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# Low Light Image Enhancement via progressive recursive network using Deep Learning

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***Abstract—***
**Low-light images have low brightness and contrast, which presents a huge obstacle to computer vision tasks. Low-light image enhancement is challenging because multiple factors (such as brightness, contrast, artifacts, and noise) must be considered simultaneously. In this study, we propose a neural network—a progressive-recursive image enhancement network (SRGAN)—to enhance low-light images. The main idea is to use a recursive unit, composed of a recursive layer and a residual block, to repeatedly unfold the input image for feature extraction. Unlike in previous methods, in the proposed study, we directly input low-light images into the dual attention model for global feature extraction. Next, we use a combination of recurrent layers and residual blocks for local feature extraction. Finally, we output the enhanced image. Furthermore, we input the global feature map of dual attention into each stage in a progressive way. In the local feature extraction module, a recurrent layer shares depth features across stages. In addition, we perform recursive operations on a single residual block, significantly reducing the number of parameters while ensuring good network performance. Although the network structure is simple, it can produce good results for a range of low-light conditions. We conducted experiments on widely adopted datasets. The results demonstrate the advantages of our method compared with other methods, from both qualitative and quantitative perspectives.**

***Keywords—Machine Learning Algorithm, Enhancement,Neural network , Recursive, Accuracy, Precision, Attributes.***

## I. Introduction

Under poor lighting conditions, such as insufficient lighting, back lighting, or underexposure, low-quality images are produced. Moreover, insufficient illumination or low sensor quality in low light make the image prone to noise. Low-light images not only diminish the viewer's experience, but also hinder computer vision tasks. For example, facial recognition cannot be reliably performed on night-time, low-light images, due to poor information transmission. Most computer vision tasks are established for target images with good exposure, necessitating methods to improve the quality of low-light images. In recent decades, researchers have proposed a variety of solutions for low-light image enhancement. Methods based on a single image can be divided into three categories: histogram based, Retinue-based, and dehazing methods. Histogram-based methods redistribute the image's tone histogram and adjust the gamma curve index. In Retinex methods , the low light image is decomposed into illumination and reflectioncomponents, and the enhanced image is produced by adjusting the illumination component. For example, single-scale Retinex (SSR) uses Gaussian filtering to smoothly constrain the illumination map. Multi-scale Retinex (MSR) uses multiscale gaussian filters and color restoration to extend SSR. However, most methods based on Retinex assume that the reflection component remains unchanged during the enhancement process, which may cause color distortion and loss of detail. LIME uses a prior structure to estimate the illumination map and determines reflectance for the final enhancement result. Inversion of a low-light image produces a hazy image, which can be used for enhancement through image dehazing. In recent years, deep learning has achieved great success in many computer vision tasks. Neural networks have been extensively studied in low-light image enhancement. LLNet used a trained deep autoencoder to learn signal features in low-light images, adaptively increase exposure, and denoise. This method improves the local contrast to prevent over-amplification of already bright pixels. Retinex-Net proposed a data-driven Retinex decomposition method, and established a deep network that integrates image decomposition and subsequent enhancement operations. The multibranch low-light enhancement network (MBLLEN) uses multiple subnets to extract different levels of rich features for enhancement, and then merges the results to produce the final enhanced image. Kind combined Retinex theory with a convolutional neural network (CNN), and divided the network into two parts: illuminance map and reflectance map estimation. Fusion-based methods such as the

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Fractional-order Fusion Model (FFM) are also widely applicable to lowlight image enhancement tasks.

## II. PROBLEM STATEMENT

Images with too dark a luminance not only affect the perception of human vision but also cause great distress to other computer vision tasks. For example, for nighttime surveillance video, low illumination prevents face recognition and traffic monitoring systems from detecting the license plate number of the offending vehicle.

Extracting light from low-light images transforms dark regions into visible regions by adding image exposure and sometimes obtains additional information from dark regions by combination techniques. carried using a progressive-recursive image enhancement network, shows that it can conquer these problems and produce high-quality enhanced images. The low light image enhancement system can upgrade the brightness and discrepancy of the original image and reduce the image declination caused by varied reasons. With the development of deep learning, computer vision tasks have come gradually important. In tasks similar to traffic target detection and saliency-based image correction humans gradually need high-quality images.

## RELATED WORK

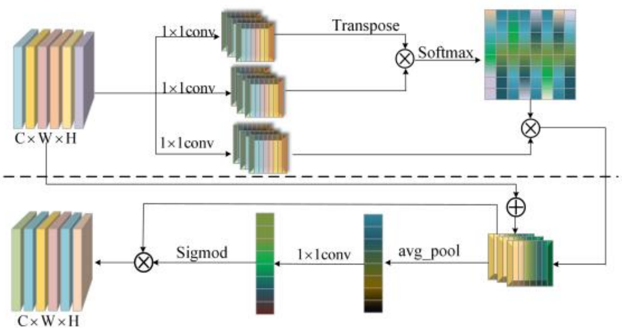
In this section we provide an overview of existing low-light image enhancement techniques. These methods can be roughly divided into two categories. First are traditional methods, mainly based on individual image enhancement and physical model methods. The second category uses deep learning, mainly based on the convolution neural network (CNN) and generative adversarial network (GAN). We briefly review some classic and advanced methods.

### A. Traditional low-light enhancement methods

Low-light images have lower overall brightness due to receiving less global light. In order to improve overall brightness, traditional low-light enhancement methods start from two aspects of image enhancement and a physical model. The histogram equalization method maps the value range of pixels to [0,1], and improves the contrast of the image by balancing the output histogram. The brightness can also be improved by gamma correction. This method can quickly increase the brightness, but it does not consider the relationship between an individual pixel and the surrounding pixels, which makes the enhancement result inconsistent with the real scene. Method contrast enhancement algorithm based on an entropy-preserving mapping prior that improves on conventional contrast enhancement methods. In contrast to previous methods, Retinex decomposes a color image into illumination and reflection components according to Retinex theory. Later method included multi-scale Retinex theories with colour restoration (MSRCR) proposed a novel enhancement framework using the response characteristics of cameras. However, the images produced by these methods usually look unnatural in color, and some areas have over-enhancement problems. Hao used an effective semi-decoupling method to decompose Retinex images, to enable low-light enhancement. In the Gaussian total variation model, the input image is used to estimate the illumination layer, and the reflection layer is estimated using the input image and the intermediate illumination layer. The illumination boost algorithm (IB) method is mainly used for night image enhancement. The algorithm processes the input image through a logarithmic scaling function, enhancing lowintensity and medium-intensity pixels, while keeping highintensity pixels from being over-enhanced. Yu proposed low light image enhancement algorithm based on a physical lighting model. Fu et al. obtained Retinex decomposition layer by adding regularization items to minimize the target function, so as to achieve image enhancement

### B. Low-light enhancement methods based on deeplearning

In recent years, deep learning has achieved great success in the field of low-light image processing, such as image denoising , super-resolution reconstruction , image-toimage conversion , and image deraining. Low-light Fig: Structure of the dual attention mechanism. Top: preattention module. Bottom: post-attention module. enhancement methods based on deep learning can be divided into two branches, CNN-based and GAN-based. Both methods depend on data-driven model training. CNN-based methods rely on paired images for supervised training, so they are resource-intensive.




However, there are relatively few paired data sets for low-light enhancement, and it is usually necessary to manually synthesize or change the camera settings during image capture to obtain paired images. For example, Lore et al. used gamma correction simulation data for training. The paired image Low-Light (LOL) data set used by Wei et al. was collected by adjusting the camera's exposure time and ISO rating during the image acquisition process. In the CNN enhancement method based on supervised learning, the Low Light Network (LLNet) constructs a network that can perform contrast enhancement and denoising at the same time. Retinex-net, proposed by Wei et al. , integrates image decomposition and illumination mapping. To remove noise in the image, Retinex-net uses a readymade denoising tool (BM3D ). After extracting the light component, the noise level in the dark area is higher than in the bright area. In this case, the unified image denoising training effect is not obvious, and more detailed denoising measures are needed. Unsupervised GAN methods do not rely on paired training data, avoiding the process of producing paired low-light and normal-light images. EnlightenGAN is an example of such a method. Although paired training data are not required, it is usually necessary to carefully select training images. ZeroDCE also proposes unsupervised training. This method uses a lightweight deep network and explores a new learning strategy, eliminating the need for paired data. It adjusts the dynamic range of an image by estimating pixel-level and higherlevel curves. proposed a novel semi-supervised learning approach for low-light image enhancement. This method used perception-based quality-oriented adversarial learning and unpaired data for network training. In our proposed PRIEN method, paired images are used for training. In contrast to this method, we adopt a progressive method for training. Specifically, we assign the feature map of the dual attention model and the original lowlight image to each stage. The dual attention module extracts global structural features, and the recursive unit mostly extracts

## IMPLEMENTATION

Many methods have been studied to improve the brightness and contrast of low-light images. Although different methods can improve the brightness of the image to a certain extent, by comparing different methods, we determine the advantages and disadvantages of each method. As shown in Fig. , and later tables, we compared our proposed method with 12 other current methods on real low-light images. We compared PRIEN with the SIRE , LIME , EFF, BIMEF, JED, MBLLEN, Retinex-Net, KinD, IB, FFM, Hao, and Zero-DCE methods. We carried out both subjective and objective evaluations

**evaluation**: We selected 7 low-light images from LOL datasets, including images taken under cloudy, backlit, and insufficient light conditions. We used 12 mainstream methods and our proposed method to enhance these images. These 7 original images and their enhancement results using the 13 different methods are shown in Fig. . In Fig. , the top row shows the input low-light images, and the second row shows the enhanced results using SIRE. We see that there are still more dark areas in the image enhanced by SIRE. The third row uses the LIME method, which is different from SIRE. The image brightness is excessively increased by this method, causing excessive enhancement in some areas of the image. The EFF method in the fourth row, the BIMEF method in the fifth row, and the FFM method in the eleventh row, are all based on the image fusion framework. The enhanced images have some dark areas that are not enhanced, but the FFM enhancement effect is relatively good. The sixth row shows the results of enhancement using the JED method. This method suppresses noise while enhancing the low light. Therefore, the generated image loses part of the texture information due to the smooth noise. MBLLEN in the seventh row, Retinex-Net in the eighth row, KinD in the ninth row, and Zero-DEC in the thirteenth row, all use convolutional neural networks for low-light enhancement, but some enhanced images show artifacts, such as the edge of the roof enhanced by Zero-DEC. Among these, the MBLLEN method combines the extracted features of multiple branch networks to produce low-light enhanced images, while the Retinex-Net and KinD methods are based on Retinex theory, which divides the network into two parts: decomposition and adjustment. Zero-DEC uses an unsupervised method for network training. From the visual effect, the enhancement result of MBLLEN is better than Retinex-Net, and KinD is better than MBLLEN. The tenth row, using Alameen's method, is rough in processing the sky, which becomes white, and image details are lost. The method of Hao in the twelfth row is also based on Retinex theory, and this method also shows some

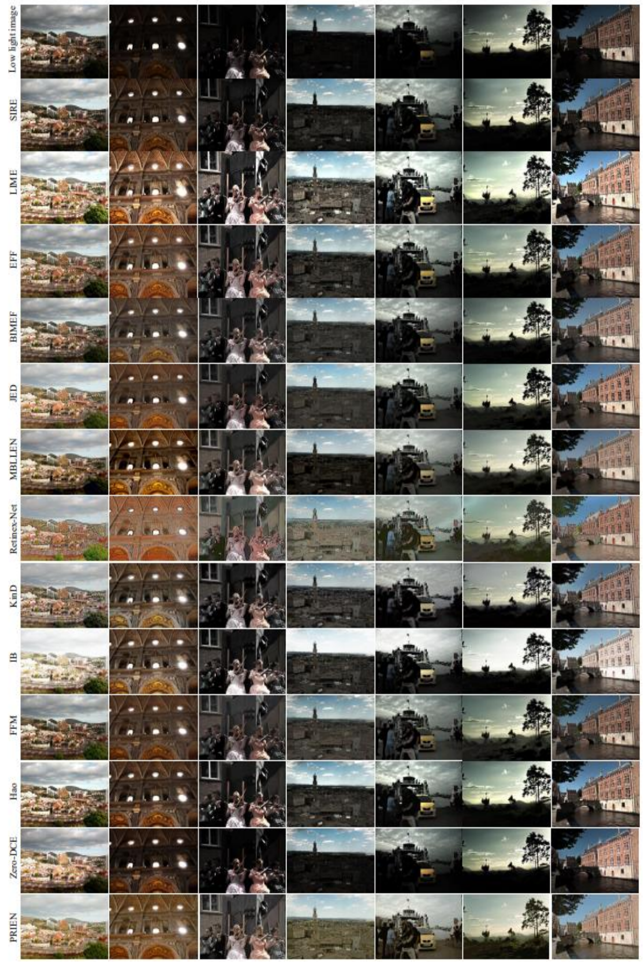



Fig: Comparison of enhancement of 7 real low-light images

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dark areas that are not enhanced. The fourteenth row shows the enhancement results of PRIEN. The overall brightness of the image is higher and there are no dark areas; the quality is better and there are no artifacts.

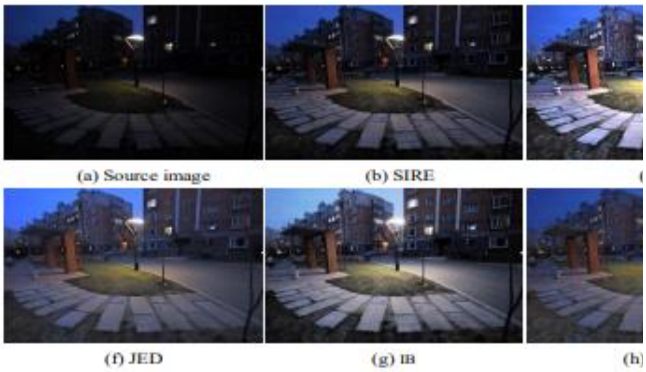


Fig. 8: Comparison of state-of-the-art low-light enha


Fig. 9: Comparison of state-of-the-art low-light enhance

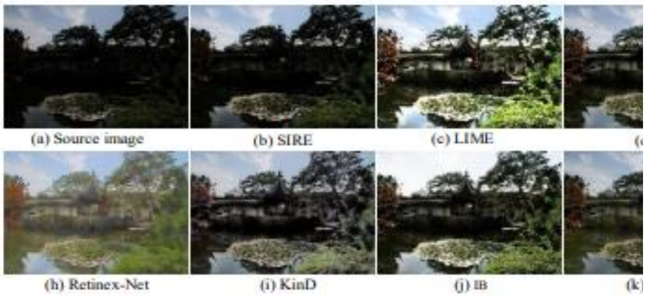


Fig. 10: Comparison of state-of-the-art low-light enhance

Fig. 8 shows a night street light scene, enhanced by 8 of the above 12 methods and our method. Street lights are usually very bright in low-light images, while the rest of the image is extremely dark. It is difficult to enhance the image because there are both well-exposed and under-exposed areas. Fig. 8 (d) using EFF, and Fig. 8 (g) using IB enhancement method, enhance the street light further. However, the image enhanced by the SIRE method in Fig. 8 (b) still has some dark areas. Compared with other methods, our method has achieved better overall enhancement effects.

In Fig. 9, we enhance an indoor low-light image under backlight conditions. Because of the backlight, the facial features of the human face cannot be clearly seen. We use low-light enhancement to make the facial expression clear. Ten different methods are used, with the face enlarged to compare the details. We see that our method (Fig. 9 (j)) preserves the original color of the image while enhancing the dark area, and the visual effect is satisfactory. Fig. 10 shows enhancement of a landscape image taken with backlight. Since the color of the input image (Fig. 10 (a)) is relatively rich, care should be taken to preserve the original color during the enhancement process. To the previous methods we have added comparisons with MBLLEN, RetinexNet, KinD, and the latest Zero-DCE based on CNN methods. We see that Fig. 10 (h) enhanced by Retinex-Net has a poor effect. Fig. 10 (f), Fig. 10 (j) and Fig. 10 (m) still have more dark areas. Fig. 10 (c) has excessive enhancement in some areas.

**TABLE** : Quantitative comparison of enhanced images in terms of average PSNR, SSIM, LOE, TMQI, NIQE, BRISQUE and Run time. The best result for each image is highlighted in bold

.

| Method | SIRE [15] | LIME [6] | EFF [26] | BIMEF [27] | JED [28] | MBLLEN [12] | Retinex-net [11] | KinD [13] | IB [23] | FFM [14] | Hao [22] | Zero-DCE [35] | Ours |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| PSNR | 12.885 | 17.310 | 15.996 | 15.167 | 15.259 | 16.216 | 17.230 | 16.042 | 16.306 | 14.832 | 14.652 | 12.184 | **19.933** |
| SSIM | 0.436 | 0.575 | 0.535 | 0.535 | 0.514 | 0.559 | 0.608 | 0.540 | 0.554 | 0.551 | 0.498 | 0.374 | **0.765** |
| LOE | 639.746 | 652.581 | 642.405 | 634.492 | 644.759 | 640.603 | 664.909 | 645.215 | 636.297 | 650.485 | 653.320 | 644.271 | **629.138** |
| TMQI | 0.883 | 0.888 | 0.914 | 0.916 | 0.906 | 0.922 | 0.937 | 0.916 | 0.912 | 0.915 | 0.900 | 0.860 | **0.951** |
| NIQE | 15.523 | 15.191 | 15.717 | 15.914 | 15.388 | 13.665 | 13.915 | 15.011 | 15.674 | 15.502 | 15.518 | 15.148 | **13.895** |
| BRISQUE | 20.721 | 20.629 | 19.159 | 19.266 | 26.201 | 25.475 | 28.056 | 26.605 | 18.927 | 23.892 | 24.882 | **18.815** | 20.430 |
| Run time | 4.187 | 0.493 | 1.580 | 0.977 | 2.250 | 4.321 | 0.163 | 3.654 | 0.587 | 4.400 | 1.613 | 3.529 | **0.013** |

In Table compares the NIQE values of the enhanced images obtained using the different methods. The best result, i.e. the lowest value, for each image is highlighted in bold. Our method scores best on the most images, followed by MBLLEN.

**TABLE** : Average performance of various enhancement methods on low-light images in public datasets, measured by NIQE and BRISQUE indices. The best result (lowest value) for each image/dataset is highlighted in bold.

| | NIQE | | | | BRISQUE | | | |
|---|---|---|---|---|---|---|---|---|
| Method | LIME dataset | MEF dataset | NPE dataset | VV dataset | LIME dataset | MEF dataset | NPE dataset | VV dataset |
| SIRE [15] | 15.897 | 15.707 | 14.782 | 11.263 | 21.984 | 23.492 | 20.566 | 19.540 |
| LIME [6] | 16.868 | 16.874 | 14.313 | 10.058 | 21.887 | 18.578 | 18.074 | 22.023 |
| EFF [26] | 14.888 | 16.336 | 13.142 | 9.304 | 20.991 | 19.272 | 22.100 | 22.596 |
| BIMEF [27] | 15.038 | 14.976 | 13.221 | 9.364 | 21.055 | 22.262 | 22.455 | 25.862 |
| JED [28] | 15.135 | 14.778 | 15.320 | 13.793 | 29.982 | 26.526 | 28.197 | 26.303 |
| MBLLEN[12] | 13.129 | 13.760 | 12.172 | 9.776 | 18.652 | 40.935 | 29.674 | 25.959 |
| Retinex-net [11] | 15.006 | 15.482 | 13.011 | 13.366 | 24.717 | 24.833 | 26.610 | 19.420 |
| KinD[13] | 13.901 | 13.901 | 21.038 | 9.550 | **18.652** | 11.064 | 20.343 | 18.993 |
| IB [23] | 14.832 | 15.524 | 12.616. | **8.748** | 23.976 | 20.195 | 27.125 | 28.382 |
| FFM [14] | 14.917 | 14.101 | 14.296 | 13.507 | 46.213 | 51.200 | 34.008 | 34.224 |
| Hao [22] | 15.330 | 14.216 | 14.440 | 11.283 | 27.760 | 29.810 | 22.879 | 23.784 |
| Zero-DCE [35] | 13.896 | 13.123 | 13.109 | 9.716 | 21.411 | 26.820 | 19.718 | 13.436 |
| PRIEN | **12.781** | **13.093** | **12.084** | 12.056 | 20.136 | **18.945** | **19.643** | **18.500** |

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**TABLE** : Average scores of subjective visual evaluation of 13 images enhanced using 13 methods by 16 subjects.

| Method | Total | Average value | Standard deviation | Variance | Z -value | Rank |
|---|---|---|---|---|---|---|
| SIRE [15] | 91 | 7.000 | 2.935 | 9.333 | 10.912 | 13 |
| LIME [6] | 126 | 9.692 | 1.380 | 2.064 | 12.110 | 2 |
| EFF [26] | 115 | 8.846 | 2.348 | 5.974 | 11.256 | 9 |
| BIMEF [27] | 88 | 6.769 | 2.454 | 6.526 | 11.082 | 11 |
| JED [28] | 104 | 8.000 | 2.386 | 6.167 | 11.421 | 7 |
| MBLLEN [12] | 127 | 9.769 | 2.860 | 8.859 | 11.850 | 4 |
| Retinex-net [11] | 56 | 4.308 | 2.366 | 6.064 | 11.166 | 10 |
| KinD [13] | 108 | 8.308 | 4.462 | 21.564 | 11.371 | 8 |
| IB [23] | 70 | 5.385 | 1.734 | 3.256 | 11.816 | 5 |
| FFM [14] | 106 | 8.154 | 3.183 | 10.974 | 11.747 | 6 |
| Hao [22] | 98 | 7.538 | 3.273 | 11.603 | 10.944 | 12 |
| Zero-DCE [35] | 110 | 8.462 | 1.393 | 2.103 | 12.038 | 3 |
| PRIEN | 128 | 9.846 | 1.406 | 2.141 | 12.273 | 1 |

The main purpose of low-light image enhancement is to improve the contrast and brightness of the image, while color perception is more inclined to human subjective judgment. In order to further subjectively evaluate the quality of low-light enhanced images, we scored images based on users' subjective views. We selected 13 images from four public datasets: LIME, MEF, VV, and NPE. First, we used 13 methods (SIRE, LIME, EFF, BIMEF, JED, MBLLEN, Retinex-Net, KinD, IB, FFM, Hao, and Zero-DCE) to enhance the 13 images. Next, we invited 16 subjects to independently score the visual effectsof the enhanced images. In our study, all 16 subjects had normal vision (10 men and 6 women); the age was 25.7±3.6. We asked 16 subjects to independently compare the output of 12 methods in a pairwise manner. Specifically, for each subject, a pair of images was randomly selected from the 13 outputs. The image pair consisted of the original low-light image and the enhanced image, and the subject was asked to evaluate the enhanced image. If the subject claimed that the low-light enhancement effect was better, the image scored 1 point; otherwise, 0 points

## CONCLUSION:

In this paper, we proposed an end-to-end low-light enhancement network. The existing methods may rely on some experience, and it is easy to ignore the image noise. To obtain higher quality enhancements of low light images, we combined the attention layer, convolution layer, and circulation layer to train a reliable and flexible network. In the network input, we input a low-light image into the network. In the network structure, we used the dual attention layer to extract global features. A loop layer was introduced into the network to share depth features across stages. In addition, residual block recursion in the recursive unit reduces the number of network parameters, but does not reduce the performance of the network. We evaluated output enhanced images qualitatively and quantitatively, and added a user study to quantify the subjective evaluation. Finally, we confirmed the rationality of the network structure through ablation experiments. In the experimental analysis our method obtained better performance in multiple evaluation indicators, and has certain advantages over other similar methods. In future research, we aim to continue to modify the network to achieve low-light video processing

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