know low-light images with the Exclusively Dark dataset," Comput. Vis. Image Underst., vol. 178, no. Journal Article, pp. 30–42, 2019, doi: 10.1016/j.cviu.2018.10.010.

[32] S. Hu and L. Li, "An attention mechanism and GAN based low-light image enhancement method," A. Bhattacharjya and X. Feng, Eds., Hangzhou, China: SPIE, May 2023, p. 143. doi: 10.1117/12.2681113.

[33] 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.

[34] 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.

[35] 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.

[36] Z. Rahman, Y.-F. Pu, M. Aamir, and S. Wali, "Structure revealing of low-light images using wavelet transform based on fractional-order denoising and multiscale decomposition," Vis. Comput., vol. 37, no. Journal Article, 2021, doi: 10.1007/s00371-020-01838-0.