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Analysis of Trends and Development of Low-Light Image Enhancement Methods in Computer Vision

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Abstract

This study investigates the development of Low-Light Image Enhancement (LLIE) methods in the field of computer vision using a Systematic Literature Review (SLR) approach. The review was conducted on 56 scientific articles selected from a total of 604 papers entirely sourced from the Scopus database based on the PRISMA 2020 guidelines. The results indicate that LLIE research has evolved from traditional methods, such as histogram equalization and Retinex, toward deep learning-based approaches including CNN, GAN, Transformer, and diffusion models. Modern methods have demonstrated superior performance in improving image illumination, preserving details, and reducing noise. In addition, real-world datasets and zero-reference approaches are increasingly adopted to improve model generalization capability. However, challenges remain regarding computational complexity, detail preservation, and model performance under extreme low-light conditions. This study concludes that future LLIE research will focus on developing models that are more adaptive, efficient, lightweight, and robust for various computer vision applications.

***Keywords**: Computer vision; Deep learning; Low-light image enhancement; Systematic literature review; Zero-reference learning*

1. Introduction

The development of digital image processing technology has increased rapidly in recent years, particularly in the field of Low-Light Image Enhancement (LLIE). This technology aims to improve the quality of images captured under low-light conditions so that object details become more visible and easier to analyze. Low-light conditions often cause images to have high noise, low contrast, unnatural colors, and loss of important details that can affect the performance of computer vision systems. Such conditions are commonly encountered in security surveillance, intelligent vehicles, medical imaging, mining, and remote sensing [1], [2], [3].

Various methods have been developed to address these problems, ranging from Retinex-based approaches, wavelet transforms, Generative Adversarial Networks (GAN), Transformers, to diffusion models. Retinex-based methods remain one of the most widely used approaches because they can separate illumination and reflectance components in images [4], [5], [6], [7]. Furthermore, the development of deep learning-based methods such as GAN and Transformer has also shown significant performance improvements in preserving image details and reducing noise [8], [9], [10], [11]. Recent research has even begun to integrate diffusion models and frequency-domain learning to obtain more stable and realistic enhancement results [12], [13], [14], [15], [16].

Although the development of LLIE methods is very rapid, existing research still shows variations in approaches, datasets, and evaluation techniques that are quite diverse. This makes it difficult to determine the most effective method for specific conditions. Therefore, a systematic literature review is needed to analyze the development of LLIE research, identify the most frequently used methods, and understand the latest research trends in this field.

Based on these problems, this study presents a Systematic Literature Review (SLR) to analyze trends and developments in Low-Light Image Enhancement (LLIE) methods in the field of Computer Vision. The research was conducted following PRISMA 2020 guidelines to ensure that the identification, selection, and analysis of literature were carried out systematically, transparently, and in a structured manner [17], [18]. Specifically, this study was designed to answer eight Research Questions (RQ) as follows:

RQ1: How has the evolution of Low-Light Image Enhancement (LLIE) methods progressed from traditional approaches to deep learning-based architectures?

RQ2: What architectural characteristics are most effective in recovering illumination without triggering noise amplification or loss of texture details?

RQ3: What is the role and transformation of dataset usage in supporting LLIE model training, particularly the shift from paired synthetic data toward zero-reference and unpaired approaches?

RQ4: To what extent can quantitative and qualitative evaluation metrics reflect the visual quality and reliability of LLIE models in real-world scenarios?

RQ5: What are the main technical and methodological challenges that still hinder model generalization under non-uniform illumination, extreme dynamic range, and domain variations?
RQ6: How do computational efficiency optimization strategies and lightweight model design affect the trade-off between image enhancement accuracy and inference speed for real-time applications?
RQ7: How is the adoption and adaptation of LLIE methods applied to specific application domains such as autonomous surveillance systems, medical imaging, autonomous vehicles, and remote sensing?
RQ8: What are the future research priority directions for LLIE, particularly regarding the integration of foundation models, multimodal approaches, benchmark standardization, and mitigation of evaluative bias?
This study is expected to provide a comprehensive overview of LLIE method development and serve as a reference for future research in developing enhancement models that are more adaptive, efficient, and robust for various computer vision applications.

2. Research methodology

This study employs a systematic literature review (SLR) to analyze the trends and development of low-light image enhancement (LLIE) in computer vision. The SLR method was chosen for its ability to provide a systematic, structured, and comprehensive examination of prior research, enabling the identification of methodological progress, research challenges, and future technological directions in LLIE.
The review process adheres to the PRISMA 2020 guidelines to ensure transparent and structured stages of identification, screening, eligibility, and synthesis [17], [18]. Initial data was obtained from a dataset of scientific articles on low-light image enhancement provided as part of a research methodology course. The dataset consisted of 604 articles compiled in a spreadsheet, which were subsequently filtered based on topic relevance, publication quality, and alignment with the study objectives.

2.1. Search strategy and sources

Data collection began with an initial dataset of 604 scientific articles on low-light image enhancement (LLIE). The dataset was compiled in spreadsheet format and covered various publications discussing image quality enhancement under low-light conditions. All entries served as the baseline for systematic identification and screening.
The literature search strategy employed keyword combinations and Boolean operators to ensure comprehensive coverage. The search focused on article titles, abstracts, author keywords, and methodological scopes. Keyword combinations such as ("low-light image enhancement" OR "low-illumination vision") AND ("deep learning" OR "CNN" OR "GAN" OR "Transformer" OR "diffusion model" OR "zero-reference") were used to capture literature explicitly discussing LLIE algorithm development in computer vision. The screening process also prioritized modern architectural developments, including attention mechanisms, frequency-domain learning, and lightweight approaches widely adopted in recent studies.

The initial identification process was conducted exclusively using the Scopus database. Selection was limited to English-language publications from 2017–2026 to capture post-deep learning methodological evolution. Prior to the PRISMA screening stage, duplicates, non-peer-reviewed documents, and irrelevant articles were eliminated to obtain a focused and analyzable literature collection.

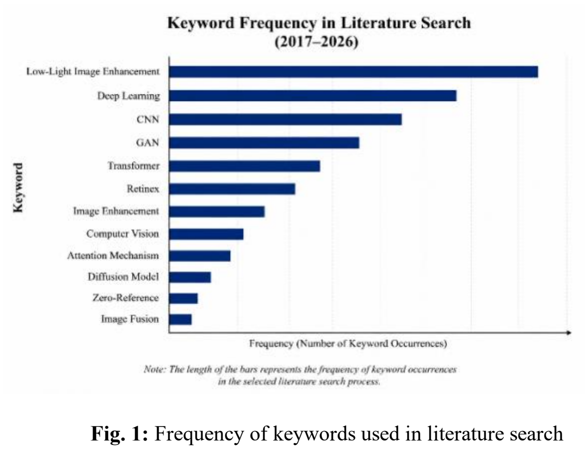

Fig. 1: Frequency of keywords used in literature search

Based on Fig. 1, "low-light image enhancement" emerged as the dominant keyword in the literature search process. Keywords such as deep learning, CNN, GAN, Transformer, and Retinex were also frequently used to broaden the scope of relevant articles. The use of multiple keywords aimed to capture literature covering both traditional methods and modern deep learning approaches.

All initial literature identification was conducted exclusively using the Scopus database. Scopus was selected due to its broad international publication coverage and relevance to research in computer vision, image processing, and artificial intelligence. After identification, articles were re-screened based on topic relevance, methodological alignment, information completeness, and connection to the research objectives and research questions. The selection process yielded 56 primary articles used as the basis for literature analysis and synthesis.

2.2. Criteria and execution

Inclusion and exclusion criteria were applied to ensure literature relevance to the study objectives. Selection was conducted in stages through title, abstract, keyword, methodology, and full-text review. Inclusion criteria encompassed: (1) focus on low-light image enhancement (LLIE), whether traditional or deep learning-based; (2) relevance to computer vision or digital image processing; and (3) publication within 2017–2026 to capture modern architectural developments (CNN, GAN, Transformer, diffusion). Articles were excluded if they were irrelevant to LLIE, duplicated, lacked complete methodology, were non-scientific documents (editorials, short papers), or did not align with the research questions. This process yielded a focused literature collection ready for synthesis analysis.

2.3. Literature selection process (PRISMA)

The literature selection process followed the PRISMA 2020 approach to ensure systematic and transparent identification and filtering stages [17], [18]. The selection stages included identification, screening, eligibility, and inclusion of all articles obtained from the initial dataset.

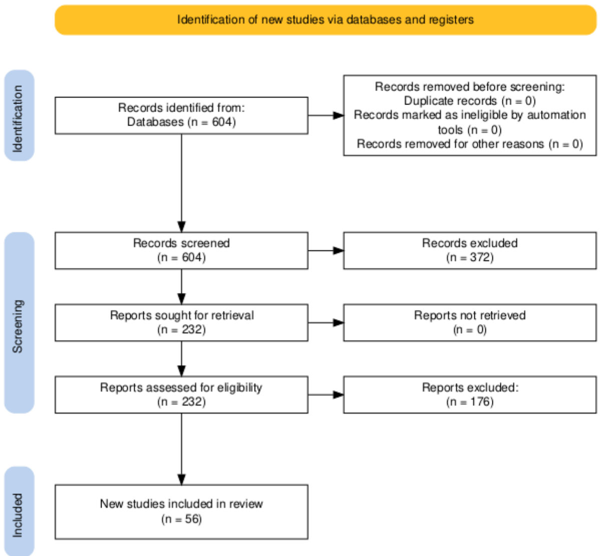

Fig. 2: PRISMA 2020 flow diagram of literature selection

Based on Fig. 2, the identification stage yielded 604 articles exclusively from the Scopus database. During screening, titles, abstracts, and research focuses were reviewed, resulting in the exclusion of 372 articles due to irrelevance. Subsequently, 232 articles proceeded to the eligibility stage for further analysis based on methodological suitability, information completeness, and alignment with research objectives.
In the final stage, 176 articles were excluded for not meeting the predetermined inclusion criteria. Consequently, 56 primary articles were obtained for literature analysis and synthesis. These articles were analyzed to address research questions related to method development, architectures, datasets, evaluation, challenges, and future directions in low-light image enhancement [18].

2.4. Data analysis technique

Data analysis employed a descriptive qualitative approach through identification, classification, and synthesis of articles that passed the selection stage. The 56 primary articles were analyzed to identify low-light image enhancement (LLIE) developments, model architectural characteristics, dataset usage, evaluation metrics, and ongoing research challenges in computer vision.
The analysis stage categorized articles based on methodological approaches, including Retinex-based methods [4], [5], [2], [6], [7], CNN and GAN approaches [8], [19], Transformer and Fourier-based methods [20], [21], [9], and diffusion model and zero-reference approaches [22], [23]. The study also analyzed lightweight method developments and computational optimization for real-time implementation [3], [19]. Categorization aimed to observe the evolution of LLIE architectures from traditional to modern deep learning methods.

Each article was further analyzed based on research contributions, datasets used, enhancement techniques, model performance, and evaluation metrics such as PSNR, SSIM, NIQE, and visual assessment. Analysis also covered model capabilities in handling noise, preserving texture details, and improving illumination quality under low-light conditions [1], [24], [25], [26], [27]. Additionally, challenges in model generalization under non-uniform illumination, extreme dynamic range, and domain variations were examined [28], [23], [9].

Literature synthesis involved comparing findings across articles to identify methodological trends, advantages and limitations of approaches, and future LLIE research directions. This stage adhered to SLR concepts emphasizing annotation, categorization, and analytical framework development. The PRISMA 2020 approach further ensured systematic and structured analysis [17], [18].

3. Results and discussion

This section presents the main findings from the systematic literature review on low-light image enhancement (LLIE) methods. Analysis was conducted thematically based on eight research questions (RQ1–RQ8) covering method evolution, architectural characteristics, dataset roles, evaluation metrics, technical challenges, computational efficiency, application domains, and future research directions. Synthesis results originate from 56 scientific articles rigorously selected using PRISMA 2020 guidelines [18].

3.1. Classification and comparison of LLIE methods

Table 1: Classification of LLIE methods based on approach

Category	Example methods	Advantages	Challenges
Traditional	Histogram, Retinex, Wavelet	Lightweight, simple	Noise amplification, detail loss
CNN-based	Retinex-Net, CNN	High accuracy, texture preservation	Requires paired data, overfitting
GAN-based	CycleGAN, EnlightenGAN	Realistic visuals, unpaired training	Training instability, artifacts
Transformer	ViT, Swin Transformer	Global context, non-uniform handling	High computation, slow inference
Diffusion	Diffusion model, Zero-DCE	Strong generalization, no ground truth	Long sampling, high memory

This table summarizes the synthesized characteristics, strengths, and main limitations of six LLIE approaches based on the analysis of 56 selected literatures.

3.2. Discussion based on research questions

Rq1: how has the evolution of low-light image enhancement methods progressed from traditional approaches to deep learning architectures?

This section discusses the development of LLIE methods from classical histogram equalization, Retinex, and wavelet transform approaches to modern deep learning architectures such as CNN, GAN, Transformer, diffusion models, and hybrid networks. Early research focused on mathematical illumination and contrast manipulation using traditional approaches like Retinex and histogram enhancement [2], [6], [29], [30], [31]. While these methods improved image brightness, they frequently resulted in noise amplification, detail loss, and color instability.

Subsequent developments shifted toward Convolutional Neural Networks (CNN) and Retinex-based deep learning, which began adaptively learning illumination distributions [4], [24], [32], [7], [33], [34], [35], [36]. These approaches significantly improved texture and detail restoration compared to traditional methods.

Later, Generative Adversarial Networks (GAN) were employed to generate more realistic images under low-light conditions [8], [19], [37], [38]. GANs provided notable visual improvements, though some studies reported training instability and potential visual artifacts.

Modern architectural transformations are evident in the adoption of Vision Transformers, frequency-domain learning, diffusion models, and hybrid CNN-Transformer networks [20], [21], [9], [10], [39], [11], [12], [13], [14], [15], [16], [40]. Recent approaches not only improve illumination but also preserve spatial structures, high-frequency details, and generalization in real-world scenarios.

Fig. 3: Evolution of LLIE methods

Rq2: which architectural characteristics are most effective in restoring illumination without triggering noise amplification or texture detail loss?

Analysis indicates that effective LLIE architectures typically integrate attention mechanisms, multi-scale feature extraction, frequency-domain learning, and Retinex decomposition. Multi-attention approaches separate illumination areas from texture details, thereby suppressing noise amplification [5], [25], [41], [42].
Several studies utilize wavelet transforms and frequency learning to preserve high-frequency details in dark regions [20], [21], [6], [13], [16], [42], [43]. These approaches prove more stable in preserving edge information compared to pixel-domain enhancement alone.
Additionally, transformer-based architectures demonstrate superior global feature modeling under non-uniform lighting [9], [10], [11], [39], [40]. However, transformer computational complexity remains a challenge for real-time implementation.

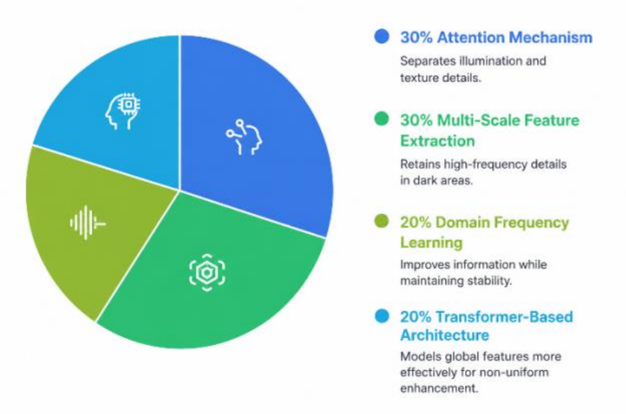

Fig. 4: Distribution of effective LLIE architectural characteristics

Rq3: what is the role and transformation of dataset usage in training LLIE models, particularly the shift from paired synthetic data to zero-reference and unpaired approaches?
Datasets play a crucial role in LLIE model development. Early studies predominantly used paired synthetic datasets created by artificially reducing the brightness of normal images [4], [24], [9], [34]. While facilitating supervised learning, this approach often introduced domain gaps relative to real-world conditions.
Recent developments have shifted toward unsupervised, zero-reference, and unpaired learning to reduce dependency on paired datasets [22], [44], [45], [37], [46], [38], [47], [48], [14]. These models leverage self-constraints, illumination priors, or perceptual learning to enhance image quality without direct ground truth.
Recent studies also increasingly adopt UHD benchmarks and real-world datasets to improve model generalization [21], [11], [49]. This shift indicates that LLIE research focus has evolved from mere visual enhancement toward robustness in real environments.

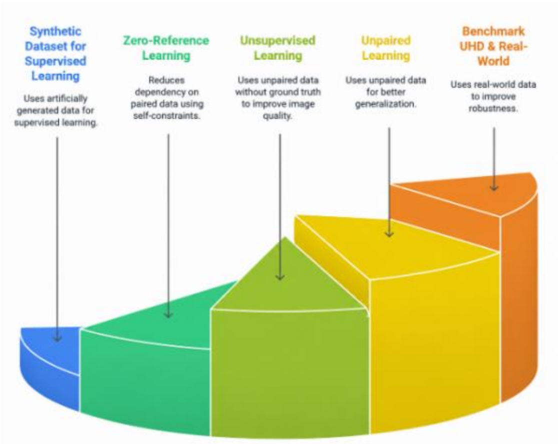

Fig. 5: Transformation of dataset usage in LLIE model training

Rq4: to what extent do quantitative and qualitative evaluation metrics reflect visual quality and model reliability in real-world scenarios?
LLIE model evaluation employs quantitative metrics such as PSNR, SSIM, NIQE, LPIPS, and entropy measurement [24], [20], [39], [11], [15]. PSNR and SSIM are widely used to measure similarity to ground truth, while NIQE and LPIPS evaluate perceptual image quality.
However, several studies indicate that quantitative metrics do not fully represent human visual perception [33], [12], [50]. Images with high PSNR scores are not necessarily visually natural. Therefore, qualitative evaluation through visual comparison and downstream task evaluation is increasingly utilized [51], [3], [52].
Recognition-oriented enhancement is also being developed to measure enhancement impact on computer vision tasks such as object detection and recognition [51], [3], [52].

Rq5: what are the main technical and methodological challenges that still hinder model generalization under non-uniform lighting, extreme dynamic range, and domain variations?

Despite significant performance improvements in LLIE models, several key challenges persist under extreme lighting, non-uniform illumination, and domain variation [28], [23], [9], [53], [11]. Supervised models often experience performance degradation when tested on different domains due to training dataset distribution dependency. Additionally, noise amplification and color distortion remain major issues in dark regions with high dynamic range [4], [25], [26], [54].
Some studies attempt to address these issues through domain adaptation, probabilistic learning, and illumination-guided enhancement [28], [23], [44], [54]. However, cross-domain generalization remains an open challenge in LLIE research.

Rq6: how do computational efficiency optimization strategies and lightweight model design affect the trade-off between image enhancement accuracy and inference speed for real-time applications?
Computational efficiency is a critical concern, particularly for edge devices, autonomous vehicles, and embedded systems. Several studies have begun developing lightweight architectures with fewer parameters and faster inference [3], [19], [46], [55], [56].
Lightweight approaches typically utilize wavelet transforms, lookup tables, knowledge distillation, and compact attention mechanisms to reduce model complexity [22], [55], [56]. Results indicate that parameter reduction increases inference speed but often causes decreased enhancement detail under extreme conditions.
The trade-off between enhancement quality and computational efficiency remains a primary focus for real-time LLIE model development.

Rq7: how are LLIE methods adopted and adapted in specific application domains such as autonomous surveillance, medical imaging, autonomous vehicles, and remote sensing?
LLIE deployment has expanded across various domains including security surveillance, autonomous vehicles, medical imaging, remote sensing, mining, and industrial vision [1], [2], [57], [3], [19], [58], [10], [49], [16].
In remote sensing, enhancement is required to improve nighttime satellite image interpretation [57]. For autonomous vehicles and intelligent surveillance, LLIE improves object detection visibility at night [3], [19], [10].
Meanwhile, medical domains such as colonoscopy video enhancement require highly sensitive biological texture detail preservation [49]. This demonstrates that enhancement requirements vary significantly across application domains.

Rq8: what are the future research priorities for LLIE, particularly regarding the integration of foundation models, multimodal approaches, benchmark standardization, and mitigation of evaluative bias?
Future research directions indicate a trend toward integrating diffusion models, foundation models, multimodal learning, and unified benchmark evaluation [21], [23], [12], [14], [15].
Recent studies increasingly combine frequency-domain learning, semantic guidance, and transformer architectures to improve model robustness [39], [13], [40]. Additionally, benchmark standardization and real-world evaluation are becoming primary concerns to reduce evaluative bias across studies.
Development of lightweight models with high generalization and adaptive capabilities across various domains is projected to be the main focus of LLIE research in the coming years.

3.3. Synthesis of findings

Based on the analysis of 56 selected articles, LLIE research has evolved from traditional methods (histogram, Retinex) to deep learning approaches (CNN, GAN, Transformer, diffusion models). Recent trends emphasize zero-reference methods, unsupervised learning, and lightweight models for real-time applications.
LLIE methods have been deployed across various domains including autonomous vehicles, intelligent surveillance, medical imaging, and remote sensing. However, primary challenges remain model generalization under extreme conditions, high computational complexity, and the need for evaluation standardization. Future research is expected to focus on developing more efficient, adaptive, and robust models for real-world implementation.

4. Conclusion

Based on the systematic literature review (SLR), low-light image enhancement (LLIE) research has rapidly progressed from traditional methods to deep learning-based approaches such as Retinex, GAN, Transformer, and diffusion models. Most studies focus on improving illumination, reducing noise, and preserving image detail and color under low-light conditions.
Analysis results indicate that Transformer-based methods, diffusion models, and attention mechanisms represent the latest trends due to their ability to produce superior enhancement quality. However, challenges such as model complexity, high computational demands, and limited generalization remain issues requiring further development. Future research should prioritize lightweight, efficient models capable of real-time operation on resource-constrained devices. Additionally, utilizing more diverse datasets and combining approaches such as Retinex, Transformer, and diffusion models presents significant opportunities to enhance image quality across varying lighting conditions..

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References

[1] Y. Zhou, L. Xie, K. He, D. Xu, D. Tao, and X. Lin, "Low-light image enhancement for infrared and visible image fusion," *IET Image Process.*, vol. 17, no. 11, pp. 3216–3234, Sep. 2023, doi: 10.1049/ipr2.12857.

[2] F. Tian, M. Wang, and X. Liu, "Low-Light Mine Image Enhancement Algorithm Based on Improved Retinex," *Applied Sciences (Switzerland)*, vol. 14, no. 5, Mar. 2024, doi: 10.3390/app14052213.
[3] H. Hussain, P. S. Tamizharasan, and P. K. Yadav, "OptiRet-Net: An Optimized Low-Light Image Enhancement Technique for CV-Based Applications in Resource-Constrained Environments," *ACM Trans. Intell. Syst. Technol.*, vol. 15, no. 6, Dec. 2024, doi: 10.1145/3700136.
[4] P. Ji, Z. Lv, and Z. Zhang, "A Retinex-Based Network for Low-Light Image Enhancement With Multi-Scale Denoising and Focal-Aware Reflections," *IET Image Process.*, vol. 19, no. 1, Jan. 2025, doi: 10.1049/ipr2.70059.
[5] J. Chen, Z. Xiao, X. Qin, and D. Luo, "Retinex-Based Low-Light Image Enhancement via Spatial-Channel Redundancy Compression and Joint Attention," *Electronics (Switzerland)*, vol. 14, no. 11, Jun. 2025, doi: 10.3390/electronics14112212.
[6] Y. Zhang *et al.*, "Low-light image enhancement method based on retinex theory and dual-tree complex wavelet transform," *Journal of King Saud University - Computer and Information Sciences*, vol. 37, no. 5, Jul. 2025, doi: 10.1007/s44443-025-00102-6.
[7] Y. Jiang, J. Zhu, L. Li, and H. Ma, "A Joint Network for Low-Light Image Enhancement Based on Retinex," *Cognit. Comput.*, vol. 16, no. 6, pp. 3241–3259, Nov. 2024, doi: 10.1007/s12559-024-10347-4.
[8] M. Abisado, "Brightness-Aware Generative Adversarial Network for Low-Light Image Enhancement." [Online]. Available: www.ijacsa.thesai.org
[9] S. Du, X. Qin, M. Zhao, J. Hu, L. Wang, and P. Li, "Non-Uniform Low-Light Stereo Image Enhancement Based on Transformer," in *ASIG 2024 - Proceedings of the 2nd Asia Symposium on Image and Graphics*, Association for Computing Machinery, Inc, Apr. 2025, pp. 164–170. doi: 10.1145/3718441.3718477.
[10] A. Rahmatulloh, E. Haerani, R. Gunawan, E. A. Firdaus, and G. F. Nugraha, "ALEX: Automated Low-Light Enhancement eXpert for Intelligent Security Systems Using Vision Transformer," *Cybernetics and Information Technologies*, vol. 25, no. 4, pp. 145–165, Dec. 2025, doi: 10.2478/cait-2025-0038.
[11] T. Wang, K. Zhang, T. Shen, W. Luo, B. Stenger, and T. Lu, "Ultra-High-Definition Low-Light Image Enhancement: A Benchmark and Transformer-Based Method," 2023. [Online]. Available: https://github.com/TaoWangzj/LLFormer.
[12] W. Lian, W. Lian, and Z. Luo, "Equipping Diffusion Models with Differentiable Spatial Entropy for Low-Light Image Enhancement," Apr. 2024, [Online]. Available: http://arxiv.org/abs/2404.09735
[13] Q. An and L. Ma, "AFMNet: A Dual-Domain Collaborative Network with Frequency Prior Guidance for Low-Light Image Enhancement," *Entropy*, vol. 27, no. 12, Dec. 2025, doi: 10.3390/e27121220.
[14] Y. Lin *et al.*, "AGLLDiff: Guiding Diffusion Models Towards Unsupervised Training-free Real-world Low-light Image Enhancement," 2025. [Online]. Available: www.aaai.org
[15] Y. Wu, G. Wu, and R. Liao, "EWRD: Entropy-Weighted Low-Light Image Enhancement via Reverse Diffusion Model," *International Journal of Intelligent Systems*, vol. 2024, no. 1, 2024, doi: 10.1155/2024/4650233.
[16] Y. Li *et al.*, "Rw-Dm: Retinex and wavelet-based diffusion model for low-light image enhancement in underground coal mines," *Complex and Intelligent Systems*, vol. 11, no. 8, Aug. 2025, doi: 10.1007/s40747-025-01966-x.
[17] S. Siringo Ringo, "Systematic Literature Review dengan Metode Prisma: Pembelajaran Berdiferensiasi pada Pendidikan Dasar," *Jurnal Didaktika Pendidikan Dasar*, vol. 9, no. 1, pp. 209–226, Mar. 2025, doi: 10.26811/didaktika.v9i1.1760.
[18] N. R. Haddaway, M. J. Page, C. C. Pritchard, and L. A. McGuinness, "PRISMA2020: An R package and Shiny app for producing PRISMA 2020-compliant flow diagrams, with interactivity for optimised digital transparency and Open Synthesis," *Campbell Systematic Reviews*, vol. 18, no. 2, Jun. 2022, doi: 10.1002/cl2.1230.
[19] H. In, J. Kweon, and C. Moon, "Squeeze-EnGAN: Memory Efficient and Unsupervised Low-Light Image Enhancement for Intelligent Vehicles," *Sensors*, vol. 25, no. 6, Mar. 2025, doi: 10.3390/s25061825.
[20] T. Zhang, P. Liu, M. Zhao, and H. Lv, "DMFourLLIE: Dual-Stage and Multi-Branch Fourier Network for Low-Light Image Enhancement," in *MM 2024 - Proceedings of the 32nd ACM International Conference on Multimedia*, Association for Computing Machinery, Inc, Oct. 2024, pp. 7434–7443. doi: 10.1145/3664647.3681083.
[21] W. Zou, H. Gao, W. Yang, and T. Liu, "Wave-Mamba: Wavelet State Space Model for Ultra-High-Definition Low-Light Image Enhancement," in *MM 2024 - Proceedings of the 32nd ACM International Conference on Multimedia*, Association for Computing Machinery, Inc, Oct. 2024, pp. 1534–1543. doi: 10.1145/3664647.3681580.
[22] Y. Lin *et al.*, "DPLUT: Unsupervised Low-light Image Enhancement with Lookup Tables and Diffusion Priors," 2025. [Online]. Available: www.aaai.org
[23] Z. Wei, Y. Wang, K. Debattista, and V. Donzella, "Rethinking probabilistic learning for counterfactual low-light image enhancement in robust engineering vision systems," *Knowl. Based. Syst.*, vol. 340, May 2026, doi: 10.1016/j.knosys.2026.115666.
[24] M. Liu, X. Li, and Y. Fang, "Low-Light Image Enhancement via Dual Information-Based Networks," *Electronics (Switzerland)*, vol. 13, no. 18, Sep. 2024, doi: 10.3390/electronics13183713.
[25] Y. Jiang and S. Guo, "Low-Light Image Enhancement Algorithm Integrating Retinex Illumination Estimation and Multi-Attention," *IEEE Access*, vol. 13, pp. 112805–112817, 2025, doi: 10.1109/ACCESS.2025.3583723.
[26] F. Zhang, X. Liu, C. Gao, and N. Sang, "Color and Luminance Separated Enhancement for Low-Light Images with Brightness Guidance," *Sensors*, vol. 24, no. 9, May 2024, doi: 10.3390/s24092711.
[27] Z. Li, "Low light image enhancement algorithm based on edge and colour information," in *ACM International Conference Proceeding Series*, Association for Computing Machinery, Apr. 2024. doi: 10.1145/3663976.3663988.
[28] Q. Li, B. Jiang, X. Bo, C. Yang, and X. Wu, "DANet: A Domain Alignment Network for Low-Light Image Enhancement," *Electronics (Switzerland)*, vol. 13, no. 15, Aug. 2024, doi: 10.3390/electronics13152954.
[29] D. Torres, C. Sbert, and J. Duran, "Combining Total Variation and Nonlocal Variational Models for Low-Light Image Enhancement," in *Proceedings of the International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications*, Science and Technology Publications, Lda, 2024, pp. 508–515. doi: 10.5220/0012386300003660.
[30] R. Weng, Y. Zhang, H. Wu, W. Wang, and D. Wang, "The Retinex enhancement algorithm for low-light intensity image based on improved illumination map," *IET Image Process.*, vol. 18, no. 12, pp. 3381–3392, Oct. 2024, doi: 10.1049/ipr2.13180.
[31] R. Zaghloul and H. Hiary, "EnGMHE: Enhanced Geometric Mean Histogram Equalization for Low-Light Image Enhancement," 2026. [Online]. Available: www.ijacsa.thesai.org
[32] J. Wang, Y. Sun, and J. Yang, "Multi-Modular Network-Based Retinex Fusion Approach for Low-Light Image Enhancement," *Electronics (Switzerland)*, vol. 13, no. 11, Jun. 2024, doi: 10.3390/electronics13112040.
[33] Z. Hu, O. Shkurat, K. Przystupa, O. Kochan, and M. Ivakhnenko, "Low-Light Image Enhancement Technology Based on Image Categorization, Processing and Retinex Deep Network," *International Journal of Image, Graphics and Signal Processing*, vol. 16, no. 5, Oct. 2024, doi: 10.5815/ijigsp.2024.05.01.
[34] Y. Chen, C. Wen, W. Liu, and W. He, "DBENet: Dual-Branch Brightness Enhancement Fusion Network for Low-Light Image Enhancement," *Electronics (Switzerland)*, vol. 12, no. 18, Sep. 2023, doi: 10.3390/electronics12183907.
[35] X. Cao and J. Yu, "LLE-NET: A Low-Light Image Enhancement Algorithm Based on Curve Estimation," *Mathematics*, vol. 12, no. 8, Apr. 2024, doi: 10.3390/math12081228.
[36] Y. Li *et al.*, "A Deep Retinex-Based Low-Light Enhancement Network Fusing Rich Intrinsic Prior Information," *ACM Transactions on Multimedia Computing, Communications and Applications*, vol. 20, no. 11, Nov. 2024, doi: 10.1145/3689642.
[37] M. Xue, Y. He, P. Xie, Z. He, and X. Feng, "LAE-GAN: a novel cloud-based Low-light Attention Enhancement Generative Adversarial Network for unpaired text images," *Journal of Cloud Computing*, vol. 12, no. 1, Dec. 2023, doi: 10.1186/s13677-023-00533-4.

[38] Y. Cai, X. Liu, H. Li, F. Lu, X. Gu, and K. Qin, “Research on Unsupervised Low-Light Railway Fastener Image Enhancement Method Based on Contrastive Learning GAN,” *Sensors*, vol. 24, no. 12, Jun. 2024, doi: 10.3390/s24123794.

[39] Y. Zhou, X. Gao, J. Guo, G. Li, L. Wang, and J. Liu, “LUXFormer: Low-light image enhancement via joint spatial-frequency illumination modeling,” *Journal of King Saud University - Computer and Information Sciences*, vol. 37, no. 8, Oct. 2025, doi: 10.1007/s44443-025-00270-5.

[40] H. Wang, H. Cui, J. Li, and Z. Hua, “HCTMIF: Hybrid CNN-Transformer Multi Information Fusion Network for Low Light Image Enhancement,” *IET Image Process.*, vol. 19, no. 1, Jan. 2025, doi: 10.1049/ipr2.70127.

[41] R. Zhou *et al.*, “Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000. A Low-Light Image Enhancement Algorithm Incorporating Cross-Mixed Attention and Receptive Field Expansion Mechanism”, doi: 10.1109/ACCESS.2023.1120000.

[42] “WMANet Wavelet-Based Multi-Scale Attention Network for Low-Light Image Enhancement”.

[43] H. Zhou, J. Li, Y. Mao, L. Liu, and Y. Lu, “DFCNet: Dual-Stage Frequency-Domain Calibration Network for Low-Light Image Enhancement,” *J. Imaging*, vol. 11, no. 8, Aug. 2025, doi: 10.3390/jimaging11080253.

[44] S. Zhang *et al.*, “Towards Illumination-Guided Bilateral Grid Learning in Zero-Reference Low-Light Enhancement,” *IEEE Access*, 2026, doi: 10.1109/ACCESS.2026.3659099.

[45] J. Zhang, H. Li, and Z. Huo, “Unsupervised Boosted Fusion Network for Single Low-Light Image Enhancement,” *IEEE Access*, vol. 12, pp. 179252–179264, 2024, doi: 10.1109/ACCESS.2024.3502654.

[46] X. Wang, L. Huang, M. Li, C. Han, X. Liu, and T. Nie, “Fast, Zero-Reference Low-Light Image Enhancement with Camera Response Model,” *Sensors*, vol. 24, no. 15, Aug. 2024, doi: 10.3390/s24155019.

[47] A. Mi, W. Luo, Y. Qiao, and Z. Huo, “Rethinking Zero-DCE for Low-Light Image Enhancement,” *Neural Process. Lett.*, vol. 56, no. 2, Apr. 2024, doi: 10.1007/s11063-024-11565-5.

[48] X. Gao, K. Zhao, L. Han, and J. Luo, “BézierCE: Low-Light Image Enhancement via Zero-Reference Bézier Curve Estimation,” *Sensors*, vol. 23, no. 23, Dec. 2023, doi: 10.3390/s23239593.

[49] G. Yue *et al.*, “SGNet: Style-Guided Network with Temporal Compensation for Unpaired Low-Light Colonoscopy Video Enhancement,” *IEEE Transactions on Image Processing*, 2025, doi: 10.1109/TIP.2025.3644172.

[50] Z. Sun, S. Hu, H. Song, and P. Liang, “Learning Wasserstein Contrastive Color Histogram Representation for Low-Light Image Enhancement,” *Mathematics*, vol. 11, no. 19, Oct. 2023, doi: 10.3390/math11194194.

[51] S. Ono, Y. Ogino, T. Toizumi, A. Ito, and M. Tsukada, “Recognition-Oriented Low-Light Image Enhancement Based on Global and Pixelwise Optimization,” in *Proceedings of the International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications*, Science and Technology Publications, Lda, 2025, pp. 222–232. doi: 10.5220/0013316800003912.

[52] N. Zheng, J. Huang, M. Zhou, Z. Yang, Q. Zhu, and F. Zhao, “Learning Semantic Degradation-Aware Guidance for Recognition-Driven Unsupervised Low-Light Image Enhancement,” 2023. [Online]. Available: www.aaai.org

[53] H. Zhang, X. S. Zhang, K. F. Yang, Y. J. Li, and L. L. H. Chan, “Retina adaptation network for low-light image enhancement,” *Pattern Recognit.*, vol. 172, Apr. 2026, doi: 10.1016/j.patcog.2025.112629.

[54] N. Zhang, X. Han, C. Liu, R. Gang, S. Ma, and Y. Cao, “Joint Luminance Adjustment and Color Correction for Low-Light Image Enhancement Network,” *Applied Sciences (Switzerland)*, vol. 14, no. 14, Jul. 2024, doi: 10.3390/app14146320.

[55] M. Y. Kuo and S. De Wang, “GWNet: A Lightweight Model for Low-Light Image Enhancement Using Gamma Correction and Wavelet Transform,” in *International Conference on Agents and Artificial Intelligence*, Science and Technology Publications, Lda, 2025, pp. 264–274. doi: 10.5220/0013148800003890.

[56] J.-C. Tang, W.-Y. Cheng, and D.-Y. Chen, “SOGKD-Lite: Lightweight Semantic Object-Guided Network for Efficient Low-Light Image Enhancement via Knowledge Distillation,” *IEEE Access*, pp. 1–1, Jan. 2026, doi: 10.1109/access.2026.3655389.

[57] V. Frants, S. Agaian, K. Panetta, and A. Grigoryan, “QWR-Dec-Net: A Quaternion-Wavelet Retinex Framework for Low-Light Image Enhancement with Applications to Remote Sensing,” *Information*, vol. 17, no. 1, p. 89, Jan. 2026, doi: 10.3390/info17010089.

[58] C. Shi *et al.*, “RICNET: Retinex-Inspired Illumination Curve Estimation for Low-Light Enhancement in Industrial Welding Scenes,” *Sensors*, vol. 25, no. 16, Aug. 2025, doi: 10.3390/s25165192.