Dynamic Attention for Enhancement of Weak Contrast Images Using Advance ASENet

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***Abstract*—Low-light photography often results in images with significant noise and insufficient brightness, making enhancement of such images a persistent and challenging task in computer vision. Although numerous techniques have been proposed to address this issue, many of them inadvertently amplify noise or fail under extremely poor lighting conditions. To overcome these limitations, this research introduces the Advanced Attention-Shift Enhancement Network (Adv-ASENet); An innovative deep learning-based approach designed to effectively enhance Weak Contrast Low-Light *(*WCLL*)* images. Adv-ASENet leverages a dynamic attention mechanism that allows the model to selectively focus on the most informative regions of a low-light image. This selective focus enables the network to enhance poorly illuminated areas while minimizing noise amplification in already well-lit regions, resulting in a more balanced and visually coherent enhancement. Weak contrast images often exhibit localized deficiencies in brightness and contrast; Adv-ASENet addresses this with dynamic attention blocks that selectively enhance such regions without overprocessing the well-contrasted areas. The spatial attention module further aids in preserving well-exposed parts of the image, ensuring that enhancements are applied only where needed. Experimental results demonstrate that the proposed network achieves competitive performance with a manageable level of complexity. Quantitative evaluations show that Adv-ASENet attains a Structural Similarity Index Measure (SSIM) of 87.9%, Peak Signal-to-Noise Ratio (PSNR) of 36.05 dB, Mean Squared Error (MSE) of 0.031, and a correlation coefficient of 98.8%, outperforming several existing state-of-the-art methods across standard metrics including SSIM, PSNR, MSE, and entropy.**

***Keywords*—image enhancement, renoir dataset, convolutional neural network, attention shift enhancement network**

I. Introduction

Due to a lack of reflected exposure to radiation, images taken in low light frequently have poor visibility. Low contrast, fading colours, small pixel ranges, and general blurriness are common characteristics of such photos. As a result, they are not appropriate for providing precise outcomes in computer vision applications. Much work has been done in the field of low-light picture enhancement to address these problems [1]. A thorough literature evaluation of both traditional and cutting-edge techniques for improving low-light images as well as impartial techniques for evaluating image quality is provided in Ref. [2]. Image improvement networks based on machine learning have attracted a lot of interest lately. Even while LIE approaches have advanced and have the potential to improve computer vision performance, it is still a difficult task [3].

Because of its straightforward operation and efficiency, histogram equalization is frequently used for enhancement of contrast in a wide range of approaches. The flattening feature of histogram equalization is the primary cause of the histogram equalization's downside, which is that it might alter an image's brightness after it has been applied. In bi-histogram equalization model for image enhancement is designed [4]. Pisano *et al.* [5] suggested an extension model of histogram called Contrast Limited Adaptive Histogram Equalization (CLAHE) for improving the identification of dense mammograms. These methodology does not concentrate on the mechanism of degrading the brightness of image. To improve the contrast level and brightness level a bi-histogram equalization method based on adaptive sigmoid functions is proposed in Ref. [6]. The sigmoid function helps to divide the image hist into two parts and are also independently equalized.

One of the regular methods proposed by Garcia *et al.* [7] is Retinex theory, it maintains that an object's colour is not controlled by the absolute strength of the reflected light but rather by its capacity to reflect light waves to make the improved image more visually consistent with human perception. The irregularity of light has no effect on the colour. Single Scale Retinex (SSR) model suggested by Jobson *et al.* [8]; which is simple to implement the theory of retinex. Then, using the weighted summation of several illumination components, the Multi-scale Retinex (MSR); Rahman *et al.* [9] suggested to

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reduce the visual artefacts that appear around the edges of the object. This improved image output unable to prevent the distortions the colour. Jobson *et al.* [10] suggested Multi-Scale Retinex with Colour Restoration (MSRCR) model to act in the local region of the augmented picture that was brought on by the amplification of noise.

The emergence of deep learning models has been used for many of the computer vision applications, such as improving low-light images, in recent years due to its superior representation and generalisation capabilities. To address the task of brightness, contrast, artifacts and Lv *et al.* [11] proposed the Multi-Branch Low-Light Enhancement Network (MBLLEN). Further development of CNN is made in this field. To improve low light photos, Lore *et al.* [12] constructed a stacked sparse denoising autoencoder using Convolutional Neural Networks (CNN). The low-light image was adaptively improved by this network, which also decreased noise in the improved image. Shen *et al.* [13] suggested an MSR-net, which employs a CNN to understand the mapping connection between lower light images and normal light images, after considering that the conventional MSR might be substituted with a Gauss convolution kernel of various sizes. A network called LightenNet was created by Li *et al.* [14] to forecast picture illumination maps. LightenNet is a non-end-to-end network that produces a matching illumination map as its output after receiving a low-light picture as input. Then, using the Retinex model, an improved picture is produced. Retinex-Net is a neural network model created by Wei *et al.* [15]. A picture is broken down by the model into two parts: a reflectance map and an illumination map. The network processes the two elements independently before fusing them to create a better picture. The first model to be trained using a genuine low-light dataset is Retinex-Net. To improve underexposed images, Wang *et al.* [16] suggested a network that predicts the illumination map based on both local and global aspects of a picture. Different lighting requirements and priors are taken into consideration while updating the network's weights. Additionally, low-light photos have been improved by the application of Generative Adversarial Networks (GANs). For the low-light picture improvement approach, an EnlightenGAN with unsupervised learning was presented [17, 18].

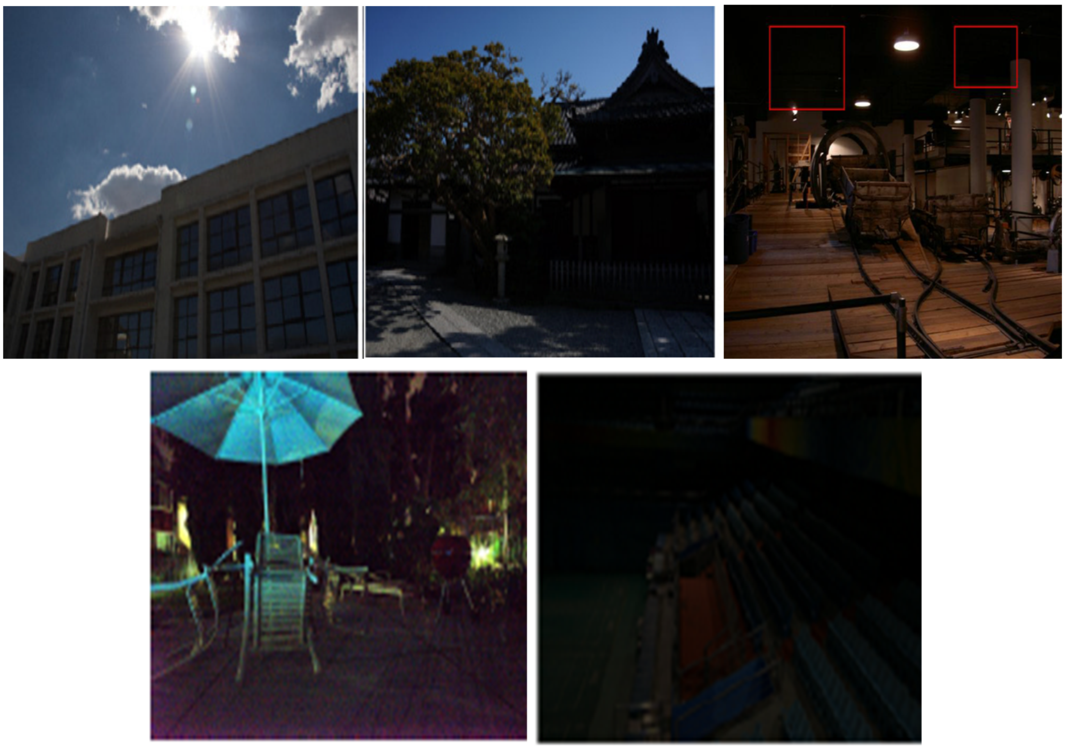


Fig. 1. Images under different light conditions.

However, a variety of light fluctuations in the natural world cause the image's fine information to become blurry, with higher level of noise and poor visibility. Fig. 1 illustrates the many kinds of low light photographs. It is quite difficult to regulate the brightness of photos taken in low light. This research proposes Adv Attention Shift Enhancement Network (Adv-ASENet), a novel Weak Contrast Low-Light Images (WCLLI) improve network. CNN designs frequently incorporate attention methods, where characteristics taken from the picture at various levels are used to construct the attention map. Two loss functions were used in the network's architecture. In addition to lighting, one loss function effectively limited a picture's feature information, and the other loss function assisted the model in learning to produce an even more accurate image. The contribution of work in this paper is as follows:

- Low light weak contrast image Renoir dataset is considered for processing.
- The process of feature extraction is performed using Adv-ASE Net model.
- The layers of proposed network model are discussed.

- The experimental results are evaluated and matched with those of other models.

II. Related Work

Recent studies have demonstrated that by extracting more appropriate picture characteristics, deep learning algorithms perform better than conventional techniques in enhancement of low light images including zero-shot, supervised, and unsupervised learning. The networks are trained in most of the early supervised learning-based research.

Using feedforward CNN with different Gaussianconvolution kernels, MSR-Net can simulate thepipeline of Multi-scale Retinex (MSR) for directly learningend-to-end mapping between dark and bright images [19]. Wang *et al.* [20] addressed the problem of real low light images captures in different scenarios by developing a GLobal illumination Aware and Detail-preserving Network (GLADN) which handle higher range of light in different conditions and concentrate on brightness of image. Zhang *et al.* [21] presented an efficient network for Kindling the Darkness (known as KinD), which breaks down pictures into two parts based on Retinex theory to improve the lighting state of the image. Light adjustment is handled by one component (illumination), and degradation removal is handled by the other (reflectance). Wang *et al.* [22] goosed one step further and decomposes a low-light image. Then, using a Retinex Decomposition Network (RDNet) for decomposition and a Fusion Enhancement Network (FENet) for fusion, the system learns to fuse the decomposed results to produce a high-quality enhanced result.

Zhang *et al.* [23] introduced a self-supervised LLI improvement method to get over the absence of paired training data. This method completely utilises Retinex technology to dissect the low-light picture and improve the reflectance map, which is then shown as the final restored image. Furthermore,

Guo *et al.* [24] used carefully crafted non-reference loss functions for training to estimate the pixel-wise and high-order curves for dynamic range correction of a low-light picture in an unsupervised manner. CNN's success in improving low-light images, Zamir *et al.* [25] proposed a Multiscale Residual Block (MRB) that maximises feature reuse and significantly improves low-light image enhancement performance by using both residual learning and an Attention Unit as its fundamental structure. As deep learning has advanced, the attention mechanism has gained popularity in the field of computer vision, leading to the derivation of a variety of attention structures. To increase the model's sensitivity to channel properties, Hu *et al.* [26] built the Squeeze-and-Excitation Networks (SE). To emphasise important aspects in both dimensions, the Convolutional Block Attention Module (CBAM); Woo *et al.* [27] technique developed the channel and spatial attention modules to progressively learn what to pay attention to and where to pay attention in the channel and spatial dimensions, respectively. Through the reduction of information dispersion and the amplification of the global interaction representation, Liu *et al.* [28] presented a global attention mechanism that can enhance the performance of deep neural networks. This is since prior attention mechanisms have neglected the significance of channel and spatial dimension information preservation to improve cross-dimensional interactions. Due to the attention mechanism's outstanding performance in computer vision's pattern categorisation, semantic picture segmentation, and target recognition.

To achieve noteworthy outcomes, a few low-light improvement techniques have also used the attention mechanism in recent years. A colour attention module was added to the picture to augment target information to improve the mapping connection between low-light and improved images, as proposed in the literature [29]. This method also provides some useful colour information for the enhancement of low-light images. Zhang *et al.* [30] used a multi-scale attention retinal network to construct an illumination attention module, which improves the visibility of the improved pictures and addresses the issue of erroneous estimation of illumination images. In order to achieve adaptive adjustment of the brightness information, the method adds an attention module to the convolutional layer of the illumination adjustment [31]. This module calculates the features by using the global correlation between the light mapping and its input feature mapping. Local areas may potentially have issues during the enhancement process, such as excessive or insufficient enhancement.

To enhance the answer to the appearance of such difficulties, the technique integrates an attention mechanism into the network model and uses the attention map to assign different weights to various areas. The technique suggests a trainable parallel network that is led by the attention mechanism and colour constancy, respectively, to solve the colour distortion issue that arises in enhanced [32, 33]. This effectively retains the image's colour and enhances contrast. The attention mechanism has been used to improve images, with surprising outcomes. However, existing approaches have not addressed the issue of inadequate detail recovery for dark regions. The target detection needs to be improved in case of lower contrast images. The shadows, edges all the corner points of the image are not considered in the existing model. Therefore, to improve the visual quality of the image and solve the distortion issue, we build a hybrid attention mechanism in this paper that discovers the broad range and connection that exists among genuine image characteristics and Lower Light Images (LLI's).

III. Methodology

Numerous computer vision issues that aim to replicate the human visual system's extensive utilisation of contextual information in comprehending RGB pictures have examined the attention process. This entails removing unnecessary areas from the image while concentrating on the more crucial areas that hold the rich elements of our vision job. To successfully direct the model to concentrate on important aspects in low-light areas, the network creates an "attention map" that emphasizes the parts of the picture that need the most improvement. The model of the system is shown in Fig. 2.

The designed Adv-ASENet is discussed in this section.

Fig. 2. Proposed system.

A. Adv-ASENet Model

The Advanced Attention-Shift Enhancement Network (Adv-ASENet) is a promising and innovative method for improving images with weak contrast lower light. Because poor contrast photos frequently need targeted improvement in certain places where contrast is absent, including low light areas, shadows, or edges, this method can be very successful. The design flow is shown in Fig. 3.

B. Image Input Layer

In this layer the input weak contrast image is accepted for processing. The image is resized to specific dimensions which is suitable for training and processing of the network. The image is tuned and normalized in this layer so that the process of enhancement can be improved.

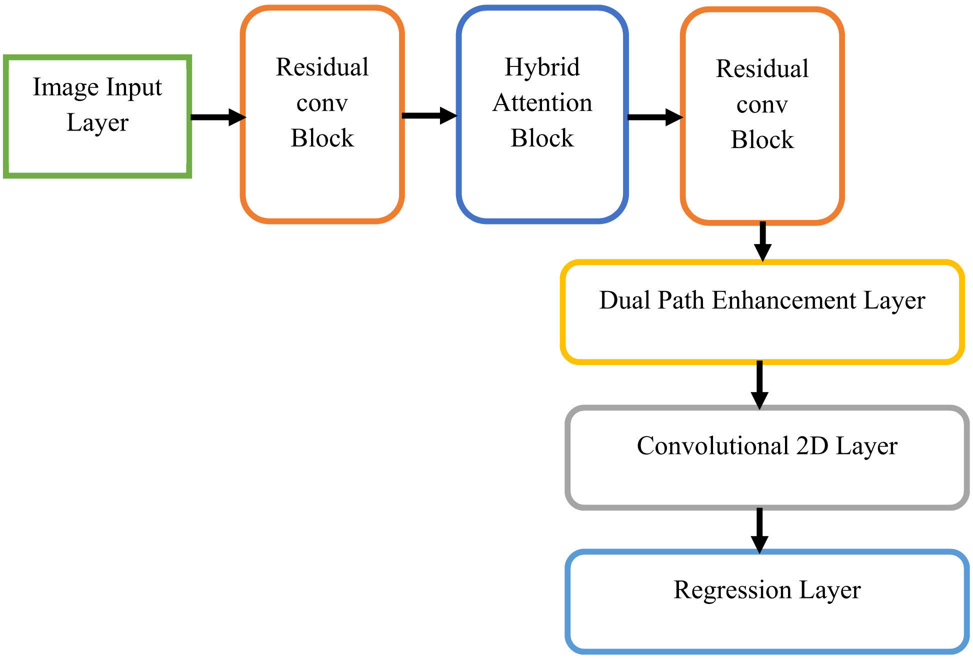


Fig. 3. Process flow of Adv-ASENet.

C. B. ResidualConvBlock

In this layer the features of the image are extracted by preserving the information of the image using the residual connections. The process of residual conv block is shown in Fig. 4.

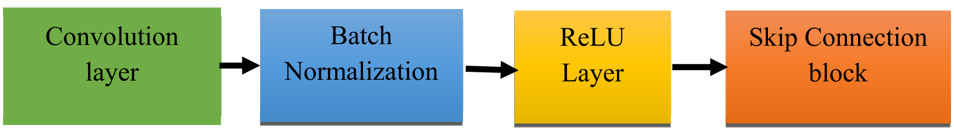


Fig. 4. Process of residual conv block.

The convolution layer extracts the features of the normalized image by utilizing the filters. The batch normalization blocks stabilize the extracted features and perform training process. The ReLU block is an activation function which introduces the concept of non-linearity by which the trained network will able to identify the complex patterns and the information present in the image will be related to the task. Finally, the skip connection blocks are utilized to avoid vanishing gradients and maintain spatial features, add the input straight to the convolution stack's output. The number of layers utilized in this process is shown in Algorithm 1.

Algorithm 1: Residual Convolution module

Start
Step1. Initiate the function layer
Step2. Conv 2d layer (1×1)
Step3. Batch normalization layer
Step4. Conv 2d layer (3×1)
Step5. Batch Normalization
Step6. Conv 2d layer (3×1)
Step7. Batch normalization
Step8. ReLU layer
Stop;

D. Hybrid Attention Block

Main module in Adv-ASENet is hybrid attention block. In this layer the feature maps are enhance by utilizing dynamic attention mechanism and spatial attention mechanism as shown in Fig. 5. The number of layers utilized in this process is shown in Algorithm 2.

Algorithm 2: Hybrid Attention Module

Start
Step1. Initialize the function layer
Step2. Channel Attention
globalAveragePooling2dLayer
fully Connected layer
ReLu Layer
fully Connected Layer
sigmoid Layer
Step3. spatial Attention
convolution2dLayer
sigmoid Layer
Step4. channel Attention
depth Concatenation Layer (2)
Stop;

The channel wise attention highlights the edges and textures of the image in the feature channel. The spatial attention blocks the significant type of spatial regions of the image. The details of the image will be preserved in this region. These two blocks are combined to form a refined feature output. This layer improves ability of the network for enhancing the features of the image.

In very dim lighting, even little disturbances can have a significant impact on the results produced by Adv-ASENet. Attention layers that are gradient-sensitive can lead to adversarial vulnerabilities. A better defence against these kinds of disturbances may be achieved by adversarial training, spectral normalisation, and loss functions driven by robustness.

Adv-ASENet uses spatial attention gradients that are guided by attention maps that are influenced by saliency-driven significance weights. By using region-specific contrast and brightness variations, Adv-ASENet's gradients enable strong feature refinement even in dimly light areas, as opposed to conventional CNNs, where gradients disperse uniformly.

E. Dual Path Enhancement Layer

This layer combines all the features which are obtained globally and locally. In this layer the overall structure of the image will be formed. The fine details and the local information of the image will be preserved by operating the layer with smaller kernels. The number of layers utilized in this process is shown in Algorithm 3.

Algorithm 3: Dual Path Enhancement module

Start
Step1. Initiate the function layer
Step2. Initiate the global path
Conv 2d layer (64×2)
Max pooling 2d layer
ReLU layer
Conv 2d layer (128×2)
ReLU layer
Transposed Conv2 layer (64×2)
Step3. Initialise the localPath
convolution2dLayer
ReLU Layer
convolution2dLayer
ReLU Layer
Step4. DepthConcatenationLayer(2)
[globalPath+localPath]
Stop

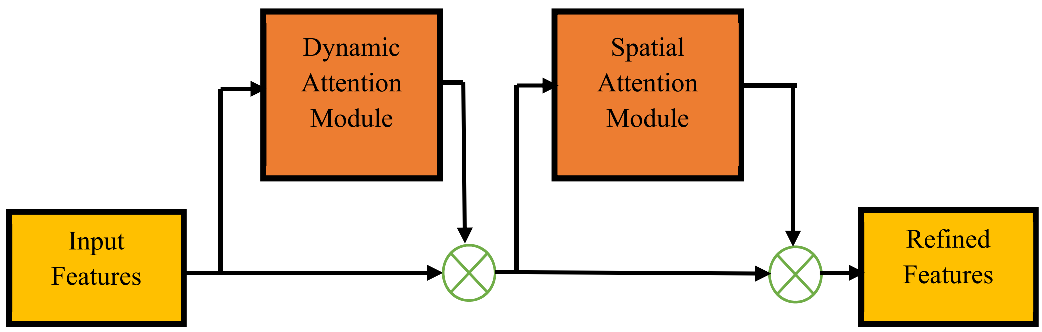


Fig. 5. Hybrid attention block [34].

F. Convolution2 Dlayer

The final output image is produced in this later with a single channel. A 3×3 standard size of kernel is utilized for processing of image by balancing the features of the image captured. One filter is utilized for producing the output. Padding operation is performed to keep the dimensions of the image same as the input image. This padding helps in preserving the information at the edges of an image and make the output image more accurate.

G. RegressionLayer

This layer helps in predicting the values of input image pixel by pixel and trains the network in modifying the pixel intensities to improve the quality of the image by contrast enhancement, reducing the noise and sharpening the details of the images. In this work, the regression layer use loss functions PSNR and SSIM to measure the difference between the enhanced image and the ground-truth image.

Finally, the enhanced image output is obtained and parameters are evaluated. ASENet adjusts its focus dynamically according on the image's local context. This is crucial for photographs with weak contrast since it guarantees that edges, textures, and key areas are improved while striking a balance between contrast enhancement and naturalness.

1) Loss function

The loss function is evaluated with the help of two metrics. One is Structural Similarity Index Measure (SSIM) and the other is Peak Signal-to-Noise Ratio (PSNR). Both measures are frequently used to assess the quality of images, especially in tasks involving DL and processing of images.

2) SSIM loss

The structural similarity between two pictures is measured using SSIM. It has a range of −1 to 1, where 1 denotes the same pictures. The standard definition of the SSIM loss function is:

$$L_{SSIM} = 1 - SSIM\ (Img_T, Img_p) \tag{1}$$

where, Img_T is the true image and Img_p is the predicted output image. The model is encouraged to maintain image structures by this loss.

3) PSNR loss

PSNR calculates the ratio of an image's noise to its maximum signal power. It is defined as follows and is measured in decibels (dB):

$$PSNR = 10 \log\left(\frac{M^2}{MSE}\right) \tag{2}$$

where, M is the maximum value of the pixel; MSE is the mean square error and is termed as average squared differnece between the values of the pixel. Higher the value of PSNR better is the quality of the image. The loss is defined as,

$$L_{PSNR} = \frac{1}{PSNR} \tag{3}$$

By combining the both metrics the loss function is given as,

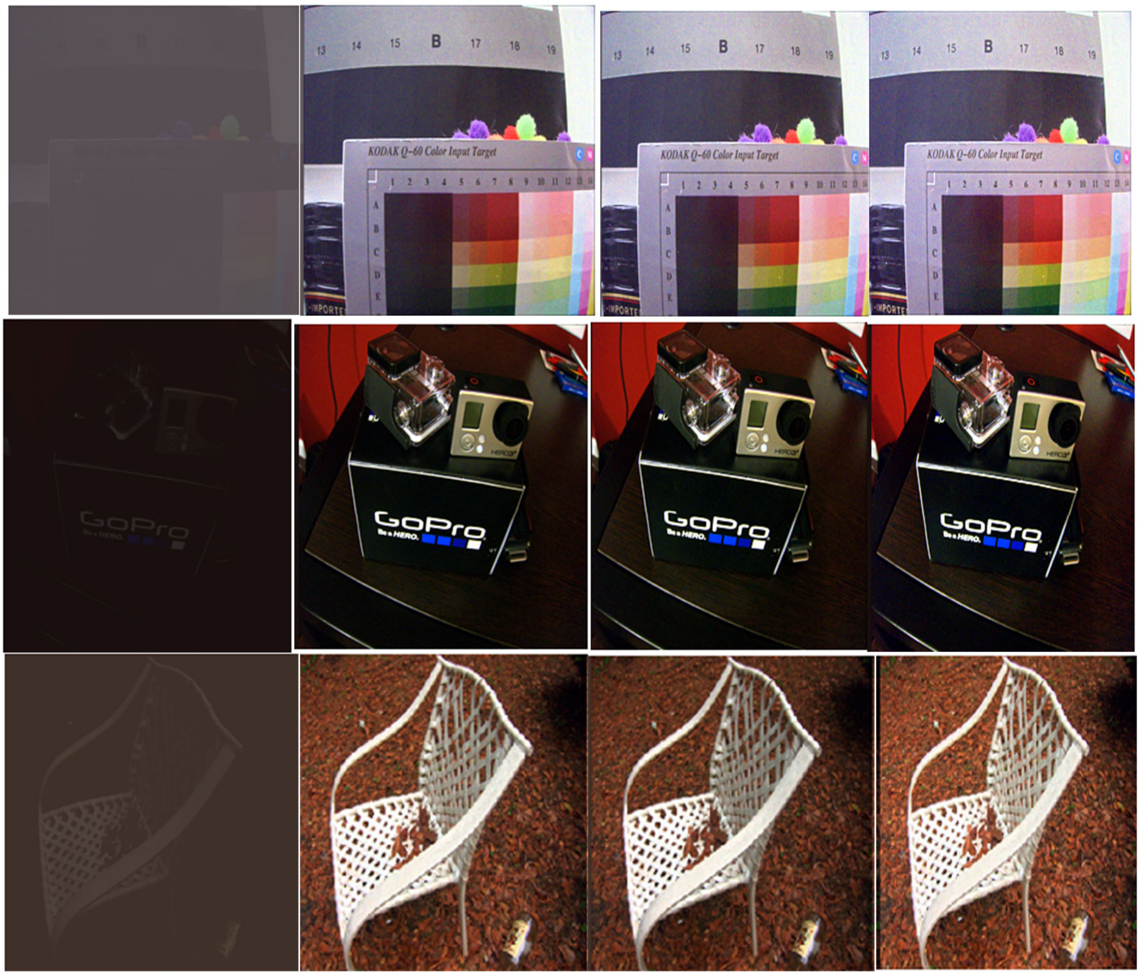
$$L_C = \alpha . L_{SSIM} + \beta . L_{PSNR} \tag{4}$$

where α and β are weights that balance the contributions of both losses.

IV. Experimental Findings

The design of weak contrast low light enhancement work is implemented utilizing the matlab tool on intel core i7 processor with 128GB RAM and 1TB harddrive space. The software tool utilized is matlab 2024 for processing the results. The dataset needs to be loaded and the network model designed using the neural network tool box.

A collection of low-light-induced natural noise-corrupted colour photos, together with low-noise photographs of the same situations that are aligned geographically and intensity. Two digital cameras and a cell phone were used to capture the dataset of photos, which included actual noise from low light conditions [35]. The size of images with S90 device is 3684×2760, T3i device is 5250×3465 and Mi3 device is 4208×3120 respectively. This dataset consists of image with different sizes and are been processed and evaluated using the proposed model. The results are evaluated with the help of RENOIR dataset by utilizing various models and the proposed Adv AES Network model results is shown in Fig. 6.

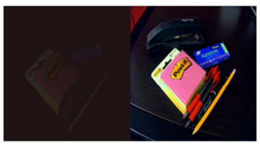


(a) (b) (c) (d)

Fig. 6. Enhanced output using different model (a) Input weak contrast image (b) ML-CNN model (c) Retinex U-Net model (d) Proposed Adv-ASE Net.

The involvement of dynamic attention mechanism and spatial attention helps to improve the quality of the output image by improving various parameters. The parameters like PSNR, SSIM, MSE, NCC, MAE, FSIM, Entropy (N), Entropy (E), correlation coefficientare evaluated and calculated for the obtained output image. The parameters evaluated to observe the performance of the proposed model is shown in Table I.

TABLE I. EVALUATION OF PARAMETERS USING ADV-ASE NET MODEL

Input/Parameter	PSNR	SSIM	MSE	NCC	MAE	FSIM	Entropy (N)	Entropy (E)	Corr-Coeff
	35.31	0.77	0.018	0.94	0.08	0.99	0.61	0.59	0.98
	34.14	0.90	0.029	0.82	0.14	0.99	0.88	0.90	0.99
	33.78	0.83	0.028	0.99	0.102	0.99	0.64	0.68	0.97

	36.05	0.88	0.032	0.99	0.128	0.99	0.75	0.73	0.98
	34.14	0.93	0.031	0.852	0.13	0.99	0.82	0.80	0.98

The model deigned to improve the quality of image outperform well when compared to other techniques like multi-layer Convolutional neural network (ML-CNN) and RETINEXU-Net Model. The values of all the evaluated parameters are shown in Table II.

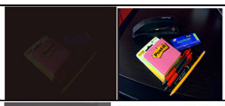
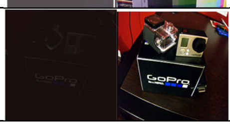
TABLE II. COMPARISON OF EVALUATED PARAMETER WITH OTHER MODELS

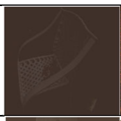
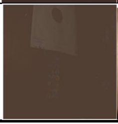
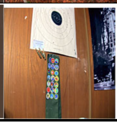
Parameter/Technique	ML-CNN	RETINEX U-Net	Proposed Adv ASE-Net
PSNR	33.287	35.085	**36.055**
SSIM	0.8572	0.8713	**0.8793**
MSE	0.03371	0.03211	**0.03111**
NCC	0.9962	0.9982	**0.9984**
MAE	0.14149	0.1311	**0.1282**
FSIM	0.9939	0.9951	**0.9957**
Entropy (N)	0.7063	0.7316	**0.7593**
Entropy (E)	0.5643	0.6715	**0.7368**
Corr Coeff	0.986	0.9875	**0.9880**

Network model is designed to obtain the spatial features and helps in restoring the original quality of the image. The shaping and tuning of the network model which is designed helps to enhance the quality structure of low light weak contrast images. Among all the parameters there are two main parameters that are most frequently evaluated by many of the researchers one is SSIM and other is PSNR. The Structural similarity index of the image with respect to the ground-truth image need to be matched and the value should be high. Next is PSNR, the noise present in the image need to removed and the value should be gradually increase to enhance the weak contrast image.

In Table III, the SSIM and PSNR value of input low light contrast image and the achieved SSIM and PSNR after performing the enhancement of image using Adv-ASE Net are shown. The input weak contrast image when compared with ground-truth image the SSIM is 18.6% and the enhanced image using proposed model having an SSIM of 88%. The evaluated results prove that proposed model performs well when compared to other techniques like Retinex U-Net and ML-CNN. The value of PSNR indicates the quality of the reconstructed image. The input image having a PSNR of 6.89, after processing the enhance image having a PSNR of 34.14, it indicates that the enhanced image is very less distorted and maintaining lower range of noise compared to the input image.

TABLE III. INPUT-OUTPUT PARAMETERS COMPARISON

Image/Parameter	Input (Low Light Weak Contrast Image)		Output (Adv-ASE Net Enhanced Image)	
	SSIM	PSNR	SSIM	PSNR
	0.186	7.23	0.88	35.31
	0.145	6.89	0.901	34.14
	0.167	6.12	0.885	33.78

		0.225	9.56	0.879	36.08
		0.26	8.21	0.934	34.14

The histogram helps in showing the distribution of pixels intensity values. For weak contrast images the histogram will be narrow and distributed within a small range. The range of histogram improves of the visual quality and benefits the models of neural network, The results shown are as below. The histograms of the LLWC input image and the enhance output image is shown in Fig. 7. Different images are considered and histogram are evaluated depending on the level of intensity of image.

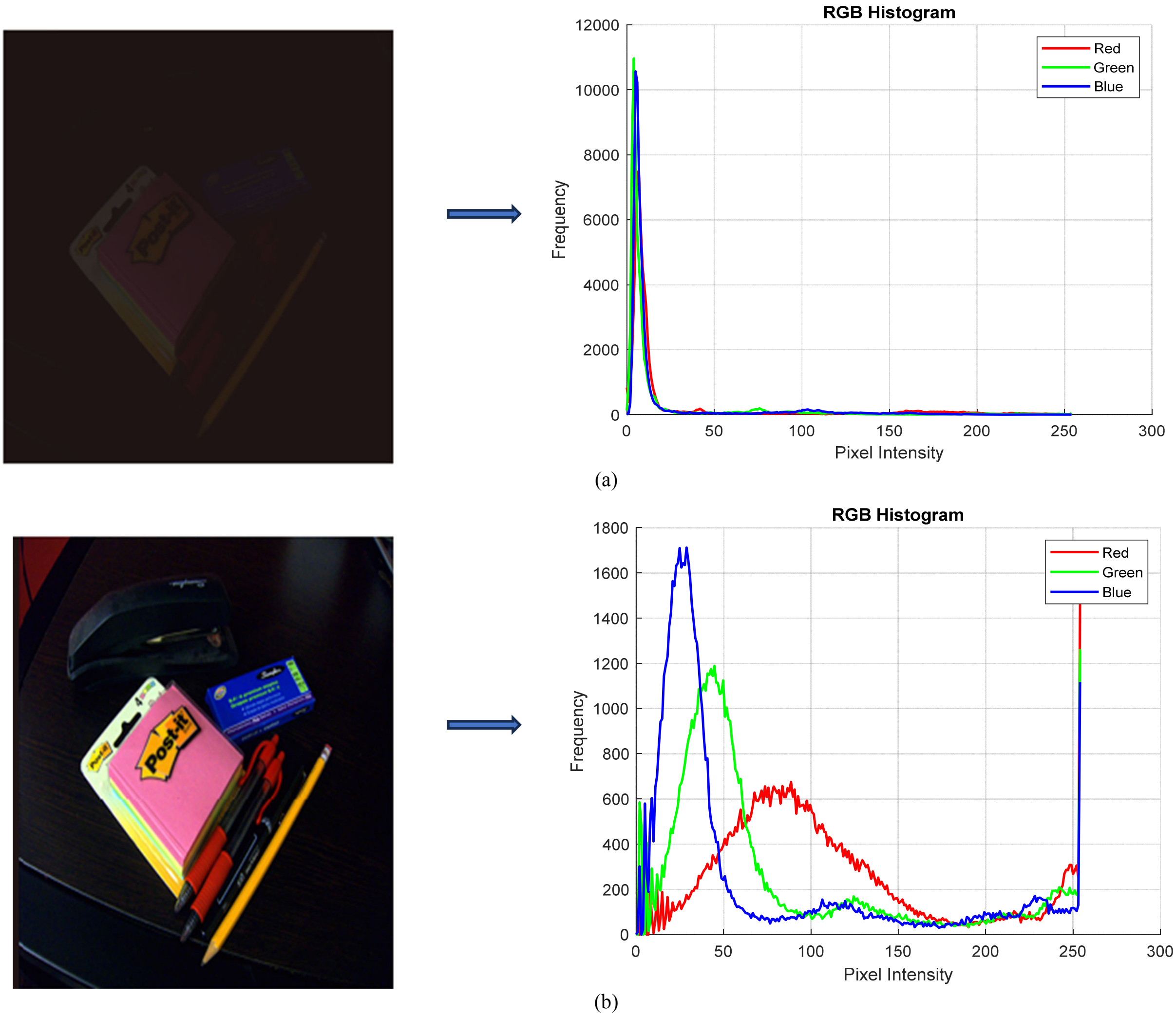
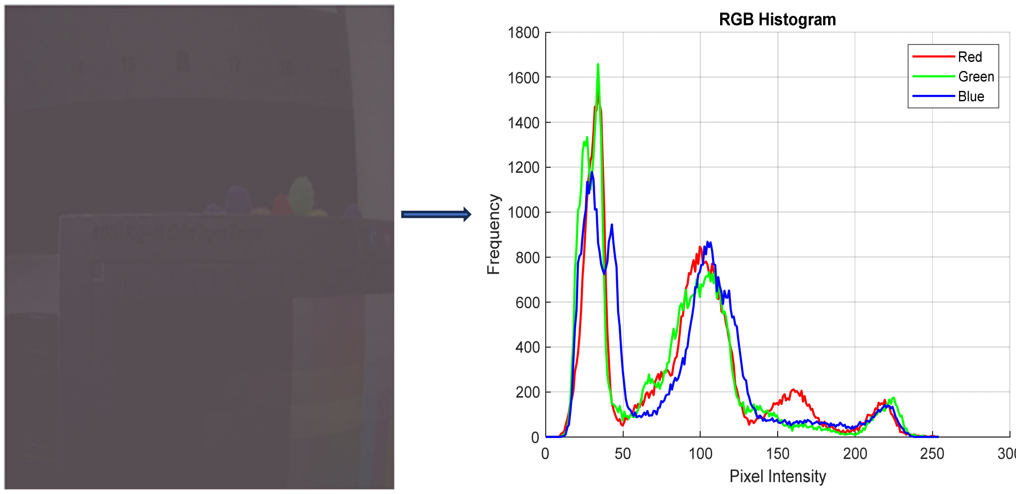


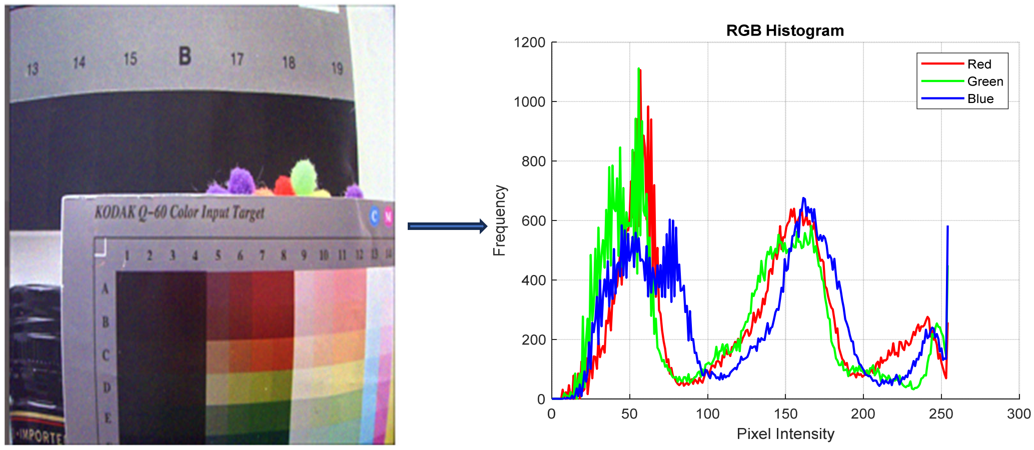
Fig. 7. (a) weak constrast image and its histogram (b) Enhanced Image and its histogram.

The distribution of pixel intensities in the image is shown in histogram graph, by which the quality of the image can be judged.

From Fig. 8 it is observed that loss of information is more in weak contrast input image due to excessive noise or compression, after enhancment using the Adv-ASE net model the information loss is less. When the spikes achieved in histogram is smooth the image is said to noise free and detailed imahe. Thus the histogram evaluation of image gives the nature of the processed image. The existing model designed by author regarding enhancement of WCLL images is compared with the proposed model and is shown in Table IV.



(a)



(b)

Fig. 8. (a) weak constrast image and its histogram (b) Enhanced Image and its histogram.

TABLE IV. Comparison of Various Techniques

Ref.	PSNR	SSIM
[36]	15.72	0.59
[17]	15.31	0.49
[37]	17.53	0.66
[38]	15.84	0.58
[39]	17.28	0.61
[40]	24.61	0.84
[41]	23.65	0.81
[42]	24.31	0.82
Proposed model	**35.31**	**0.88**

From Table IV, the results shows that the Adv-AESNet for image enhancement is an efficient model where the SSIM obtained is 88% and PSNR is 35.31. The values of PSNR and SSIM need to be larger and the value of MSE need to be reduced, this scenario indicates that the enhanced image is of goof quality. In the proposed design the involvement of hybrid attention block helps to improve the network model and finally achieve good results.

The proposed model when compared to complete self-attention in transformer models, Adv-ASENet's dynamic attention mechanism is computationally lighter. For images with a high resolution, transformer self-attention is not practical since it scales quadratically with N pixels, $O(N^2)$. Alternatively, Adv-ASENet uses hierarchical spatial feature refinement and an attention mechanism that is both locally focused and adaptively weighted, all while using fewer parameters. Since the memory and processing cost are drastically reduced, it is better suited for enhancing high-resolution images.

V. Conclusion

Attention mechanisms can dynamically modify the enhancement level depending on the local brightness and significance of each pixel, in contrast to conventional picture brightening techniques that evenly raise brightness throughout the image. This study used an advance attention shift enhancement network approach to propose a poor contrast low-light image improvement network. To restore the brightness of low-light visual features, the suggested network integrates both a spatial attention mechanism and a dynamic attention mechanism. The analysed findings with PSNR 35.31 and SSIM 88% demonstrate that the suggested model offers improved performance, making it effective for low light enhancement applications. The SSIM observed in existing model is 82%. The resulting histogram graphs demonstrate that improved images have better visibility and are less susceptible to noise.

In future, the model can be tested on different low light image datasets. Extremely low-light photos can be taken into consideration for improvement activities to integrate DL and optimisation models. A Reinforcement learning be employed to dynamically adjust hyperparameters in Adv-ASENet during real-time enhancement tasks.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

M Harika conducted the research work, collected the data, and wrote the paper. Gottapu Sasibhushana Rao and Rajkumar Goswami supervised the work; all authors had approved the final version.

REFERENCES

[1] W. Kim, "Low-light image enhancement: A comparative review and prospects," *IEEE Access*, vol. 10, pp. 84535−84557, 2022.

[2] M. T. Rasheed *et al*., "A comprehensive experiment-based review of low-light image enhancement methods and benchmarking low-light image quality assessment," *Signal Process*, vol. 204, 108821, 2023.

[3] C. Li *et al*., "Low-light image and video enhancement using deep learning: A survey," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 44, pp. 9396−9416, 2022,

[4] Y. T. Kim, "Contrast enhancement using brightness preserving bi-histogram equalization," *IEEE Trans. Consum. Electron.*, vol. 43, no. 1, pp. 1–8, 1997.

[5] E. D. Pisano *et al*., "Contrast limited adaptive histogram equalization image processing to improve the detection of simulated spiculations in dense mammograms," *J. Digit. Imag.*, vol. 11, no. 4, pp. 193–200, 1998.

[6] E. F. A. Garcia, R. E. S. Yanez, J. R. Pinales, and M. G. G. Hernandez, "Adaptive sigmoid function bihistogram equalization for image contrast enhancement," *J. Electron. Imag*., vol. 24, no. 5, 053009, 2015.

[7] E. H. Land, "The retinex theory of color vision," *Scientific American*, vol. 237, no. 6, pp. 108–128, 1997.

[8] 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. 7–21, 1997.

[9] Z. Rahman, D. J. Jobson, and G. A. Woodell, "Multi-scale retinex for color image enhancement," in *Proc. 3rd IEEE* International *Conference on Image Processing*, Lausanne, Switzerland, 1996, pp. 1003−1006, vol. 3.

[10] 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," in *Proc. IEEE Transactions on Image*, 1997, vol. 6, no. 7, pp. 965−976.

[11] F. F. Lv *et al*., "MBLLEN: Low-light image/video enhancement using CNNS," *Bmvc*., vol. 220, no. 1. 2018.

[12] 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, 2017.

[13] L. Shen *et al*., "Msr-net: Low-light image enhancement using deep convolutional network," arXiv preprint, arXiv:1711.02488, 2017.

[14] C. Li, J. Guo, F. Porikli, and Y. Pang, "LightenNet: A convolutional neural network for weakly illuminated image enhancement," *Pattern Recognit. Lett*., vol. 104, pp. 15–22, 2018.

[15] C. Wei, W. Wang, W. Yang, and J. Liu, "Deep retinex decomposition for low-light enhancement," arXiv preprint arXiv:1808.04560, 2018.

[16] R. Wang, Q. Zhang, C. W. Fu, X. Shen, W. S. Zheng, and J. Jia, "Underexposed photo enhancement using deep illumination estimation," in *Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2019, pp. 6849−6857.

[17] Y. Jiang *et al*., "EnlightenGAN: Deep light enhancement without paired supervision," *IEEE Transactions on Image Processing*, vol. 30, pp. 2340−2349, 2021.

[18] Q. V. Le, "Building high-level features using large scale unsupervised learning," in *Porc. IEEE Int. Conf. Acoust. Speech Signal Process*, 2013, pp. 8595–8598.

[19] L. Shen *et al*., "Msr-net: Low-light image enhancement using deep convolutional network," arXiv preprint, arXiv:1711.02488, 2017.

[20] W. Wang, C. Wei, W. Yang, and J. Liu, "GLADNet: Low-light enhancement network with global awareness," in *Proc. 2018 13th IEEE International Conference on Automatic Face and Gesture Recognition (FG 2018)*, Xi'an, China, 2018, pp. 751−755.

[21] Y. H. Zhang *et al*., "Kindling the darkness: A practical low-light image enhancer," in *Proc. 27th ACM International Conference on Multimedia*, 2019, pp.1632–1640.

[22] J. Wang, W. Tan, X. Niu, and B. Yan., "Rdgan: Retinex decomposition based adversarial learning for low-light enhancement," in *Proc. 2019 IEEE International Conference on Multimedia and Expo (ICME)*, 2019, pp. 1186−1191.

[23] Y. Zhang *et al*., "Self-supervised low light image enhancement and denoising," arXiv preprint, arXiv:2103.00832, 2021.

[24] C. Guo, C. Li, J. Guo, C. C. Loy, J. Hou, S. Kwong, and R. Cong, "Zero-reference deep curve estimation for low-light image enhancement," in *Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2020, pp. 1780−1789.

[25] S. W. Zamir *et al*., "Learning enriched features for real image restoration and enhancement," in *Proc. 6th European Conference, Glasgow,* 2020, pp. 492−511.

[26] J. Hu, L. Shen, and G. Sun, "Squeeze-and-excitation networks," in *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, 2018, pp. 7132−7141.

[27] S. Woo, J. Park, J. Y. Lee, and I. S. Kweon, "Cbam: Convolutional block attention module," in *Proc. European Conference on Computer Vision*, 2018, pp. 3−19.

[28] Y. Liu, Z. Shao, and N. Hoffmann, "Global attention mechanism: Retain information to enhance channel-spatial interactions," arXiv preprint, arXiv:2112.05561, 2021.

[29] Y. Atoum, M. Ye, L. Ren, Y. Tai, and X. Liu, "Color-wise attention network for low-light image enhancement," in *Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*, 2020, pp. 506−507.

[30] X. Zhang and X. Wang, "MARN: multi-scale attention retinex network for low-light image enhancement," *IEEE Access*, vol. 9, 2021.

[31] X. Chen, J. Li, and Z. Hua, "Retinex low-light image enhancement network based on attention mechanism," *Multimedia Tools Appl.*, pp. 1−21, 2022.

[32] A. Ali, Y. Zhu, and M. Zakarya, "A data aggregation-based approach to exploit dynamic spatio-temporal correlations for citywide crowd flows prediction in fog computing," *Multimedia Tools Appl*., vol. 80, no. 20, pp. 31401−31433, 2021.

[33] X. Wang, Y. Zhai, X. Ma, J. Zeng, and Y. Liang, "Low-light image enhancement based on GAN with attention mechanism and color constancy," *Multimedia Tools Appl*., pp. 1−19, 2022.

[34] Y. N. Wang and Z. B. Zhang, "Global attention retinex network for low light image enhancement," *Journal of Visual Communication and Image Representation*, vol. 92, 2023.

[35] J. Anaya and A. Barbu, "RENOIR—A dataset for real low-light image noise reduction," *Journal of Visual Communication and Image Representation*, vol. 51, pp. 144−154, 2018.

[36] Y. Zhang *et al*., "Beyond brightening low-light images," *Int. J. Comput. Vis*., vol. 129, pp. 1013−1037, 2021.

[37] F. Lv *et al*., "Attention guided low-light image enhancement with a large scale low-light simulation dataset," *Int. J. Comput. Vis*., vol. 29, pp. 2175−2193, 2021.

[38] K. Lu and L. Zhang, "TBEFN: A two-branch exposure-fusion network for low-light image enhancement," *IEEE Trans. Multimed*., vol. 23, pp. 4093−4105, 2021.

[39] W. Wu *et al*., "URetinex-Net: Retinex-based deep unfolding network for low-light image enhancement," in *Proc. 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2022, pp. 5891−5900.

[40] X. Xu *et al*., "SNR-aware low-light image enhancement," in *Proc. 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2022, pp. 17693−17703.

[41] T. Wang *et al*., "Ultra-high-definition low-light image enhancement: A benchmark and transformer-based method," in *Proc. 37th AAAI Conference on Artificial Intelligence*, 2023, pp. 2654−2662.

[42] S. M. Chun *et al*., "Low-light image enhancement network using informative feature stretch and attention," *Electronics*, vol. 13, no. 19, p. 3883, 2024.