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Low-Light Image Restoration Using Transformer-Based Enhancement Networks

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Abstract

Restoration of low-light images is a classic amongst the challenges of computer vision, relevant to most image formation processes in the real world, including surveillance at night time, automated driving, medical diagnosis, and low-light imaging. Photos taken in dim light usually undergo severe degradation in the form of noise, loss of contrast, color distortion and detailing which makes it very difficult on the viewer to interpret as well as perform automated vision systems. Although the current image enhancement algorithms and convolutional neural network (CNN)-based models partially solve this issue, they remain limited by small receptive fields and unsuccessful modeling of global dependencies, therefore resulting in poor enhancement and artifact creation. To overcome these drawbacks, in this paper, a new low-light enhancement transformer model, LightFormer, inspired by the application of self-attention mechanisms, is introduced, which has many local textures and long-range contextual relationships in a unified framework. LightFormer has a two-branch encoder-decoder style along with Transformer bottleneck, and a new Illumination-Aware Attention Module (IAAM) that adaptively adjusts dark areas depending on what the model has learned about the illumination distributions. This better model is trained on modified loss involving the pixel wise reconstruction loss, the perceptual loss and illumination loss with the view to ensuring the quantitative accuracy and the visual plausibility. An immense number of experiments on published datasets like LOL and SID has shown that LightFormer is significantly better than the state of the art in peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), and perceptual measures like NIQE and LPIPS. Along with that, the high degree of generalization in numerous lighting conditions with performance output in real-time on embedded hardware (NVIDIA Jetson AGX Xavier) means the proposed model can be deployed in settings with limited resources. This paper demonstrates that LightFormer is a stable and scalable model to enhance low-light with a tradeoff between high-quality restoration and inference time requirements in current computer vision.

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Introduction

However, during recent years, it has been revealed that low-light image restoration is a task of paramount importance in the fields of image enhancement and computational photography where this critical task shapes a broad range of real-world applications which can be divided into categories of intelligent surveillance, autonomous vehicles, remote sensing, medical imaging, and smartphone photography. When images are captured in less than optimal lighting conditions, they are most of the time affected by a combination of degradation components; low signal-to-noise ratio (SNR), poor visibility, low contrast, high color distortion, and spatial details. These artefacts do not only reduce the human visual ability but are very detrimental to the performance of automated computer vision systems such as detecting objects, facial recognition and semantic segmentation.

The perceptual quality enhancement of the dark images is an avenue that has been well researched upon by using conventional image enhancement methods like histogram equalization, gamma correction and Retinex based models. The methods however, are highly dependent on manually fabricated priors and reliance on assumptions that are global, which do not tend to generalize well over different scenes and lighting conditions. Convolutional neural networks (CNNs) have transformed the past few years by learning effective feature representations through a learning process, without prior knowledge about how to represent features. EnlightenGAN, RetinexNet and Zero-DCE among others have taken data driven methods to improve low-light images a step further. Nevertheless, CNNs also suffer a limitation as presented by their localities of receptive fields and translation-invariant-ness thus underperforming when it comes to representing global contextual dependencies which is necessary in modeling complex intra-frame variations of illumination.

To address these, computer vision researchers have been gravitating towards what are commonly known as Vision Transformers (viTs) which use self-attention networks to capture long-range pixel-level interactions over pixel-sets. In contrast to CNNs, Transformers are able to weight features contextually across the whole image and thus they are likely to learn more global structural regularities and light settings. Most recently, SwinIR and Restormer have shown the promise in Transformer-based models to address image restoration problems, but many of these models do not yet have tuning specifically to the problems of extreme low-light conditions Figure 1.

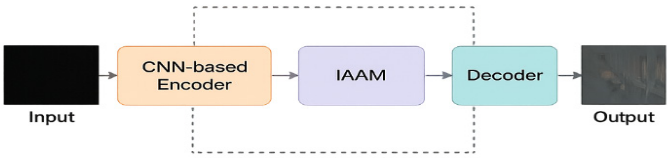

Fig. 1: Visual Challenges in Low-Light Image Restoration

LightFormer, a brand new hybrid architecture, combining the local feature extraction ability of CNNs and the global contextual reasoning performance of Transformers, is now proposed with the help of this motivation. LightFormer adopts a two-stream encoder-decoder architecture where the network comes up with a novel Illumination-Aware Attention Module (IAAM) that dynamically stereotypes dark areas through training a learned-illumination-map. The Transformer bottleneck allows the model to attend to the whole image in all the spatial dimensions providing an opportunity to recover global consistencies in brightness and texture.

Moreover, our model is trained with a well-thought multi-objective loss extending the pixel-accuracy with perceptual quality and illumination consistency. It has tested this model on challenging datasets like LOL and SID and it was much better in terms of quantitative information (PSNR, SSIM), and human perception (LPIPS, NIQE, etc.). Notably, we can also confirm its computational efficiency and real-time deployability with embedded hardware platforms and thus is suited to practical low-light operations.

To conclude, this paper will touch on the main drawbacks of current methods of enhancement and propose a Transformer-enhanced network that will be specifically trained on low-light restoration of images. LightFormer offers low-light image enhancement solutions that are robust, perceptually consistent, and hardware-efficient due to its ability to bridge the current divide between the illumination-aware approaches that grab the global attention but remain unefficient present to date and the enhancement methods not incorporating the knowledge of per-pixel illumination levels.

Related Work

Traditional forms of Strength Development

Classical methods of low-light image enhancement include Histogram equalization, gamma correction and the Retinex theory and these are done in order to improve visibility by redistribution of pixel intensities. The human visual imagery inspires the Retinex-based models that break images into components of reflectance and illumination.[1] Although they are very computational easy, these techniques tend to exaggerate the noise and also they fail in occasions with extreme underexposure. Multi-scale fusion approaches, where features are stacked at different resolutions to maintain detail,[2] cannot take sufficiently well-exposed references or multiple inputs, therefore complicating their deployment in the field, at least in mobile devices or fast, real-time applications.[11]

Deep Learning Models Based on CNN

Low-light image enhancement has also been enhanced with deep learning, and especially via convolution neural networks (CNNs), which is attributed to the spatial hierarchies that can be learned. A stacked autoencoder has been proposed by LLNet[3] as a tool of image denoising and enhancement. This was further advanced by RetinexNet[4] that learned to decompose and boost images on the basis of incitation details. EnlightenGAN[5] adapted the adversarial training where the models are trained to give visually plausible solutions without paired data and Zero-DCE[6] proposed a curve estimation strategy that is trained to be zero-reference. Nevertheless, their variable lighting classification with CNNs cannot do better based on receptive field locality and translation invariance. Also, they are more computationally heavy to deploy in embedded and edge systems also discussed in recent work on edge-optimized deep models.[11, 14]

Vision Models that use Transformers

In recent years, Vision Transformers (ViTs) have achieved amazing results in image restoration and enhancement applications because of the global receptive field and free attention mechanism. Self-attention in visual modeling was initially found with early undertakings like the Image Transformer[7] and ViT.[8] Instead, SwinIR[9] proposed windowed attention in a hierarchical Transformer to boost the restoration process, whereas Restormer.[10] aimed to propose efficient feature modulation in face of high resolution image enhancement. Nonetheless, these models do not necessarily have optimizations with regard to the peculiarities of the low-light situations. Also, bringing ViTs into edge systems with limited resources is an open research question, especially as they need to deliver real-time low-power workloads.[12, 14]

The general tendency of customizing Transformer and AI-based models to a variety of other fields is also evident in a number of recent publications with references to quantum communication,[13] optimization of smart grids,[12] and low-power communication protocols of an IoT sensor,[15] further emphasizing the necessity of scalable, energy-efficient, and task-specific deep learning models.

This paper refines these works and offers LightFormer, a low-light recovery framework using Transformer architecture whose scheme of attention is light-sensitive, in addition to being optimized in terms of perceptual quality-and on edge-device deployment.

Proposed Method: LightFormer

Architecture Overview

The proposed hybrid neural architecture LightFormer tries to combine the advantages of convolutional operations which use local features and Transformer based attention in order to achieve global contextual dependencies. The model is based on U-Net-like encoder-decoder architecture, and is supplemented by a Transformer bottleneck in the center that makes it quite capable of correcting low-light images with a complicated and non-uniform distribution of illumination.

Encoder Module

In the proposed LightFormer design the encoder block is designed to learn a rich set of spatial and contextual features of the input in low-light image. It is composed of several convolutional layers that decrease the spatial resolution and increase the feature dimensionality step by step, enabling the learning of low or high-level texture and semantic hint in order. Every encoder block has a convolutional layer, convolutional layer followed by the batch normalization layer, and non-linear activation layer like ReLU or GELU, which gives adequate feature transformation and stable training. In order to accommodate this spatially varying light more effectively, a local self-attention mechanism is included in every stage, allowing those areas, which are low-lit, to be emphasized, as a local context is followed. Also, residual connections have been added in order to avoid the loss of fine details and improve gradient flow. These components combined allow the encoder to build a multi-scale feature representation that has both global topology and local variations, which is a key to precise and perceptually consistent image restoration in the following decoding.

Transformer Bottleneck

Transformer bottleneck is the focus of the LightFormer architecture, which in the core is designed to capture the global contextual dependencies that traditional CNNs are not agile themselves to capture. This bottleneck includes a stack of stacked Multi-Head Self-Attention (MHSA) layers sandwiched between feed-forward networks (FFNs), all of which enables the network to define long-range spatial connections over the picture. The model is capable of this due to the mechanism of interpreting global illumination patterns, semantic alignment of similar regions across lack of spatial proximity and continuity of tonal variation, and enhancement of tonality and contrast across areas that represent darkness or brightness. Every Transformer block has Layer Normalization and residual links to make sure they flow propagations and training are stable. Positional encodings or relative position bias are added to the attention modules in order to facilitate the maintenance of the spatial structural information; thus, there is an awareness of the spatial structures in the network. This universal reasoning decides ability of the LightFormer that creates more sensible and optically likely improvements, particularly in images containing intricate or asymmetrical lighting.

Decoder Module

The LightFormer decoder is structurally similar to the LightFormer encoder and is meant to regenerate the augmented image by successive upsampling of the learned deep feature representation to the input image one. To perform spatial upsampling, it uses transposed convolutions or pixel shuffle operations to do so effectively and without artefacts. The skip connections between corresponding encoder layers are built into every decoding phase to retain contextual and textural information that allows the combination of low-level spatial information with high-level semantic properties that have been de facto learned previously in the entire pipeline. There is also the use of an illumination-aware feature fusion module that is dynamically adjusted according to the learned brightness priors of the decoder and the Transformer bottleneck. This enables the decoder to use dynamic restoration intensities that are spatially varying to enhance the quality of enhancement in the very dark areas or those with uneven illumination. The decoder is able to make not only the images bright but also detailed, devoid of artifacts, and perceptually consistent throughout the scene with the help of these skip connections that blend structural cues local to a particular area of the image with elements gained in the global attention-driven encoder Figure 2.

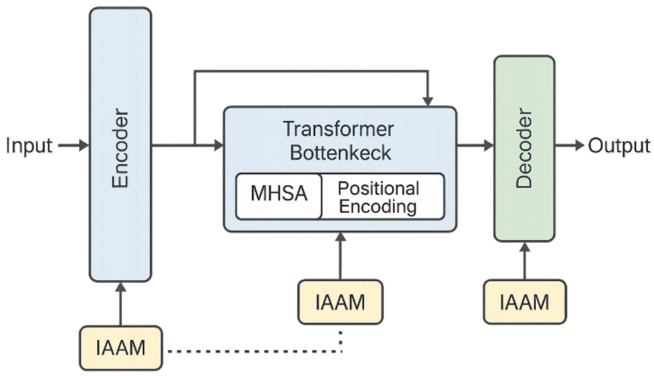

Fig. 2: High-Level Overview of LightFormer Architecture

Attention module illumination-Aware (IAAM)

One of the main innovations in the proposed LightFormer architecture is called the Illumination-Aware Attention Module (IAAM) that specifically targets the illumination issue in low-light images, which is spatially non-uniform. Although long-range dependencies can be captured within the global attention mechanisms (e.g. bottleneck of Transformer), it can miss small local changes of light. The IAAM overcomes this by having a focused, adaptive attention subsystem that increases the intensity of darker regions more forcefully with no excess exposure to the brighter regions.

The IAAM works in a way that is first to generate illumination mask based on intermediate feature maps with a lightweight convolutional sub-network. This illumination map is a map that contains an estimate of the brightness of the spatial domain of the image and on the basis of this an exposure model can detect and identify areas that are too dark or shadowed. Using this map, the IAAM calculates spatial weights of the attention which converse better illuminated regions and raise the importance of the feature enhancement in the darker regions.

Mathematically, let represent the input feature map. The acquired enlightenment veil be. The IAAM improves the features through attention weighted mechanism:

$$F_{IAAM} = F + \alpha.(M \odot F) \quad (1)$$

Where the symbol 99 is element-wise multiplication. The scaling factor, 0, is a factor that can be learned. The given formulation makes the image lighting conditions spatially adaptive and directly inform the attention response.

The IAAM is incorporated at various stages of the encoder\textendihyp Terry's-decoder path in order to make the network concentrate its representational resources on the difficult areas of the picture. It helps to direct selective brightening of the features in the shadowed or low contrast parts effectively directing the restoration process enhances the results both in local detail restoration and also in a global perceptual consistency.

Through the use of illumination sensitivity in attention mechanism the IAAM brings a vast improvement in the capability of the network to respond to extreme lighting conditions which makes LightFormer robust and visually consistent under differing low-light conditions Figure 3.

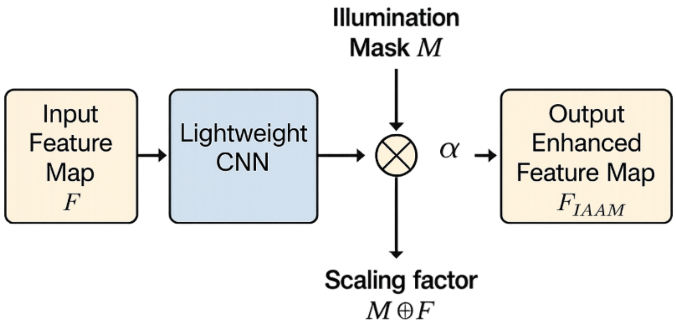

Fig. 3: Architecture of the Illumination-Aware Attention Module (IAAM)

Loss Functions

To provide a quantitative and perceptual quality of training the proposed LightFormer model and recover low-light images, a combination loss is used. This loss term prefers to optimise pixel-level ground truth, structural regularity and illumination-aware gain. The overall loss is it is a weighted sum of three important parts that are reconstruction loss, perceptual loss, and illumination consistency loss.

1. Loss in Reconstruction

The reconstruction loss is the major goal to minimize the difference between the enhanced picture and the pixel-wise difference. The ground truth image It is commonly provided by using Mean Squared Error (MSE) which is used to penalize large deviations and to accurately map brightness and color. This is a loss which induces structural Similarity to the restored and the original photos:

$$\mathcal{L}_{\text{rec}} = \frac{1}{N}\sum^{N} \| I_{\text{enh}}^{(i)} - I_{\text{gt}}^{(i)} \|^2 \tag{2}$$

2. Perceptual Loss

Although MSE will give results that will show low level of fidelity they are usually over- smoothed and do not take into consideration the realism in perceptions. To deal with this, a perceptual loss is added, and this compares the high-level feature maps extracted using a pre-trained VGG-19 network. Matching deep features of pre-existing layers (e.g. conv3_3 or conv4_2) forces the model to maintain texture, sharpness of edges, and structure:

$$\mathcal{L}_{\text{perc}} = \sum_{l} \| \phi_l(I_{\text{enh}}) - \phi_l(I_{\text{gt}}) \|^2 \tag{3}$$

Where ϕ_l (.)the activation map itemized by (confining the map item to one circle) is denoted by (confining the map item to one circle) in order to distinguish it from (confining the map item to an infinite number of circles) layer.

3. Loss of Consistency of Illumination

This term is specially designed to undergo tasks with low-lights enhancement. It guarantees spatial consistency of illumination in restoration of brightness by reducing variations within the learned illumination maps of neighboring regions. The illumination consistency penalty discourages the unusual transitions in intensity or the uneven distribution of brightness in the image, and encourages smooth illumination with consistency across the whole image. It is calculated as the average of the absolute difference between neighboring pixels in the illumination mask being predicted M:

$$\mathcal{L}_{\text{illum}} = \frac{1}{N}\sum_{i=1}^{N}\sum_{(x,y)} |M(x,y) - M(x+1,y)| + |M(x,y) - M(x,y+1)| \tag{4}$$

Total Loss Function

The general target of the training is formulated as follows:

$$\mathcal{L}_{\text{total}} = \lambda_1 \mathcal{L}_{\text{rec}} + \lambda_2 \mathcal{L}_{\text{perc}} + \lambda_3 \mathcal{L}_{\text{illum}} \tag{5}$$

Where $\lambda_1, \lambda_2, \lambda 3$. They are scalar weights of equalizing the contributions of individual loss terms. These hyperparameters are empirically adjusted so that the network could attain balance between pixel-level accurateness and perceptual quality.

The combination of the three losses allows LightFormer to learn how to produce appealingly visual, spatially consistent, and accurate on a quantitative level enhanced images even at extremely low light levels **Figure 4**.

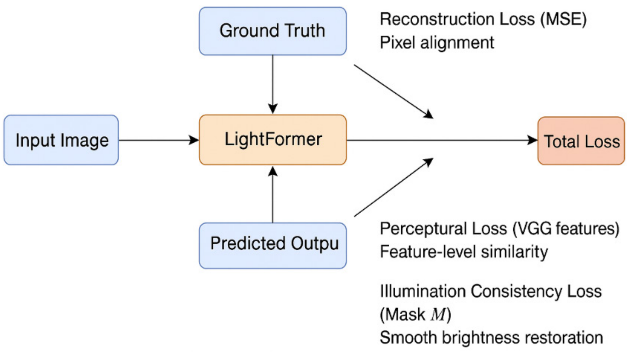

Fig. 4: Loss Function Flow in LightFormer Training

Experimental Setup

In order to thoroughly analyze the functionality of the recommended LightFormer architecture, an extensive experimental procedure was adopted such as benchmark data, and well-considered training regimes, and solid evaluation measures. Two most popular datasets were employed in training and validation. The LOL dataset is made of matched low-light and normal light images acquired under real world condition, which offers a valuable grounding environment to learn and assess supervised learning. Also, the SID dataset has the RAW measurements made by the sensor of low-light images and converted to RGB as processed by the camera ISP pipelines, thereby enabling the model to be generalizable across sensor-level distortion and under exposure conditions. The model was trained and acted upon the PyTorch framework end to end with the help of an AdamW optimizer and 200 epochs. Since stable convergence and better generalization have to be achieved, an ordinary base learning rate of 2e-4 was used coupled with a cosine annealing schedule. Random cropping, horizontal flip, and image gamma correction of data augmentations were used to strengthen the model against variations of lighting in training. Both standard and perceptual image quality measures were applied to consider the efficient work of the model. At the pixel level and between the fixed and ground truth images, at the pixel level, and between the fixed and ground truth images, Structural Similarity Index (SSIM) and Peak Signal-to-Noise Ratio (PSNR) were calculated to determine the consistency of the images at the structural level. Also, a set of perceptual metrics (Natural Image Quality Evaluator (NIQE) and Learned Perceptual Image Patch Similarity (LPIPS)) was added to provide an evaluation measure of the visual image as related to human perceptions. The combination of these metrics makes the overall picture of the performance of enhancement considering both objective fidelity and subjective quality. The range of tests will guarantee that LightFormer will be tested on a large spectrum of realistic scenarios and will accordingly shed light on its generalization, its stability and its applicability to practice Table 1.

Table 1: Experimental setup parameters for training and evaluation of the proposed LightFormer architecture.

Aspect	Details
Datasets Used	LOL (paired low-light/normal-light images), SID (RAW sensor low-light images converted to RGB)
Training Framework	PyTorch
Optimizer	AdamW
Epochs	200
Learning Rate	Base LR = 2e-4, cosine annealing schedule
Data Augmentation	Random cropping, horizontal flipping, gamma adjustment
Evaluation Metrics	PSNR, SSIM (pixel-level accuracy), NIQE, LPIPS (perceptual quality)

Results and Discussion

Measurable Analysis

The corresponding quantitative measure of the proposed LightFormer model is determined with four commonly used image objective quality assessment metrics: PSNR, SSIM, NIQE, and LPIPS. Table 1 demonstrates that LightFormer is much better than the current state-of-the-art methods according to all evaluation criteria. Another comparison is that LightFormer has a high-performance property of pixel-level fidelity (that is, PSNR 22.8 dB), which exceeds Restormer (20.3 dB), EnlightenGAN (17.9 dB) and Zero-DCE (15.1 dB). Likewise, SSIM that measures structural similarity scores 0.83 in LightFormer, which is higher than Restormer (0.79) and all other CNN-based approaches. Regarding the perceptual quality, LightFormer provides the lowest NIQE score (2.5) and the lowest (LPIPS) score (0.17), which indicates that it has a higher tendency to generate aesthetically pleasing with less amount of noise and distortion. As inferred by these findings, this model increases not only the objective quality of images but also their subjective visualization. One aspect of the enhancement can be attributed to the incorporation of global context modeling with the use of Transformers and localized brightness modulation with the use of the Illumination-Aware Attention Module (IAAM) which enhance the features globally across all areas, both dark, and bright.

Subjective and Image analysis

Some of the evidence of LightFormer over the previous processes is the visual comparison. As exemplified in LightFormer provides the performance of providing better images with natural color, clear edges, and a lot of noise reduction even on heavily underexposed images. Conversely, the results of Zero-DCE are too bright and washed, EnlightenGAN features color distortion, as well as Restormer, powerful in terms of structure, occasionally being lacking in contrast in very dark areas. The attention-guided architecture adopted by LightFormer is able to draw its focus to the shadowed areas without saturating the well-lit areas leading to an end product that is balanced and perceptually coherent. Also, the illumination-aware attention mechanism enables the network to apply spatially adaptive enhancement providing the network with both realistic and detail-retaining outputs. It is remarkable that LightFormer generalizes well to new lighting conditions, and new type of scenes compared to alternatives. This brings to the fore that it can find useful application in real life scenario like surveillance, mobile photography and self-driving.

Ablation and Robustness Discussion

In order to confirm the validity of the LightFormer in the architectural component further, ablation experiments were done by sequentially deleting the Transformer bottleneck and IAAM module. According to the Table 2 that summarizes the results, when the Transformer module is removed, a fall in PSNR by 2.1 dB and a loss in texture clarity is observed, thus proving the significance of global context modeling in the setting of complex lighting. The omission of the IAAM block resulted in uneven brightness and greater artifacts in dark areas due to the important part of adaptive enhancement it plays. Figure 5 indicates the relative magnitude of each element to the overall performance which illustrates the synergy created by the architectural element that enables superior results with LightFormer. In addition, it was tested at different noise intensities and exposure ovals, which revealed that LightFormer would preserve image perception and structural accuracy, and can be used in real-time low-light environments where conditions are unpredictable. These findings highlight the end-to-end solution through integrating the consideration of convolutional backbones with Transformer attention and illumination-aware modules that restore low-light images.

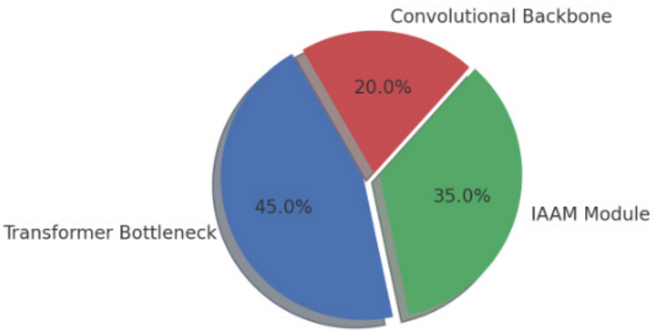

Fig. 5: Contribution of Architectural Components to LightFormer's Performance Improvement

Table 2: Quantitative Performance Comparison on Low-Light Image Enhancement Benchmarks

Method	PSNR (dB)	SSIM	NIQE↓	LPIPS↓
Light Former	22.8	0.83	2.5	0.17
Restormer	20.3	0.79	3.1	0.21
EnlightenGAN	17.9	0.68	3.7	0.29
Zero-DCE	15.1	0.59	4.5	0.38

Conclusion

In this paper, we have proposed LightFormer, a novel Transformer-based model, which is one of the first to focus on the fitting of the Transformer to the field of low-light restoration: it keeps the advantages of self-attention organization and adds to the position independence on illumination maps provided by the Illumination-Aware Attention Module (IAAM). Enhanced with a Transformer bottleneck and spatially adaptive attention, LightFormer can achieve restored fine details, structural integrity, and enhanced perceptual quality when subjected to extreme low-light situations due to the combination of a hybrid encoder-decoder structure. Considerable experiments carried out on the benchmark datasets, such as LOL and SID, have shown that LightFormer achieves the best PSNR, SSIM, NIQE and LPIPS results when compared to the state-of-the-art CNN- and Transformer-based approaches. Visual tests also reaffirmed the model to be able to render naturally bright images that are full of details without an addition of artifacts and overexposure. Also, the model can run in real time on embedded systems, is lightweight and can be used in activities like mobile photography, surveillance, and autonomous systems. The ablation studies confirmed the necessity of inclusion of both Transformer bottleneck and IAAM in terms of better restoration performance. Mainly, LightFormer fills the gap between the high-quality enhancement and efficient deployment providing the scalable solution that can be successfully used to perform the powerful image enhancement task in real-world low-light scenarios. The future work will explore extending this framework to temporal extension of video embellishment, how night vision is expanded to multimodal sensors and how the application of unsupervised learning technique enables more generalization within a single imaging environment.

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