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ENHANCEMENT OF LOWER VISIBLE IMAGES USING CONVOLUTIONAL RESNET

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Abstract–An image may be disturbed by impulse noise during transmission or acquisition. For image processing applications, it is crucial to repair the disturbed image effectively. This research proposes an encoder-decoder architecture with separate convolution layers to address the problems with low-light picture improvement. Using both clean and noisy photos from an unique low-light image dataset (LID), the architecture is trained from beginning to end. Convolutional Resnet architecture is used in this research to aid in the extraction of the image's features. The top signal-to-noise ratio, the primary comparability record network, the visual data devotion, and the average brightness are some of the evaluation measurements. Using the Matlab tool, the experimental results were produced.

***Index terms*— Resnet, C-Lie-net, Convolutional neural network, Multi-context Feature Extraction Module (MC-FEM), Lower visible images.**

1.INTRODUCTION

It is now being researched how to improve low-light image quality so that the acquisition system can still take high-quality pictures in dim lighting. Self-driving cars, photography, the military, object detection, and spying are just a few examples of its applications. Several factors are considered by low-light picture improvement (Untruth) calculations. These variables incorporate variety contrast, brilliance, picture goal, and dynamic reach. The dynamic range of intensities is often equalised by image processing techniques like histogram equalisation (HE) [1], which is used by many researchers to improve low-light photographs. Furthermore, approaches for histogram equalisation only work to improve image contrast[33]; they don't deal with problems with illumination. Linear and non-linear low-light picture enhancement techniques, as indicated in [2], are straightforward and quick to develop but have limited enhancement potential because they don't take into account image distribution. The use of spatial filters and other image processing techniques has helped enhance the quality of low-light photographs, but these methods are useless in noisy settings.The filters often amplify noise since they depend on a narrow area. These arguments support the necessity for deep learning to improve low-light photos because these techniques are capable of learning dynamically and handling both noisy and clean images.

2.LITERATURE SURVEY

a.LIE Algorithms Using Retinex

Edward H. Land's Retinex theory, which takes into consideration colour constancy and human perception, is used in one class of LIE algorithms [3], [4]. According to this theory, the picture intensity results from the interaction of the reflectance and brightening coefficients. Calculations in light of the retinex hypothesis work out the enlightenment map by eliminating the reflectance part and applying it to improve the image. With an end goal to gauge light from an image, strategies like single-scale and multi-scale Retinex (MSR) utilize an encompass capability [5, 6]. Notwithstanding, these strategies often compromise between rendition quality and dynamic range reduction. A multi-scale reconstruction (MSR) with adaptive weighting is proposed to improve pictures with both colour consistency and local enhancement (see [7] for details). Low-light image enhancement (LIME) [8] is another method of improving images using Retinex. It does this by figuring out how much light each individual pixel is getting and then adjusting accordingly. The illumination map is additionally subjected to a structure prior in order to enhance and improve the initial map. In a different approach [9], which replaces LIME, low-light enhancement is combined with noise removal. The enhancement component handles brightness estimation and image restoration, but it doesn't produce better results because there is still a lot of image noise.

b.LIE Algorithms Using Deep Learning

Denoising, dehazing[19], super-resolution, and other computer vision challenges are only a few examples of image processing jobs where deep learning has demonstrated promise advances. In order to improve photos with poor lighting, the LLNet employs stacked auto-encoders rather than convolutional layers [10]. LLCNN can manage the disappearing slope issue by utilizing a module to extricate the multi-scale include maps [11]. An MBLLEN [13] combines enhancements from many subnets to get the desired effect. With the use of a unique loss function that takes into account underlying, context oriented, and territorial data, MBLLEN had the option to acquire higher outcomes in clamor free pictures. GLADNet is one more convolutional brain network model that utilizes an encoder-decoder to recover worldwide, earlier lighting data and a CNN to reproduce better elements. [14].

To improve low-light pictures with the utilization of consideration, the procedure recommended in [15] utilizes two consideration maps. In the first map, underexposed and well-exposed pixels are distinguished, while in the second, real textures are extracted from background noise. In this study, we offer a unique four-part loss function that accounts for the attention and enhancement loss in addition to the other requirements for enhancing low-light pictures. However, its effectiveness decreases when dealing with compressed images and pictures with large swaths of darkness. In the field of picture handling, Generative Ill-disposed Organizations (GANs) [16] have become more famous close by CNN-based approaches [17] [20]. Edify GAN [21], an exceptionally compelling unaided GAN, was prepared without low-or customary light picture pairings. To enhance the picture, a UNet is utilised, and then two discriminators are used. However, the quantitative measures show that this algorithm is inferior to others, despite its superior performance in visual perception.

c.LIE Algorithms Using Retinex and Deep Learning

Most processes wouldn't even consider the possibility of noise, and in some cases they actually make things a lot noisier. As a result of this shortfall, new techniques for enhancing low-light images using deep learning and the Retinex theory have emerged. Decomposition and enhancement nets are combined in [22] to form a Retinex-Net with a deep layer. After the image is decayed into its reflectance and enlightenment parts, an improvement network is used to change the light part. In contrast, this method cannot be used to improve the image's saturation, brightness, or contrast. To combat the issues of noise and over-illumination, a CNN-based progressive Retinex model was recently created in [23]. The patterns of both noise and light are deduced using two point-wise convolutional networks. While Progressive Retinex may aid in noise reduction, it is unable to record the underlying structural details of a picture. The combination of Retinex and GANs is suggested in [24]. The local-optimal solution is here avoided thanks to regularisation loss. According to [25], a two-step method is optimal for low-light enhancement since it allows for both denoising and augmentation to take place in parallel. [26] proposes a pseudo-Retinex based method for learning the global context that combines content and edge information in two directions using a hybrid network. This approach also makes use of RNNs, making it a complicated network.

d.Separable and Dilated Convolution

Convolutional layers are a common feature of the majority of the models discussed above. However, utilising convolutional layers in complicated design has a high computational cost. The task of improving performance in low light requires deep networks, which are often more complex and need more layers. Complex models, such as the least-squares linear neural network (LLCNN) [11], outperform simpler ones, such as the attention-guided network design [15]. Instead of using traditional convolutional layers, separable convolution is used to strike a balance between the two competing goals of computational complexity and performance.

For each layer, the number of parameters may be reduced by using separable convolutions, as shown in [12]. For comparison, the same architecture using separable convolution requires just 5 million parameters, whereas a convolutional layer-based reduced version of U-Net may have up to 30 million. Moreover, we discovered that most of the deep architectures currently used to improve low-light images ignore contextual information. By combining dilated convolutions with arous spatial pyramid pooling (ASPP) for semantic division, organizations may now learn setting touchy data [27,28]. For a given information x, we might compute the resultant y utilizing the arous convolution and channel w as displayed in [27].

3. Proposed Method

For the majority of applications, clear photographs are necessary to acquire the greatest information possible. Improving photos taken in dim conditions is challenging because of the presence of low brightness, poor contrast, and high noise. The acquisition system can acquire high-quality photographs even in low-light situations thanks to active research in low light image enhancement. It may be used to a wide variety of fields, including autonomous vehicles, photography, the armed forces, object recognition, and spying. Color contrast, brightness, picture quality, and dynamic range are only few of the factors considered by low-light image enhancement (LIE) algorithms. The image quality used in this research is improved by convolutional neural networks with distinct network design.

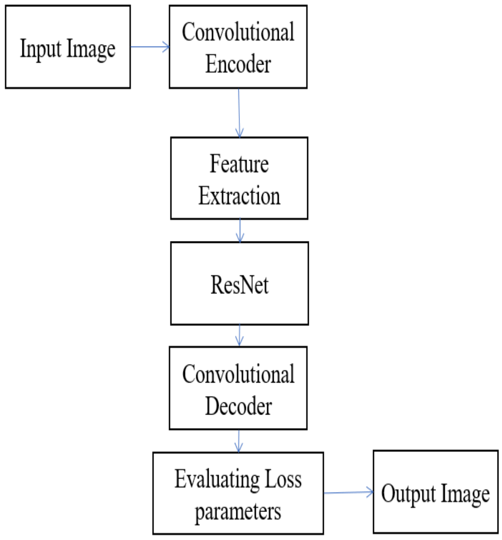

Fig -1: Block Diagram of Proposed model

a. Input Dataset: To simulate low-light conditions in simulated images, researchers at MIT employed a collection of indoor and outdoor situations. Gamma correction is used to simulate low-light conditions. To create the low-light image dataset (LID) for this study, 5000 photos from the MIT dataset were used. To mimic real-world situations, LID includes both clear and chaotic images[31]i.

b. Convolutional Neural Network:

In particular, image-related activities like image classification, recognition, segmentation, etc., CNN is highly helpful in a variety of applications. The foundation of a standard CNN model is comprised of three layers: a convolution layer, a pooling layer, and a completely associated (FC) layer. An element map is produced by the convolution[32] layer by applying the activity to the info map. The element (enactment) map got from the convolution layer is utilized as contribution to the pooling layer, where aspect decrease and information space reflection through sub-testing are used to selectively extract strong features while ignoring weak ones. In order to calculate anything at the FC layer, both the input and the output must be computed for every element.

The FC's layer will likely utilize every conveyed portrayal (highlights) in the ongoing layer to construct highlights with additional strong abilities in the following layer. As the last layer, softmax layers are frequently utilized in CNN to get grouping or acknowledgment results. A CNN model that has been prepared for one job may be used for other tasks by fine-tuning it on the target datasets. A residual network is employed in this CNN to extract characteristics.

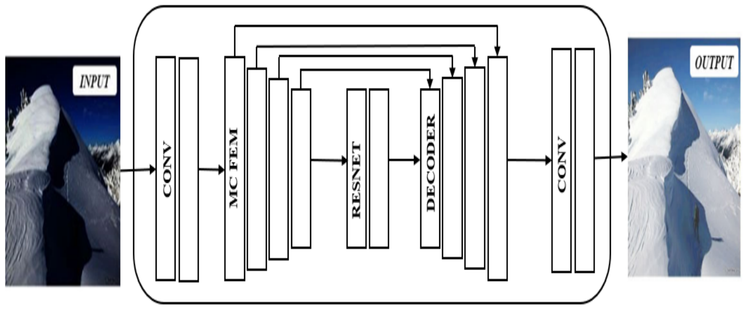

Fig -2: Architecture of Context ResNet

c.ResNet-101:

Residual Blocks are included into this design to solve the vanishing/exploding gradient problem. In this organization, we utilize a procedure called "skip associations." The skip association interfaces the enactments of one layer to those of different layers by skirting part of the in the middle between. It leaves a solid mass of residue behind. Resnets are constructed by stacking these unused construction materials. Based on its technique, this network may instead be trained to suit the residual mapping rather of having layers learn the underlying mapping. ResNet-101 is a convolutional brain network with 101 layers.

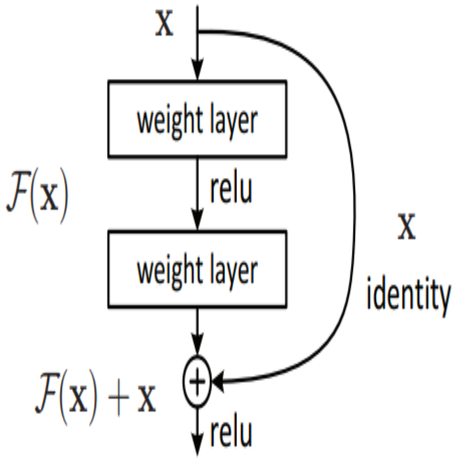

Fig -3: ResNet Model

d. Context ResNet Architecture:

Above is an illustration of the planned context LIE-ResNet architecture. As an alternative to the usual convolution layers, we executed a multi-setting highlight extraction module in the encoder (MC-FEM). To increase the network's generalizability at the decoder, we used ResNet convolution. Applications like low-light picture improvement, which lack natively labelled data, rely heavily on generalisation. To achieve this speedup, we first perform convolution on each channel independently, and then combine the intermediate results. Compared to conventional convolution layers, this approach requires fewer parameters, which lowers the possibility of over-fitting. With the use of skip connections between the encoder and decoder blocks, we may more easily restore image data and features that were lost during the encoding or down sampling processes. Intricate mappings between the picture and its characteristics are recorded by the network thanks to the inclusion of convolution layers at the earliest reference point and end of the organization.

e. Multi-context Feature Extraction Module (MC-FEM):

Multi-contextual features are extracted by the proposed MC-FEM, then features are compressed. The multi-context characteristics are extracted using residual networks. Remaining network layers are processed using a fixed 33 filter size. To accomplish feature compression, a stack of decoupled convolution layers is utilised, which takes as input a chained feature pyramid and prunes it of any superfluous information. Through the integration of these two methodologies, MC-FEM is feasible to extricate additional particular and pertinent data from a neighborhood with a wide geological degree. This module is exceptionally valuable in loud conditions because of its capacity to record an enormous spatial area utilizing layered enlarged layers with expanding expansion rates. Skip associations are moved from these modules to ensuing pieces of the model to help remaking.

f. Loss Function Evaluation:

The preservation of features, noise reduction, and low-light image enhancement are all included in a three-part loss function that is proposed. Our new loss function is represented as follows:

$$L_{Total} = w_{per}L_{per} + w_{ssim}L_{ssim} + w_{wpw}L_{wpw}$$

L_{per}- perceptual loss and corresponding weight is w_{per}

L_{ssim}- loss based on structural similarity index and its weight is w_{ssim}

L_{wpw}- weighted patch-wise Euclidean loss and its weight is w_{wpw}

Perceptual Loss: Due to their inability to distinguish between similar pictures with just a one-pixel variation in intensity, per-pixel based misfortune capabilities like Euclidean neglect to catch the distinctions in significant level qualities between the anticipated and ground-truth pictures.

By using a perceptual misfortune capability to limit the contrast between undeniable level elements removed by pre-prepared CNNs, the organization can separate a scope of low-, medium-, and significant level properties. [29].

Structural Loss: The structural comparability list network (SSIM) analyzes the likenesses between two pictures with regards to brilliance, difference, and design, and claims that the underlying data is preserved even when the luminance component or contrast are altered[30].
In light of the fact that the human visual system is often better at detecting structural information in pictures, the SSIM loss is included in the proposed loss function.

Weighted Patch-wise Euclidean Loss: The run of the mill Euclidean misfortune capability might be supplanted with the weighted fix wise (WPW) Euclidean misfortune capability. For this strategy, Euclidean misfortune is registered by parceling the anticipated picture into patches and appointing more noteworthy load to the patches with below powers.

Districts with a below normal in the anticipated picture keep on flagging that they are low lit even after upgrade, demonstrating the viability of the low-light picture enhancer.

Parametric Evaluation

The following factors are used to evaluate how effectively the suggested methodology performs:

1.Peak Signal to Noise Ratio (PSNR)
2.Structural Similarity Index (SSIM)
3.Visual Information Fidelity (VIF) and
4.Average Brightness (AB)

Peak Signal to Noise Ratio (PSNR):

PSNR is a crucial consideration when assessing the effectiveness of a proposed technique. The peak signal-to-noise ratio (PSNR) measures how well a picture may be represented by comparing its maximum power to the power of corrupting noise. It is important to compare an image to a perfect, clean image with the most power available in order to measure its PSNR. The quality of the compressed or rebuilt image improves with increasing PSNR. The PSNR is written as, for input image X and denoised image R.

$$PSNR = 10 \times log_{10}\left(\frac{255 \times 255}{MSE}\right)$$

Structural Similarity Index (SSIM):

The SSIM is a perceptual model that considers important perceptual phenomena like luminance and contrast masking terms and considers image deterioration to be an apparent shift in structural information. The distinction between these methods and others is that they estimate absolute errors, unlike MSE or PSNR. According to structural information theory, pixels that are near together in space have strong dependence on one another [30].

$$SSIM\ (x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

Visual Information Fidelity (VIF):

For a comprehensive evaluation of an image's quality, one might use the Visual Information Fidelity (VIF)[34] metric, which evaluates pictures by comparing them to a theoretical ideal. The VIF method uses natural scene statistics (NSS), high-velocity statistics (HVS), and an image distortion (channel) model to assess the information that an image may potentially extract from a reference picture and the information that is lost owing to distortion.

Average Brightness:

Average pixel value is calculated by adding together each pixel's brightness and dividing it by the total number of pixels (width * height).

4.EXPERIMENTAL ANALYSIS

Fig:4 Input

Fig:5 Enhanced Image using C-LIE-NET

Fig:6 Enhanced Image using RES-ENH-NET

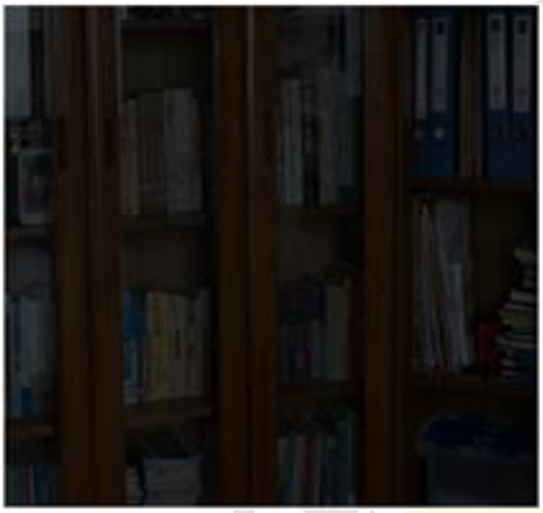

Fig:7 Input Fig:8 Enhanced Image using C-LIE-NET

Fig:9 Enhanced Image using RES-ENH-NET

5. Comparison table of different models of lower visible image enhancement

INPUT DATA		C-LIE-NET	RES-NET
Input 1	PSNR	25.959291	29.547216
	SSIM	0.812972	0.859009
	VIF	0.351502	0.389602
	AB	0.540117	0.113859
Input 2	PSNR	25.141886	29.421761
	SSIM	0.848721	0.891881
	VIF	0.491898	0.529998
	AB	0.118751	0.053415

6. CONCLUSION

In this study, we use dilated convolution to propose a unique architecture called Context-ResNet. Then, we created a novel three-part loss function that examines the structural and contextual information. A special multi-context feature extraction module, C-ResNet is comprised of layers which are refined by the decoder at a deeper level, also, skip associations between the encoder and the decoder. With the assistance of the multi-setting highlight extraction module, the organization can get on unobtrusive qualities like brilliance, differentiation, and commotion while noticing a more extensive setting. On the performance measure, the proposed C-ResNet is a better option than the C-LieNet. The proposed three-section misfortune capability containing perceptual, primary, and weighted[35] fix wise misfortune parts brings about a better picture with higher objective quality contrasted with standard misfortune capabilities.Hyper-parameter optimization on a per-component basis has to be thoroughly explored. It is possible that a single model cannot be used for the improvement of both noisy and clean images. We have left these limitations to the low-light picture research community for now. Image denoising, demosaicing, deraining[18], and many more are just a few of the picture-enhancing applications that may make use of the ideas presented in this study.

7. REFERENCES

[1] M. Abdullah-Al-Wadud, M. H. Kabir, M. A. A. Dewan, and O. Chae, ``A dynamic histogram equalization for image contrast enhancement,'' *IEEE Trans. Consum. Electron.*, vol. 53, no. 2, pp. 593_600, May 2007.

[2] W. Wang, X. Wu, X. Yuan, and Z. Gao, ``An experiment-based review of low-light image enhancement methods,'' *IEEE Access*, vol. 8, pp. 87884_87917, 2020.

[3] E. H. Land, ``The Retinex,'' *Amer. Sci.*, vol. 52, no. 2, pp. 247_264, 1964.

[4] E. H. Land, ``The Retinex theory of color vision,'' *Sci. Amer.*, vol. 237, no. 6, pp. 108_128, Dec. 1977.

[5] D. J. Jobson, Z. Rahman, and G. A.Woodell, ``Properties and performance of a center/surround Retinex,'' *IEEE Trans. Image Process.*, vol. 6, no. 3, pp. 451_462, Mar. 1997.

[6] D. J. Jobson, Z. Rahman, and G. A. Woodell, ``A multiscale Retinex for bridging the gap between color images and the human observation of scenes,'' *IEEE Trans. Image Process.*, vol. 6, no. 7, pp. 965_976, Jul. 1997.

[7] C.-H. Lee, J.-L. Shih, C.-C. Lien, and C.-C. Han, ``Adaptive multiscale Retinex for image contrast enhancement,'' in *Proc. Int. Conf. Signal-Image Technol. Internet-Based Syst.*, Dec. 2013, pp. 43_50.

[8] 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, Feb. 2017.

[9] M. Yang, X. Nie, and R. W. Liu, ``Coarse-to-_ne luminance estimation for low-light image enhancement in maritime video surveillance,'' in *Proc. IEEE Intell. Transp. Syst. Conf. (ITSC)*, Auckland, New Zealand, Oct. 2019, pp. 299_304.

[10] K. G. Lore, A. Akintayo, and S. Sarkar, ``LLNet: A deep autoencoder approach to natural low-light image enhancement,'' *Pattern Recognit.*, vol. 61, pp. 650_662, Jan. 2017.

[11] L. Tao, C. Zhu, G. Xiang, Y. Li, H. Jia, and X. Xie, ``LLCNN: A convo- lutional neural network for low-light image enhancement,'' in *Proc. IEEE Vis. Commun. Image Process. (VCIP)*, Dec. 2017, pp. 1_4.

[12] F. Chollet, ``Xception: Deep learning with depthwise separable convo- lutions,'' in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jul. 2017, pp. 1800_1807.

[13] F. Lv, F. Lu, J. Wu, and C. Lim, ``MBLLEN: Low-light image/video enhancement using CNNs,'' in *Proc. Brit. Mach. Vis. Conf.*, 2018, pp. 1_13.

[14] W. Wang, C. Wei, W. Yang, and J. Liu, ``GLADNet: Low-light enhancement network with global awareness,'' in *Proc. 13th IEEE Int. Conf. Autom. Face Gesture Recognit. (FG)*, May 2018, pp. 751_755.

[15] F. Lv, Y. Li, and F. Lu, ``Attention-guided low-light image enhancement,'' 2019, *arXiv:1908.00682*. [Online]. Available: http://arxiv.org/abs/1908. 00682

[16] I. J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, ``Generative adversarial networks," 2014, *arXiv:1406.2661*, 2014. [Online]. Available: http://arxiv. org/abs/1406.2661
[17] C. Ledig, L. Theis, F. Huszar, J. Caballero, A. Cunningham, A. Acosta, A. Aitken, A. Tejani, J. Totz, Z. Wang, and W. Shi, ``Photo-realistic single imacvprge super-resolution using a generative adversarial network," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jul. 2017, pp. 4681_4690.
[18] H. Zhang, V. Sindagi, and V. M. Patel, ``Image de-raining using a conditional generative adversarial network," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 30, no. 11, pp. 3943_3956, Nov. 2020.
[19] R. Li, J. Pan, Z. Li, and J. Tang, ``Single image dehazing via conditional generative adversarial network," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, Jun. 2018, pp. 8202_8211.
[20] 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 *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, Jun. 2018, pp. 6306_6314.
[21] 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," 2019, *arXiv:1906.06972*. [Online]. Available: http://arxiv.org/abs/1906.06972
[22] C. Wei, W. Wang, W. Yang, and J. Liu, ``Deep Retinex decomposition for low-light enhancement," in *Proc. Brit. Mach. Vis. Conf.*, 2018, pp. 127_136.
[23] Y. Wang, Y. Cao, Z.-J. Zha, J. Zhang, Z. Xiong, W. Zhang, and F. Wu, ``Progressive Retinex: Mutually reinforced illumination-noise perception network for low-light image enhancement," in *Proc. 27th ACM Int. Conf. Multimedia*, Oct. 2019, pp. 2015_2023.
[24] Y. Shi, X. Wu, and M. Zhu, ``Low-light image enhancement algorithm based on Retinex and generative adversarial network," 2019, *arXiv:1906.06027*. [Online]. Available: http://arxiv.org/abs/1906.06027
[25] Y. Guo, Y. Lu, R. W. Liu, M. Yang, and K. T. Chui, ``Low-light image enhancement with regularized illumination optimization and deep noise suppression," *IEEE Access*, vol. 8, pp. 145297_145315, 2020.
[26] W. Ren, S. Liu, L. Ma, Q. Xu, X. Xu, X. Cao, J. Du, and M.-H. Yang, ``Low-light image enhancement via a deep hybrid network," *IEEE Trans. Image Process.*, vol. 28, no. 9, pp. 4364_4375, Sep. 2019.
[27] L.-C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille, ``DeepLab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFs," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 40, no. 4, pp. 834_848, Apr. 2018.
[28] J. Long, E. Shelhamer, and T. Darrell, ``Fully convolutional networks for semantic segmentation," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2015, pp. 3431_3440.
[29] J. Johnson, A. Alahi, and L. F.-Fei., ``Perceptual losses for real-time style transfer and super-resolution," in *Proc. Eur. Conf. Comput. Vis.*, 2016, pp. 694_711.
[30] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, ``Image quality assessment: From error visibility to structural similarity," *IEEE Trans. Image Process.*, vol. 13, no. 4, pp. 600_612, Apr. 2004.
[31] A. Quattoni and A. Torralba, ``Recognizing indoor scenes," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2009, pp. 413_420.
[32] S. Guo, Z. Yan, K. Zhang, W. Zuo, and L. Zhang, ``Toward convolutional blind denoising of real photographs," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (l)*, Jun. 2019, pp. 1712_1722.
[33] Z. Chen, B. R. Abidi, D. L. Page, and M. A. Abidi, ``Gray-level grouping (GLG): An automatic method for optimized image contrast enhancement-part I: The basic method," *IEEE Trans. Image Process.*, vol. 15, no. 8, pp. 2290_2302, Aug. 2006.
[34] H. R. Sheikh and A. C. Bovik, ``Image information and visual quality," *IEEE Trans. Image Process.*, vol. 15, no. 2, pp. 430_444, Feb. 2006.
[35] X. Fu, D. Zeng, Y. Huang, X.-P. Zhang, and X. Ding, ``A weighted variational model for simultaneous re_ectance and illumination estimation," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2016, pp. 2782_2790.