ISSN 2959-6157

Implementation of Adjustable Light Enhancement Based on Deep-Retinex-Net

Anheng Wen

School of Materials Science and Engineering, Shanghai University, Shanghai, 200444, China
23122014@shu.edu.cn

Abstract:

The Deep-Retinex-Net (DRN) method enhances low-light images by decomposing them into reflectance and illumination components, which are independently processed using convolutional neural networks (CNNs) and then recomposed. However, a significant limitation of this approach is its inability to adaptively adjust output brightness according to user-specific requirements, this is because the mapping relationship it established is fixed on the light and dark relationship of the image pairs in the dataset. To address this issue, this paper proposes the Control-Deep-Retinex-Net (C-DRN) framework. The proposed method introduces modifications in dataset construction, optimizes the training strategy, and refines the network architecture. By incorporating a maximum likelihood estimation (MLE) model, C-DRN enables continuous and customizable brightness adjustment—from extremely dark to normal lighting conditions—during the low-light enhancement process. Experimental results demonstrate that the framework achieves 96.3% accuracy in brightness control, significantly improving the model's adaptability and learning capability. The approach not only produces visually pleasing results but also supports precise and user-oriented illumination customization.

Keywords: Deep-Retinex-Net (DRN) Method, Convolutional Neural Networks (CNNs), Maximum Likelihood Estimation (MLE), Brightness Adjustment, Low-light Enhancement.

1 Introduction

Images serve as crucial carriers of information, yet they are often compromised by environmental constraints during capture, resulting in low-light images characterized by insufficient brightness, low contrast, significant noise, and even loss of critical details. Simple physical interventions, such as directly increasing light sources, often lead to overexposure and distortion in bright areas. The application of machine learning and convolutional neural networks has opened new avenues for low-light enhancement: by training on extensive pairs of low-light and normal-light images, models can learn the mapping

ISSN 2959-6157

between illumination defects and restoration patterns, enabling precise enhancement of previously unseen low-light images. The Retinex model serves as a key theoretical foundation for low-light enhancement, centering on the concept of decomposing an image into an illumination component, which determines overall brightness, and a reflectance component, which captures the intrinsic colors and textures of objects independent of lighting conditions [1]. Algorithms based on this model have continuously evolved and improved by refining this decomposition-and-adjustment framework [2].

Early deep learning techniques combined with the Retinex model gave rise to algorithms such as Single-Scale Retinex (SSR) and Multi-Scale Retinex (MSR) [3]. SSR employs single-scale Gaussian filtering to estimate the illumination component. It is computationally simple and can improve image contrast to some extent, but its enhancement effectiveness is highly influenced by the scale of the Gaussian kernel, limiting its adaptability [4] [5]. MSR, on the other hand, integrates results from multiple Gaussian filters at different scales, achieving a better balance between detail enhancement and dynamic range compression [6]. The Multi-Scale Retinex with Color Restoration (MSRCR) further incorporates a color restoration step on the basis of MSR, which ameliorates color distortion issues in low-light conditions [7]. However, these methods still suffer from an inability to eliminate the significant noise hidden in dark regions and issues like blurred edges [8].

Deep-Retinex-Net (DRN) demonstrates performance significantly superior to traditional algorithms in complex low-light environments, particularly excelling in detail recovery and noise suppression [9]. Nevertheless, DRN still has certain limitations in practical applications. A notable drawback is that once training is complete, the network optimizes the illumination component based on a fixed mapping relationship, making it difficult to flexibly adjust the enhanced brightness according to different scene requirements or user preferences [10]. Consequently, the network cannot fulfill personalized user needs, such as maintaining a slightly darker atmosphere after enhancement or increasing the brightness further to obtain a clearer overall visual effect. This shortcoming restricts the algorithm's flexibility in real-world applications.

To address the limited flexibility in brightness adjustment of DRN, this paper proposes a new model named Control-Deep-Retinex-Net (C-DRN), which effectively enables controllable brightness enhancement in low-light conditions. The paper first introduces the architecture and constraint logic of the C-DRN network. It then elaborates on the modifications made to the dataset and loss function to achieve continuous brightness mapping, as well as the application of maximum likelihood estimation. Finally, the enhancement performance is evaluated through experimental data and visual analysis. The proposed model extends the applicability of DRN to a wider range of scenarios and demonstrates excellent performance under diverse user-specific brightness requirements.

2 Constructing the C-DRN Model

2.1 Principles and Construction of the Decomposition Network

The C-DRN consists of two main components: a decomposition network and an enhancement network. The decomposition network is responsible for separating the input low-light image into an illumination component, which reflects the environmental lighting conditions, and a reflectance component, which represents the intrinsic surface properties of objects. The enhancement network then processes and adjusts the separated illumination component through learned transformations to ultimately produce the enhanced image. Since the core process of achieving adjustable illumination enhancement primarily takes place within the enhancement network, this model retains the decomposition network (Decom-Net) from the original DRN architecture.

The Decom-Net takes both a low-light image and a normal-light image as inputs. It first employs four 3×3 convolutional layers to extract features from the input images. After processing with ReLU activation functions, a subsequent 3×3 convolutional layer maps the RGB images into reflectance and illumination information. Finally, a sigmoid function is applied to refine the outputs, constraining both the reflectance and illumination values to the range [0,1]. This process simultaneously estimates the reflectance R and illumination I for both the low-light and normal-light images.

To ensure the accuracy of the decomposition process, the loss function for the Decom-Net is designed as follows:

$$\mathcal{L} = \mathcal{L}_{recon} + \lambda_{ir}\mathcal{L}_{ir} + \lambda_{is}\mathcal{L}_{is}, \tag{1}$$

Where $\mathcal{L}_{recon}$ represents the reconstruction loss, $\mathcal{L}_{ir}$ denotes the invariable reflectance loss, and λ_{is} stands for the illumination smoothness loss. The coefficients in the formula are empirically determined values.

$\mathcal{L}_{recon}$ constrains the accuracy of the decomposed illumination and reflectance maps. $\mathcal{L}_{ir}$ enforces consistency between the reflectance maps of the low-light and normal-light image pair. λ_{is} ensures that the decomposition results exhibit smoothness in textured details while preserving structural boundaries.

2.2 Principles and Construction of the Enhance Network

In the dataset used in this study, the brightness ratio between the normal-light and low-light images within each pair exhibits significant variation, approximately ranging from 2 to 50 times. This indicates that different image pairs correspond to distinct brightness amplification factors and luminance relationships. By learning from these paired images, the network can master the brightening effect corresponding to various ratios, thereby establishing a mapping between the amplification factor and the enhancement result to achieve adjustable brightness enhancement. The quantification of image brightness is performed by converting each image pair into grayscale using the classical grayscale conversion formula. The grayscale values, which represent image brightness, are then used to calculate the brightness ratio RA for each image pair in the dataset.

After obtaining the RA value, it is fed into the enhancement network along with the illumination map L_low and reflectance map R_low extracted from the low-light image by the decomposition network. The enhancement network first expands the input into a uniform image of the same size as the original, representing the transformation relationship from the dark to the bright image. The network adopts an encoder-decoder architecture: the input image is progressively downsampled to a small scale through downsampling blocks composed of stride-2 convolutional layers and ReLU activation, which suppress local noise while preserving global illumination features. Subsequently, based on the large-scale illumination features, upsampling is performed using stride-1 convolutional layers and ReLU to reconstruct fine details. Finally, a 3×3 convolution layer generates the enhanced illumination map Î, which is then combined with the original reflectance map to produce the enhanced reconstructed image. The learning objective of the network is to establish a mapping regulated by RA across different brightness regions: darker areas receive stronger enhancement than brighter ones, achieving continuous yet nonlinear brightness improvement. This approach highlights subjects in dark regions while preventing over-exposure, resulting in reconstructed images with realistic illumination and texture. Fig. 1 illustrates the overall architecture of the enhancement process.

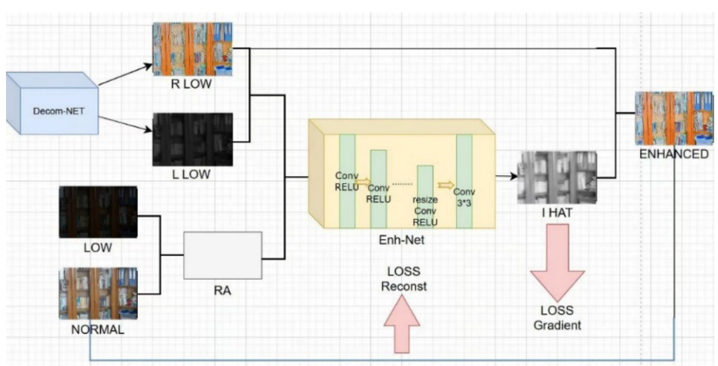

Fig. 1. Flowchart of the Enhancement Process Structure.

To ensure the model establishes the correct mapping relationship, the loss function for the enhancement network (Enh-Net) is designed as follows:

$$\mathcal{L}_{Enh} = 0.5\mathcal{L}_{recon} + 0.5\mathcal{L}_{gradient} \quad (2)$$

$$\mathcal{L}_{recon} = \left| R_{low} \circ \hat{I} - S_{normal} \right| \quad (3)$$

$$\mathcal{L}_{gradient} = \sum_{i=low,normal} ? \left\| \nabla I_i \circ exp\left(-\lambda_g \nabla R_i\right) \right\| (4)$$

where $\mathcal{L}_{recon}$ denotes the enhanced reconstruction loss, which is numerically equivalent to the absolute pixel-wise difference between the enhanced image (obtained by multiplying the enhanced illumination map with the reflectance map) and the original normal-light image. $\mathcal{L}_{gradient}$ represents the gradient loss,

$\mathcal{L}_{recon}$ constrains the discrepancy between the enhanced result (generated from the output illumination map and the reflectance map) and the normal-light image. $\mathcal{L}_{gradient}$ preserves perceptually salient edges in regions with structural boundaries or necessary illumination discontinuities through the weighting term $exp\left(-\lambda_g \nabla R_i\right)$.

3 Constructing the C-DRN Model

3.1 Dataset and Data Preprocessing

The mapping relationship established by the network cap-

ISSN 2959-6157

tures the correspondence between brightness amplification factors and enhancement effects across different image pairs. The enhancement not only adjusts brightness based on the ratio derived from the dataset but also preserves the intrinsic illumination texture of the input image. This relationship is nonlinear: under the same target brightness ratio, darker regions receive stronger enhancement than brighter areas, thereby highlighting overall content while avoiding over-exposure.

The learning of this mapping relies heavily on the dataset. This study uses the publicly available paired low-light enhancement dataset LOL, which consists of 485 low-light/normal-light image pairs. These images were captured in real-world scenarios with a fixed camera and constant parameters, adjusting only exposure time and environmental lighting. The dataset covers diverse scenes including buildings, vehicles, streets, stairs, plants, and household environments, representing both indoor and outdoor low-light enhancement scenarios.

The model's ability to adjust brightness under different conditions depends on the distribution of brightness ratios within the LOL dataset. In the original LOL dataset, the 485 image pairs exhibit significantly varying brightness ratios, with most concentrated in the 5–15× range. This distribution enables the model to perform reliable enhancement within this interval but leads to insufficient mapping capability outside this range, limiting its overall adaptability. As shown in Fig. 2, most practical brightness amplification requirements fall within the 1–30× range. To improve the model's adaptability and performance across the full range of potential brightness ratios, the distribution of brightness ratios in the dataset should be restructured to achieve a more balanced coverage of the effective range.

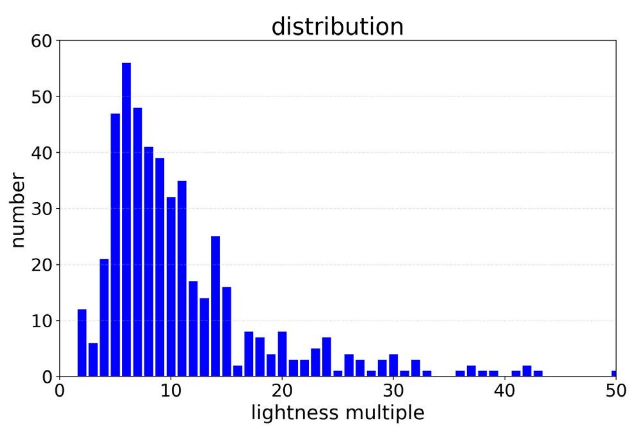

Fig. 2. The distribution of brightness amplification ratios in the LOL dataset.

To meet experimental requirements, the LOL dataset was homogenized to achieve a more uniform distribution of brightness ratios. Specifically, 100 distinct scenes were selected from the original dataset. For each scene, the brightness of the normal-light image was programmatically adjusted. Using a randomized procedure, 30 image pairs were generated per scene, with brightness amplification factors randomly sampled between 1× and 30×. This large-scale augmentation ensures both the uniformity and statistical stability of the data under ample sample size.

As shown in Fig. 3, the brightness ratios of the resulting image pairs are approximately uniformly distributed. This enhancement not only improves the reliability and representativeness of the dataset, but also provides a more solid foundation for model training.

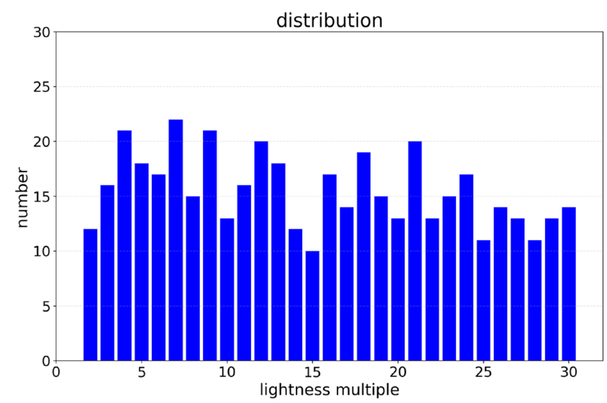

Fig. 3. The distribution of brightness amplification ratios in the homogenized LOL dataset.

3.2 Achieving Continuous Mapping

Loss Function Refinement. Due to the inherent limitations of photographic data, even a homogenized dataset—while improving training outcomes—can only provide discrete brightness amplification ratios, resulting in a discontinuous mapping relationship. However, both during testing and in practical applications, the model is required to establish a continuous mapping to accommodate diverse real-world requirements.

To address this discrepancy, a more effective approach is to introduce constraints through the loss function during training that compensate for the lack of continuity in the dataset. By designing the loss to enforce smooth transitions and coherent behavior between discrete ratio points, the model can learn a continuous and nonlinear brightness mapping from inherently discrete training examples.

The refined loss function is designed as follows:

$$\mathcal{L}_{consis} = \mathcal{L}_{bound} + \mathcal{L}_{mono} \tag{5}$$

where $\mathcal{L}_{consis}$ denotes the continuity loss, $\mathcal{L}_{bound}$ represents the boundary constraint loss, and $\mathcal{L}_{mono}$ refers to the monotonicity loss.

$$\mathcal{L}_{bound}=Max\left(0,f\left(a\right)-f\left(l\right)\right)Max\left(0,f\left(l\right)-f\left(b\right)\right) \quad (6)$$

$$\mathcal{L}_{mono}=Max\left(0,\lim_{n\to l}f\left(l\right)-f\left(l\right)\right) \quad (7)$$

where l represents the introduced training point, and *f(a) and f(b) denote the two* nearest existing mapped values adjacent to *l*.

The $\mathcal{L}_{bound}$ loss constrains the brightness amplification factor of the newly introduced training point to be bounded between the values of its two nearest existing mapped points. Meanwhile, the $\mathcal{L}_{mono}$ loss enforces that the expanded mapping maintains a monotonically increasing property.

Instead of measuring the discrepancy between the enhanced image and the normal-light reference, the constraint strategy now focuses on ensuring boundedness and monotonicity between the newly inserted mapping points and the existing ones. It can be shown that, as sufficiently many new discrete points are added under these constraints, the model can approximate a continuous mapping from originally discrete relationships. Accordingly, $\mathcal{L}_{bound}$ is designed to enforce the continuity of the overall mapping.

Thus, the $\mathcal{L}_{Enh}$ can be revised as follows:

$$\mathcal{L}_{Enh}=0.4\mathcal{L}_{recon}+0.4\mathcal{L}_{gradiet}+0.2\mathcal{L}_{consis} \quad (8)$$

Where the enhanced loss function $\mathcal{L}_{Enh}$ now incorporates the continuity loss $\mathcal{L}_{consis}$ after optimization. The coefficients of these three sub-loss functions are empirically determined based on experimental results.

Maximum Likelihood Estimation. Maximum Likelihood Estimation (MLE) is a widely used parameter estimation method in statistics. Its core idea is to find the parameter values that maximize the probability of observing the given data. The MLE framework provides theoretical support for the design of our model, explaining the relationship between the discrete dataset and the continuous mapping learned by the network. The essence lies in identifying a continuous mapping that maximizes the weighted sum of compatibility with nearby training mappings.

Due to the previous randomization process, each brightness amplification ratio between 1× and 30× in the dataset follows a uniform distribution. The original discrete mapping $f_{k_i}\left(x\right)$ thus obeys a uniform probability distribution. For any amplification ratio ki (where *i*=1, 2, …), the probability of the mapping $f_{k_i}\left(x\right)$ occurring under ratio ki is constant. For an unseen ratio k, the «compatibility probability» between mapping $f_{k_i}\left(x\right)$ and k depends solely on the distance between k and ki: the closer k is to ki, the higher their compatibility. Therefore, the function can be simplified as follows:

$$L\left(k\ddot{}O\left\{k_i,f_{k_i}\right\}\right)=\sum_{i=1}^{m}?\omega_i\left(k\right)\cdot\left(f_{k_i}\ddot{}Ok\right) \quad (9)$$

Where $\omega_i\left(k\right)$ *represents the weigh, satisfying* $\sum_{i=1}^{m}?\omega_i\left(k\right)$ =1. Since the compatibility likelihood increases as the new target ratio k moves closer to a known ratio ki, the weight $\omega_i\left(k\right)$ *grows accordingly. Thus, the following holds:*

$$\omega_i\left(k\right)\propto\frac{1}{\left|k-k_i\right|} \quad (10)$$

When a user-specified brightness amplification ratio lacks a direct mapping in the model, the model calculates the distance between the target ratio and existing discrete mappings to determine compatibility weights. These weights quantify the relevance of each known mapping to the target ratio. A continuous mapping is then generated via weighted interpolation, ensuring statistical consistency with the training data. Importantly, inherent nonlinear characteristics of the enhancement process—such as differential brightening in dark versus bright regions—are preserved in the continuous mapping.

As a result, the discrete mappings established during training generalize effectively to continuous adjustment requirements during inference. As shown in Fig. 4, experimental results validate the rationality of this approach: fine-grained brightness adjustments between 5× and 6× amplification on the same image demonstrate a near-ideal fit between the target ratio and the actual enhancement effect, confirming that the model has successfully learned a continuous mapping within this interval.

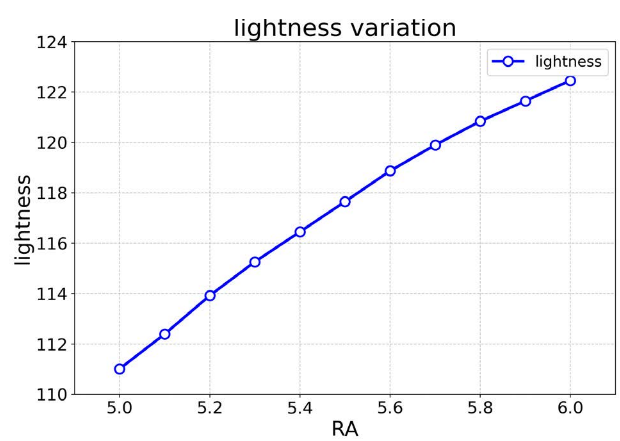

Fig. 4. Continuous nonlinear variation of brightness with amplification ratio.

ISSN 2959-6157

4 Results Analysis

The findings of this study demonstrate the relative performance of the improved DRN in adjusting image brightness according to user-defined requirements. The effectiveness and overall performance of the model were evaluated based on metrics such as accuracy loss and precision, supplemented by visual analysis.

4.1 Visual Analysis

Fig. 5 displays the output results of the model at brightness amplification factors of 3×, 4×, 5×, and 6×. It can be observed that the model has successfully acquired the capability to adjust different brightness ratios, allowing users to freely control the amplification level to achieve diverse visual effects.

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

Fig. 5. Enhanced images under different amplification factors: (a) Low-light image; (b) 3× enhancement; (c) 4× enhancement; (d) 5× enhancement; (e) 6× enhancement.

Compared to direct brightness adjustment, the proposed model's advantage lies in its integration of convolutional neural networks with brightness regulation, which enables the generation of a nonlinear brightening mapping. Under the same amplification factor, darker regions receive stronger enhancement than brighter areas. This approach simultaneously emphasizes overall image content and effectively avoids overexposure—a result that cannot be achieved through simple brightness adjustment alone.

For example, as shown in Fig. 6, when using direct brightness adjustment, preserving details in dark regions leads to noticeable distortion in bright areas such as the upper right corner. In contrast, the result from the proposed model (Fig. 6(b)) demonstrates significantly superior performance in color fidelity and noise control compared to the direct adjustment method (Fig. 6(a)).

(a) (b)

Fig. 6. Comparison of enhancement result: (a) Result via direct brightness adjustment;(b) Result from the proposed model.

4.2 Data Analysis

This study employs accuracy as a metric to quantify the deviation percentage between the model's achieved brightness amplification factor and the user's desired target ratio. A smaller deviation indicates higher accuracy. This metric provides an overall assessment of the model's performance on the dataset. The brightness of an image is calculated using its grayscale value in this work.

$$accuracy = 1 - \frac{RA - \frac{E_{grey}}{L_{grey}}}{RA} \tag{11}$$

Where RA is the user-defined target brightness amplification ratio; E_{grey} is the grayscale value of the enhanced image, representing its output brightness; L_{grey} is the grayscale value of the input low-light image.

To ensure the reliability and rigor of the evaluation, 30 low-light images from 15 different scenes in the dataset were selected for testing. These images correspond to normal-light images in the original dataset with approximately ten times the brightness of their low-light counterparts. Each image was processed by the model with target amplification ratios set to 8×, 10×, and 12×, simulating real-world scenarios where users may desire slightly darker, normal, or slightly brighter results. This produced 90 enhanced image pairs for accuracy calculation.

The influence of training epochs on model accuracy was analyzed alongside the convergence behavior of the loss function. As shown in Fig. 7, accuracy increased rapidly from 35.2% to 86.4% within the first 10 epochs, followed by a slower yet steady rise over the next 20 epochs, eventually reaching 96.3% after 30 epochs. Meanwhile, Fig. 8 demonstrates the loss convergence: it decreased sharply within the first three epochs and then gradually stabilized around 0.05 by the 30th epoch, confirming the effectiveness of the loss constraints.

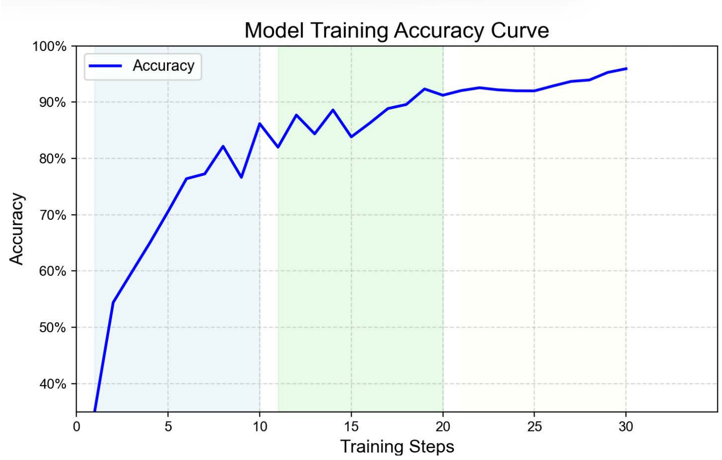

Fig. 7. Variation of accuracy with training epochs.

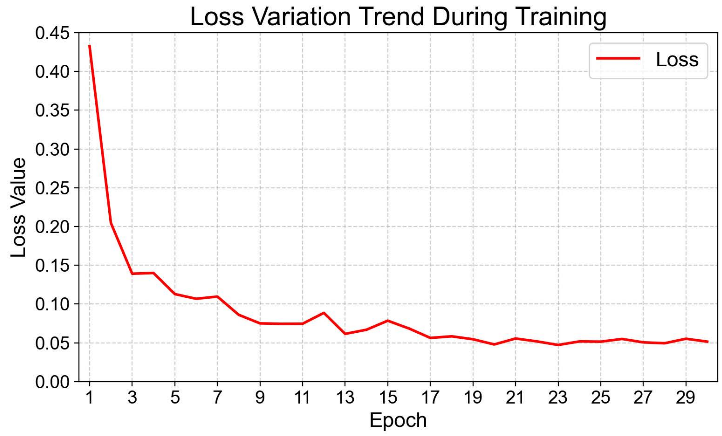

Fig. 8. Variation of Loss with training epochs.

5 Conclusion

This study introduces the C-DRN model, which incorporates brightness adjustment functionality, by redesigning the dataset, modifying the loss function constraints, and refining the network architecture based on the original DRN low-light enhancement framework. By optimizing the loss function and incorporating maximum likelihood estimation, a continuous mapping relationship was established, allowing users to flexibly adjust the brightness enhancement ratio within a reasonable range. To validate the effectiveness of the proposed method, quantitative and visual analyses were conducted using benchmark datasets. The results demonstrate that the model achieved an accuracy of 96.3% within 30 training epochs, while the loss function converged below 0.05. Furthermore, integrating explainable AI techniques and mathematical theoretical foundations could further enhance the model's interpretability and rationality. In conclusion, this study provides a novel approach for achieving personalized brightness adjustment in low-light enhancement models, yielding promising results, improving learning capability, and broadening its application scenarios and practical value.

References

1. Land, E. H., McCann, J. J.: Lightness and retinex theory, Journal of the Optical society of America 61(1),1-11 (1971).
2. Li, C., Guo, C., Han, L., et al.: Lighting the darkness in the deep learning era, Signal, Image and Video Processing 21(4), 29-70 (2021).
3. Kumar, P. R., Prakash, K., Teja., B. R. S., et al.: A novel

ISSN 2959-6157

brain MRI classification framework integrating tuned single scale retinex and empirical wavelet entropy features, Scientific Reports 15(1), 29-76 (2025).
4. Song, X., Huang, J., Cao, J., et al.: Multi-scale joint network based on Retinex theory for low-light enhancement, Signal, Image and Video Processing 15(6), 1257-1264 (2021).
5. Rong, L., Zhang, S. H., Yin, M. F., et al.: Reconstruction efficiency enhancement of amplitude-type holograms by using Single-Scale Retinex algorithm, Optics and Lasers in Engineering 17(6), 97-108 (2024).
6. Sun, Y., Zhao, Z., Jiang, D., et al.: Low-illumination image enhancement algorithm based on improved multi-scale Retinex and ABC algorithm optimization, Frontiers in Bioengineering and Biotechnology 10(5), 820-865 (2022).
7. Lai, X., Chen, H.: Enhanced MSRCR optical frequency segmented filter algorithm for a low-light vehicle environment, Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering 236(9), 2070-2086 (2022).
8. Zhang, L., Peng, T.: Underwater image enhancement based on improved adaptive MSRCR and Gamma function, IEEE Transactions on Image Processing 21(4), 246-252 (2024).
9. Wei, C., Wang, W., Yang, W., et al.: Deep retinex decomposition for low-light enhancement, IEEE Transactions on Image Processing 18(8), 45-60 (2018).
10. Yang, W., Wang, W., Huang, H., et al.: Sparse gradient regularized deep retinex network for robust low-light image enhancement, IEEE Transactions on Image Processing 30(20), 2072-2089 (2021).