Progressive Information Flow based Non-Linear Dark Image Restoration Method

Tanisha Jain, Shivam Taneja, Kriti Singhal, Naman Chaudhary, Shatakshi Saxena, Kartik Koul, and Suresh Raikwar

[1] Tanisha Jain Thapar Institute of Engineering and Technology (TIET), Patiala, Punjab, India
tjain1$_be21@thapar.edu@thapar.edu$
[2] Shivam Taneja Thapar Institute of Engineering and Technology (TIET), Patiala, Punjab, India
shivam.taneja@thapar.edu
[3] Kriti Singhal Thapar Institute of Engineering and Technology (TIET), Patiala, Punjab, India
kriti.singhal@thapar.edu
[4] Naman Chaudhary Thapar Institute of Engineering and Technology (TIET), Patiala, Punjab, India
naman.chaudhary@thapar.edu
[5] Shatakshi Saxena Thapar Institute of Engineering and Technology (TIET), Patiala, Punjab, India
ssaxena1$_be21@thapar@thapar.edu$
[6] Kartik Koul Thapar Institute of Engineering and Technology (TIET), Patiala, Punjab, India
kartik.koul@thapar.edu
[7] Suresh Raikwar Thapar Institute of Engineering and Technology (TIET), Patiala, Punjab, India
suresh.raikwar@thapar.edu

Abstract. The night image restoration is a challenging task due to its ill-posed nature. The existing methods focus on solution with limited applicability. They produced dark results with reduced brightness and by losing fine details. Therefore, the proposed method focuses on improvement of the brightness while preserving the information using progressive information flow in non-linear way. The proposed non-linear information flow is capable to preserve the fine details and produces bright results in compared the state-of-the-art (SOTA) methods. The proposed method is validated and verified using bench mark dataset.

Dehazing, Enhancement, Progressive Learning, Dark channel prior

1 Introduction

Images are captured for multiple applications including, but not limited to, surveillance, face recognition and identification. However, there are suboptimal conditions, such as poor lighting, low contrast, etc. during cloudy days, indoors, at night time and light reflections which have serious implications on the quality of images. This leads to great difficulties in the later stages of various computer vision tasks including but not limited to object detection, object recognition and scene understanding. Hence, it is important to improve the quality of images taken under poor lighting conditions. As implied by the name, low light, refers to those environments, where the conditions for the normal standard lighting are not met.[1] Low light images are extremely common in real world applications. However, these images pose a problem since the majority of the images used to train the algorithms are taken under normal standard lighting. Hence, extra care is necessary to avoid compromising the performance of an algorithm. Diverse approaches have been utilised for the task of low-light image enhancement. Traditional approaches addressed the problem either in the spatial or the frequency domain. The other methods relied on the Retinex theory, which recovers the intrinsic features of the captured images by reducing the influence of reflection, under the assumption that images can be decomposed into reflection and illumination components. In the recent years, researchers have focused their efforts towards various deep learning-based approaches as they have shown great potential. Unlike various traditional methods, the deep learning methods laid extra emphasis on the spatial features in the images. This made the model robust to noise and allows better preservation of details. The enhanced precision along with efficiency and robustness have also lead to the immense popularity of the deep learning solutions. This approach however has a high dependency on the training dataset and may not generalise well.[2]

This paper presents a method based on progressive information flow in non-linear manner. The progressive information flow allows the brightness to be improved gradually while preserving minute details. Section 2 presented related work, the proposed method has been discussed in Section 3, the detailed discussion on the results is presented in Section 4 and Section 5 concluded the proposed work and analysis of this paper with future scope.

2 Related Work

The night image enhancement is explored in the past as well. Recently, CNN based methods have been proved to be effective. Therefore, latest existing work based on CNN has been studied for this work and presented here.

The method in [3] presented an unpaired learning method for image enhancement, where given a set of images with the desired characteristics, this method learns an image enhancer that transforms an input image into an enhanced image with those characteristics. The method is based on the framework of two-way Generative Adversarial Networks(GANs) with several improvements. The advantage of this method is that with its unpaired setting, the process of collecting training images became easy. Further, the Enhanced U-Net for image processing by augmenting global features is used, which improved the stability of GAN training for the application by an adaptive weighting scheme. However, this technique applies only to unpaired learning methods for image enhancement.

A dual-purpose method is discussed in [4] to achieve satisfactory performance in enhancing the visibility of both underwater and low-light images in a unified manner. Experiments revealed that method in [4] could output high-quality images with ameliorated contrast and brightness. Qualitative comparisons indicated that their method demonstrated improved visibility and natural appearance. Additionally, the quantitative evaluation indicated the excellent performance of this method in terms of several objective criteria. For underwater images, the proposed method performs well in terms of noise suppression and color distortion correction of foreground area. However, it does not significantly affect background areas with severe scattering and absorption effects, which presents a limitation in certain applications.

To automatically enhance images using learned spatially local filters of different types, an approach introduced in [5] in addition to a deep neural network, dubbed Deep Local Parametric Filters (DeepLPF), which regresses the parameters of these spatially localized filters that are then automatically applied to enhance the image. This method estimated a sequence of image edits using graduated, elliptical, and polynomial filters whose parameters can be regressed directly from convolution features provided by a backbone network e.g., U-Net. Their localized filters produce interpretable image adjustments with visually pleasing results and filters constitute pluggable and reusable network blocks capable of improving image visual quality. However, the exploration of automatic estimation of the optimal sequence of filter application is still pending for the future.

To strengthen the representation power of the input of the lightening process, method in [6] introduced a network that works in an end-to-end way, which makes it easy to implement and hence outperforms other recent state-of-the-art approaches (conventional, CNN-based, and GAN-based methods) in quantitative and qualitative aspects.

A two-stage design is adapted in [7] to generate enhanced results with well reconstructed details and visually promising contrast and color distributions. However, it is a semi-supervised learning method that has been created and it is not fully supervised.

The method in [8], a lightweight and efficient Luminance-aware Pyramid Network (LPNet) to reconstruct normal-light images in a coarse-to-fine strategy is proposed. This method could not only brighten up low-light images with rich details and high contrast but also significantly ameliorate the execution speed. Low-light image enhancement based on deep convolutional neural networks (CNNs) has revealed prominent performance in recent years. However, it is still a challenging task since the underexposed regions and details are always imperceptible.

The EnlightenGAN is proposed in [9], which operates and generalizes well without any paired training data. It was found that EnlightenGAN can be easily adapted to real noisy low-light images and yields visually pleasing enhanced images. This paper did propose solutions to the disadvantages of the few previously works. Despite all its advantages, how to control and adjust the light enhancement levels based on user inputs in one unified model and integration of method with sensor innovations are yet to be explored.

In the work in [10], the undesirable enhanced results including amplified noise, degraded contrast and biased colors is removed. It also removed the low-amplitude structures and preserved major edge information, which facilitated extracting paired illumination maps of low/normal-light images. The evaluation of both synthetic and real images, particularly on those containing intensive noise, compression artifacts and interleaved artifacts, presented the effectiveness of this method, which significantly outperformed the state-of-the-art methods.

Benefiting from the pre-training on the dataset, the model in [11] could effectively alleviate overfitting. Afterwards, a cascaded hierarchical net with hierarchical degradation concatenation is used, which could effectively measure the hierarchical degradation on the overall image quality. Experiments of cross-database verification have further proved the high generalizability of the Cascaded CNN with hierarchical degradation concatenation.

The method in [12] showed that a pre-trained GAN can be used as a generative latent bank in an encoder-bank-decoder architecture. The generality of the notion of GAN-based dictionary allowed GLEAN to be potentially extended to not only diverse architectures but also various imaging tasks, such as image denoising, inpainting and colorization. This approach achieved a large scale super-resolution of up to 64 times of the upscaling factor.

The method in [13] can train a lightweight deep network that generalizes well to diverse lighting conditions. It excels in both enhancement performance and efficiency. However, it still demands additional work. By re-designing the network structure, reformulating the curve estimation, and controlling the sizes of the input images, the proposed Zero-DCE can be further improved. This approach is significantly light weight and fast for practical applications. The method in [14] proposed an efficient Industrial Internet of Things(IIoT) system capable of handling protocol identification and video quality enhancement. This method was also implemented on an embedded platform.

To tackle the limitations of the existing methodologies, a low-light image enhancement method that combines the dual attention module convolutional block attentional module and the multi-scale feature fusion module multi-scale inception U-Net is proposed by in [15]. The intermediate enhanced image was stitched with the original input image and fed into the recursive iteration. The intermediate enhancement result provided higher-order feature information, and the original input image provided lower-order feature information. This method could recover the details and increase the brightness of the image and reduce the image degradation compared to the other methods. However, the U-Net model is yet to achieve a higher standard of low-light image enhancement and can be improved further.

The work presented in [16] has inroduced a GPAnet solution that implemented first-order and second-order gradient prior features to handle low-light image enhancement to extract edge features and remove unwanted noise. However, this approach lacked the generalization ability of deep networks in different low-light scenarios and it still remains a challenge. Therefore, to adapt the network to different low-light scenarios is one of the prominent issues which needs to be addressed. Additionally, the third or higher gradient features are not introduced, which could have provided greater insights.

The work in [17] provided results that are superior to those yielded by existing methods regarding image brightness, contrast, noise suppression, and color information. The advantages is more evident in the subjective visualization of multiple datasets and with reference to the objective evaluation metrics, including peak signal-to-noise ratio(PSNR), Structural Similarity Index (SSIM), entropy, etc. Practical applications showed that this method can effectively improve the performance of night-time face recognition detection. Although for use in applications with very low-light images and for backlit images, the information enhancement is not satisfactory yet.

In summary, the existing methods lack in capturing minute details in real-time. Therefore, the proposed method presents a technique to obtain quality visual results in real-time.

3 The Proposed Method

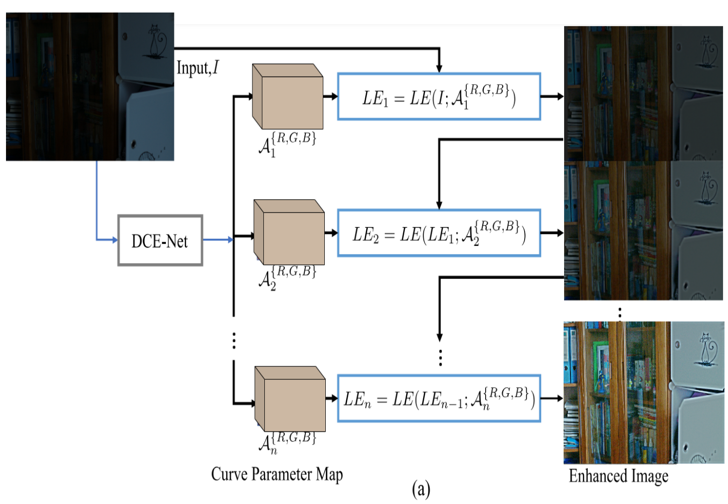


Fig. 1. Framework of Zero-DCE

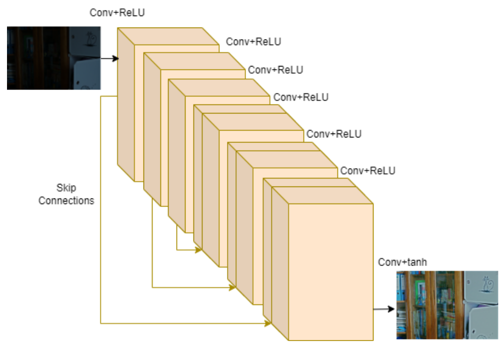


Fig. 2. Architecture of DCE-Net

4 Result and Discussion

The proposed method has been evaluated and validated by using *ssim* [18], *mse*, and *psnr*. Two types of datasets have been used in the proposed work.

4.1 Dataset

The LOw-Light (LOL) dataset was used for training and testing all the methodologies. The dataset comprises of 500 pairs of images featuring both low-light and normal-light conditions. These pairs are further categorized into 485 pairs for training and 15 pairs for testing. The low-light images may exhibit noise generated during the image capture process. The majority of the images depict indoor scenes, and they all share a resolution of 400×600.

The proposed method have been evaluated qualitatively and quantitatively.

4.2 Qualitative Analysis

The accompanying photos provide a comparative examination of image restoration models, allowing for numerous qualitative findings to be made. The photographs illustrate the efficacy of several techniques in rejuvenating luminosity and safeguarding intricate elements, with a specific emphasis on the suggested approach.

1. **Ground Truth Image:** The reference image is used to evaluate the quality of the recovered photos. It symbolizes the optimal result that the restoration processes strive to attain.
2. **Dark Input Image:** The dark input image demonstrates the common difficulties encountered in night image restoration projects. The image has insufficient luminosity and significant loss of information, making it an appropriate candidate for assessing the efficacy of various restoration techniques.

3. **Results of SOTA Methods:**
   The comparative column displays the results of established techniques such as RUAS, LLformer, and MBPnet. Although these technologies aim to enhance brightness, they still have limitations in maintaining intricate details. The restored photos may exhibit increased luminosity compared to the original input, but frequently experience a decrease in sharpness and clarity.
4. **Proposed Method:** The final column, which displays the outcomes of the proposed method, exhibits substantial enhancements compared to current methodologies. The proposed method significantly improves brightness and preserves fine features by using advanced non-linear information flow techniques. The restored image has exceptional clarity and precision, closely approximating the original image. This demonstrates the exceptional efficacy of the suggested strategy when compared to the most advanced techniques currently available.

Upon visual examination, it is clear that the suggested method yields brighter outcomes with improved preservation of details in comparison to alternative methods. The suggested method produces images that closely resemble the ground truth, with more detailed textures and well-preserved edges. This qualitative analysis supports the assertion that the suggested method excels in night picture restoration tasks, overcoming the constraints of current methodologies.

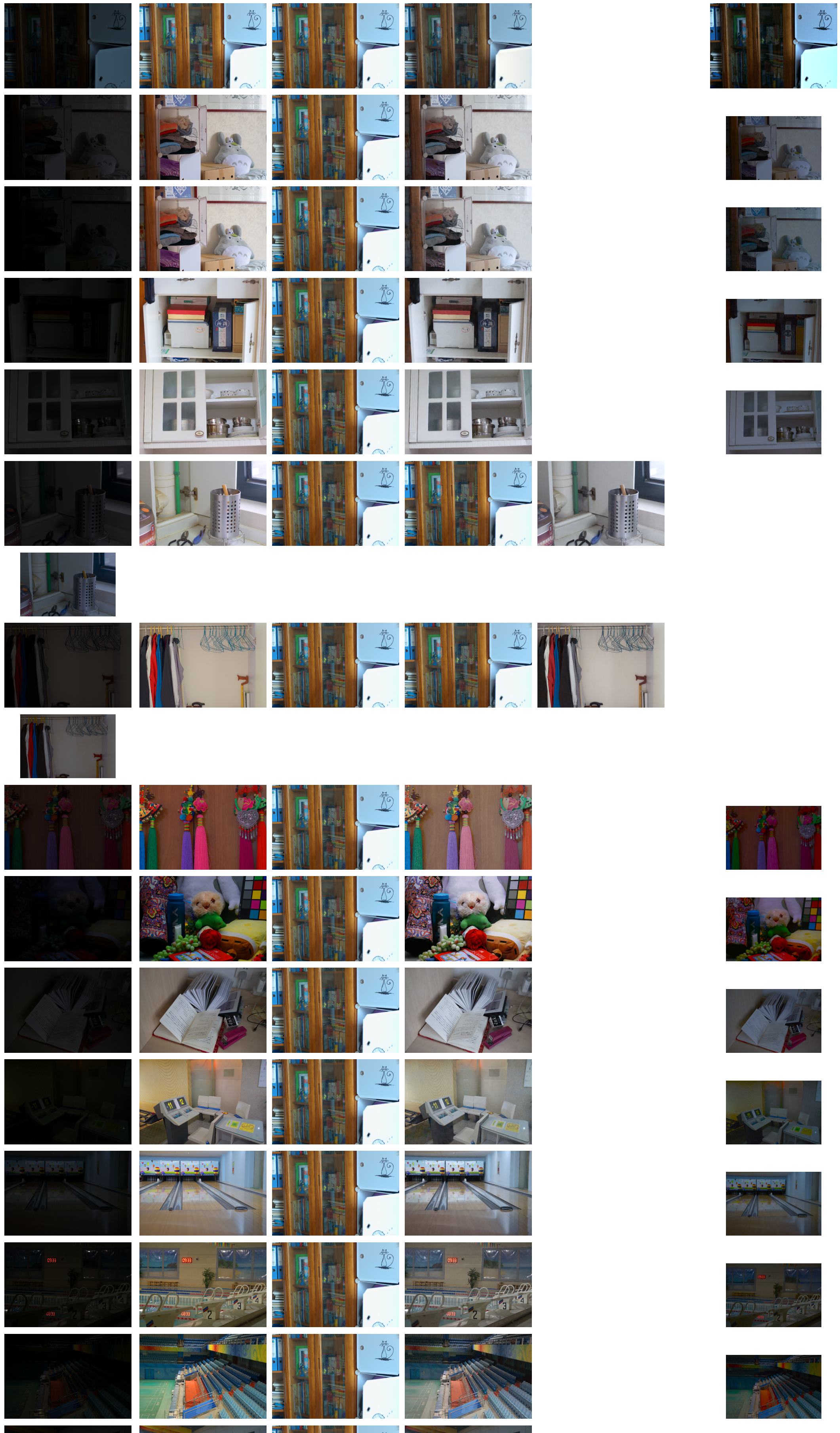
In summary, the qualitative analysis of the compared photos reveals that the suggested method effectively addresses the issues of restoring night photographs. It achieves brighter outcomes while preserving fine details, hence demonstrating its superiority over state-of-the-art methods.

4.3 Quantitative Analysis

5 Conclusion

Acknowledgment

The authors would like to thank CSED, TIET for providing resources and motivation to carry this work.



References

1. M. Kim, D. Park, D. K. Han, and H. Ko, "A novel framework for extremely low-light video enhancement," in *Proc. IEEE International Conference on Consumer Electronics*, January 2014, pp. 91–92.
2. Z. Tian, P. Qu, J. Li, Y. Sun, G. Li, Z. Liang, and W. Zhang, "A survey of deep learning-based low-light image enhancement," *Sensors*, vol. 23, p. 7763, 2023. [Online]. Available: https://doi.org/10.3390/s23187763
3. Y.-S. Chen, Y.-C. Wang, M.-H. Kao, and Y.-Y. Chuang, "Deep photo enhancer: Unpaired learning for image enhancement from photographs with gans," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2018, pp. 6306–6314.
4. C. Dai, M. Lin, J. Wang, and X. Hu, "Dual-purpose method for underwater and low-light image enhancement via image layer separation," *IEEE Access*, vol. 7, pp. 178 685–178 698, 2019.
5. S. Moran, P. Marza, S. McDonagh, S. Parisot, and G. Slabaugh, "Deeplpf: Deep local parametric filters for image enhancement," in *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, 2020, pp. 12 826–12 835.
6. L.-W. Wang, Z.-S. Liu, W.-C. Siu, and D. P. Lun, "Lightening network for low-light image enhancement," *IEEE Transactions on Image Processing*, vol. 29, pp. 7984–7996, 2020.
7. 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 *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, 2020, pp. 3063–3072.
8. J. Li, J. Li, F. Fang, F. Li, and G. Zhang, "Luminance-aware pyramid network for low-light image enhancement," *IEEE Transactions on Multimedia*, vol. 23, pp. 3153–3165, 2020.
9. Y. Jiang, X. Gong, D. Liu, Y. Cheng, C. Fang, X. Shen, J. Yang, P. Zhou, and Z. Wang, "Enlightengan: Deep light enhancement without paired supervision," *IEEE transactions on image processing*, vol. 30, pp. 2340–2349, 2021.
10. W. Yang, W. Wang, H. Huang, S. Wang, and J. Liu, "Sparse gradient regularized deep retinex network for robust low-light image enhancement," *IEEE Transactions on Image Processing*, vol. 30, pp. 2072–2086, 2021.
11. J. Wu, J. Ma, F. Liang, W. Dong, G. Shi, and W. Lin, "End-to-end blind image quality prediction with cascaded deep neural network," *IEEE Transactions on Image Processing*, vol. 29, pp. 7414–7426, 2020. [Online]. Available: https://api.semanticscholar.org/CorpusID:220568805
12. K. C. Chan, X. Wang, X. Xu, J. Gu, and C. C. Loy, "Glean: Generative latent bank for large-factor image super-resolution," in *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, 2021, pp. 14 245–14 254.
13. C. Li, C. Guo, and C. C. Loy, "Learning to enhance low-light image via zero-reference deep curve estimation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 44, pp. 4225–4238, 2021. [Online]. Available: https://api.semanticscholar.org/CorpusID:232076237
14. L. Chen, L. Liu, and L. Zhang, "An efficient industrial internet of things video data processing system for protocol identification and quality enhancement," *IET Cyber-Physical Systems: Theory & Applications*, vol. 8, no. 2, pp. 63–75, 2023.
15. F. Liu, Z. Hua, J. Li, and L. Fan, "Low-light image enhancement network based on recursive network," *Frontiers in Neurorobotics*, vol. 16, p. 836551, 2022.

16. Y. Lu, Y. Gao, Y. Guo, W. Xu, and X. Hu, "Low-light image enhancement via gradient prior-aided network," *IEEE Access*, vol. 10, pp. 92 583–92 596, 2022.
17. C. Xie, H. Tang, L. Fei, H. Zhu, and Y. Hu, "Irnet: An improved zero-shot retinex network for low-light image enhancement," *Electronics*, vol. 12, no. 14, p. 3162, 2023.
18. Z. Wang, A. Bovik, H. Sheikh, and E. Simoncelli, "Image quality assessment: from error visibility to structural similarity," *IEEE Transactions on Image Processing*, vol. 13, no. 4, pp. 600–612, 2004.
19. 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," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 37, no. 3, 2023, pp. 2654–2662.
20. K. Zhang, C. Yuan, J. Li, X. Gao, and M. Li, "Multi-branch and progressive network for low-light image enhancement," *IEEE Transactions on Image Processing*, vol. 32, pp. 2295–2308, 2023.
21. R. Liu, L. Ma, J. Zhang, X. Fan, and Z. Luo, "Retinex-inspired unrolling with cooperative prior architecture search for low-light image enhancement," in *2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. Los Alamitos, CA, USA: IEEE Computer Society, jun 2021, pp. 10 556–10 565. [Online]. Available: https://doi.ieeecomputersociety.org/10.1109/CVPR46437.2021.01042