International Journal of Research Publication and Reviews, Vol 4, no 12, pp 4871-4875 December 2023

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Low Light Image Enhancement Using Deep Learning Techniques

Laveti Chandini

Computer Science and Engineering Department,
GMR Institute of Technology, Rajam, Andhra Pradesh, India

ABSTRACT –

Real-life photos often have dull colours, low contrast, and noise due to poor lighting and awkward angles. These issues not only affect the visual appeal but also pose challenges for computer vision tasks. Enhancing low-light images using deep learning is a digital image processing method to improve the visual quality of these low-light images. There are many deep learning-based techniques that can be used that can help us achieve performance, but the major problem is the amount of time taken by these methods. In this study, U-Net architecture and pre-processing techniques are used to safeguard the textures and edges. Embed Channel Attention is used to restore colour and rightness. Models like Res FFT, ReLU, and Pixel Shuffler are used to reduce noise and preserve high-frequency components. Finally, the deep learning techniques used in this study provide better value than the other traditional techniques.

Keywords - Low light, Image enhancement, Image processing, Deep learning, Learning parameters

1. Introduction

Low light refers to a situation where there is insufficient light to capture a clear and detailed image. This can occur in environments such as dimly lit rooms, outdoor scenes at night, or in situations where the subject is not well-lit. When pictures are taken in places with little light, it can be hard for computer programs that understand images. The pictures might have dark spots, lots of fuzziness, not much difference between light and dark areas, strange colors, and things might disappear because of bright lights. These problems can make it difficult for computer programs that look at pictures to work well. These programs are used in lots of different areas, like industrial production, watching videos, smart traffic systems, object tracking, finding objects, semantic segmentation, recognizing faces, and many others. Therefore, the enhancement of dim light images is an essential task.

Image enhancement involves employing software to digitally modify a stored image. Various tools like filters and image editors are utilized for altering either the entire image or specific sections, showcasing the diverse array of software for this purpose. The primary objective is to employ algorithms to adjust brightness, contrast, and color information, ensuring optimal display outcomes, especially in low-light conditions. However, improving images captured in low light or at night is problematic because it requires a deep understanding of the underlying physics of light and image formation, advanced image processing, and machine learning techniques.

There are many traditional methods like gray transformation, histogram equalization, Retinex model, image fusion model used for image enhancement. Histogram equalization and Retinex model are mainly focused in the past. Histogram equalization enhances contrast by stretching the pixel value range, making dark and bright areas more distinguishable in an image. However, it may create an unnatural appearance in images intentionally designed with low contrast, exaggerating noise and imperfections. Retinex model provides color constancy, ensuring consistent appearance in varying lighting conditions, benefiting color correction and object recognition. However, it can introduce halos, impacting image quality, especially in images with significant lighting variations.

2. Literature Survey

Matsui discussed about to enhance and brighten the low light images by using Unet architecture, Embedded Channel Attention, Res-FFT-ReLU, and Pixel Shuffler techniques and to achieve high performance than conventional methods. This method effectively process the low illumination images and improve visual effects of low light images [1]. Zhang developed a two stage network that is LUM and NDM for low light image enhancement.This method results best for both synthetic and real world dataset. However, it is not suitable for challenging environments [2]. Liu proposed a new approach to low-light image enhancement using a Dual Unet network with an attention mechanism. This method is advantageous because of its effectiveness and superiority compared to other state-of-the-art methods. However, Real time performance is not effective [3]. J. Hai created a Real-low to Real-normal network for low Light image enhancement by Retinex method. This method results good performance and effectiveness. However, it is not effective for Video enhancement [4]. Gasparyan created a new framework for enhancing visibility in low-light and nighttime environments. An iterative Retinex decomposition is used to improve the quality of the image. The method outperforms various conventional methods and improves accuracy, effectiveness of downstream algorithms.It describe the performance assessment of the proposed framework on face detection in extremely dark images using the DARK

FACE dataset [5]. Zhang developed RFCTNet model to enhance the rain removal effect. This method results best for both synthetic and real world dataset. The paper mentions the use of the Rain100H dataset and the Rain100L dataset for training and evaluation purposes. However the deep learning model used in the network suffers from the problem of catastrophic forgetting [6]. H. Tang developed a method to enhance low light images using several deep learning techniques. These methods works effective in contrast enhancement ,noise reduction, and brightness. The author also summarizes and 4872nalyses existing low-light image datasets, although specific datasets used in the reviewed algorithms are not mentioned [7]. Su developed methods to improve the quality and vfx of low light images. By using IE algorithm and BE algorithm the image enhancement is achieved. This method Improves performance and reduces the processing time. However, this method is only useful for low light images taken in daily life and not for medical or other scenarios [8]. Wang X developed a contrast enhancement method(ESIHE) for image quality and to enhance low light images. The proposed contrast enhancement algorithm improves contrast while preserving original image features [9]. Yu developed a generative adversarial network for unsupervised low light image enhancement. It recovers more detailed information. However, there are still challenges in low-light image enhancement, including uneven illumination, noise, artifacts, overexposure, underexposure, and colour deviation [10]. C. Wei proposed a deep Retinex-Net method for low-light image enhancement, which includes a Decom-Net for decomposition and an Enhance-Net for illumination adjustment . The method achieves visually pleasing quality for low-light enhancement and provides a good representation of image decomposition [11]. Zhang proposed a method that uses the combination of Swin-Transformer module and CNN that completes low-light restoration and noise removal tasks with a single training. The method achievs excellent results in evaluation indicators, denoising effects, and visual perception effects [12]. Huang proposed a method that integrates a SA term into the Retinex-based TV model, such that it results an optimized illumination image. The method out performs other methods and on custom datasets. This results good performance on most of the metrics [13]. Liu proposed a low-light image enhancement method based on multi-scale network fusion to address the problems of poor brightness, low contrast, and noise in images obtained in low-light environments. The method achieves better enhancement effects on different datasets compared to current mainstream methods [14]. Garg proposed a fast and lightweight deep learning-based algorithm, called LiCENt, for low-light image enhancement using the light channel of the Hue Saturation Lightness (HSL) color space. The author highlights the advantages of the proposed method for Brilliance Perception Adjustment, which helps avoid over-enhancement and color distortion issues [15].

3. Methodology

Research in low-light enhancement has transitioned from conventional techniques like histogram equalization and Retinex to approaches centered around deep learning. These deep learning methods can be further categorized into supervised and unsupervised learning based on how they are trained. There are many supervised learning methods such as LLNet, UNet. And unsupervised learning methods such as CycleGAN, UDNet, RetinexNet etc., that are aimed at image enhancement. However, Unsupervised learning in image enhancement faces challenges due to the absence of ground truth labels, complicating performance assessment. These methods may struggle to produce tailored enhancements and could require more data or preprocessing for optimal results compared to supervised learning approaches. In this study, a supervised learning technique is used to address the above problem. A speedy and straightforward UNet framework is employed to harmonize color, illumination, and noise reduction effectively. It combines convolutional and deconvolutional layers to extract features and reconstruct the enhanced image. It enhances visibility while preserving crucial edges and textures, vital for object structure information.

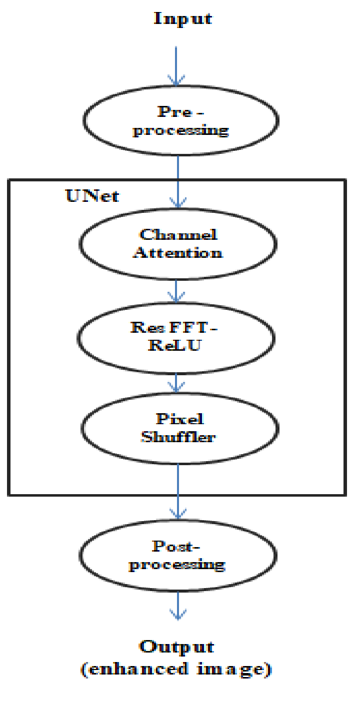

Fig. Network Structure

Preprocessing

There are many preprocessing techniques like edge enhancement[1], histogram equalization[3], Local Binary Pattern operator[2], Decom-Net[4], HSL[15] etc. Enhancing edges and textures is important during preprocessing. An image processing technique called edge enhancement is used to emphasize and highlight the edges or boundaries of objects and structures within an image. This method incorporates a classical spatial filtering approach. First, the RGB image is converted to grayscale. This simplifies the image to only intensity information, allowing the subsequent filters to focus on contrast and edge detection. The Laplacian filter is then applied to the pre-processed grayscale image. The eight-nearest-neighbor Laplacian filter is particularly effective for edge detection, as it highlights edges and textures in not just horizontal and vertical directions but also diagonally.

Network Architecture

Many conventional methods adopt a decomposition approach, where they separately enhance intermediate products and the final image. Recent CNN-based methods have often led to complex structures. In contrast, this network follows a simpler end-to-end (UNet) structure. It directly takes a low-light image (Slow) as input and produces the final enhanced image (Senhanced) as output, simplifying the process into a single step. This is expressed by the equation

$$S_{enhanced} = G_{(Slow)} ,$$

where G represents the function of the proposed network, emphasizing the network's streamlined approach to low-light image enhancement.Instead of complex subnetworks, the method prioritizes effective preprocessing, learning modules, and a well-designed loss function to achieve high-quality image enhancement.

Learning modules

Channel Attention Block

Attention mechanisms are used to enhance image restoration, particularly in the context of low-light image enhancement (LLIE). There are two types of attention modules are mentioned: Channel Attention and Spatial Attention.

Channel Attention is an attention mechanism that focuses on adjusting the importance of different channels in a feature map. Spatial Attention, on the other hand, adjusts the importance of positions or regions within an image.

The preprocessed images are fed into the UNet architecture with Channel Attention. This modification allows the model to selectively focus on important features in the images during the extraction process, improving the quality of feature representation.

Res FFT-ReLU

Res FFT-ReLU involves applying the Fast Fourier Transform to the image to analyze its frequency components.FFT converts spatial domain to frequency domain. After performing the Fast Fourier Transform (FFT) on the input data, the block applies ReLU(Rectified linear unit) to the frequency domain features. This introduces non-linearity in the frequency domain, allowing the network to capture complex frequency patterns and relationships in the image. The non-linearity is essential for the network to enhance high-frequency components and suppress noise effectively. The output from UNet, enriched with channel attention, undergoes Residual FFT ReLU processing.

Pixel Shuffler

Pixel Shuffler is then applied to upscale the resolution of the images. It reorganizes the data in the input feature map and redistributes it into the desired output map format. It accomplishes this by taking into account the channel information, magnification ratio, and spatial coordinates and generates high resolution images from lower resolution feature maps.

Loss Function

The loss function is a way to measure how well a neural network is doing. Here, two loss functions are used for training the network : LL1 loss and MS-SSIM loss.

$$L_{total} = \mu 1 L_{L1} + \mu 2 L_{MS\text{-}SSIM},$$

where µ1 is a coefficient or weight that you can adjust. It determines the relative importance of the LL1 term in the overall loss function and µ2 is a coefficient that determines the weight given to the LMS-SSIM term in the loss function. You can adjust this weight to emphasize or de-emphasize this term.

LL1 loss is an L1-Norm error between the input low-light image and the enhanced image. It measures the pixel-wise difference between the two images. This part of the loss function helps to preserve the general structure, colors, and brightness in the enhanced image.

MS-SSIM (Multi-Scale Structural Similarity) loss is a method for measuring the similarity of two images in terms of luminance, contrast, and structure. It is an advanced form of SSIM that preserves contrast in the high-frequency domain better than other loss functions. The weights and biases of the network are trained by minimizing the total loss function, which is a combination of LL1 loss and MS-SSIM loss.

4. Results and Discussions

Low light images can be enhanced by using various models like UNet architecture , GAN architecture , Retinex model, Multi-scale network fusion or based on Swin-transformer etc.Each model uses different preprocessing methods like histogram equilization, edge enhancement, HSL etc. The results are obtained by performing these methods on LOL dataset. The results are differentiated based on PSNR, SSIM, NIQE, LPIPS values. PSNR(Peak Signal-to-Noise Ratio) quantifies how well the compressed or reconstructed version of an image or video approximates the original, with a higher PSNR indicating better quality. SSIM(Structural Similarity Index) measures how well the local patterns of pixel intensities are preserved between the original and the compressed or processed images , a higher SSIM value suggests better image quality.

TABLE: Quantitative comparison of different image enhancement processing models on the LOL dataset.

Model	**PSNR**	**SSIM**
UNet	24.31	0.854
R2R Net	20.20	0.816
Retinex	16.86	0.484
Swim Transformer	19.234	0.817
HSL	18.44	0.71

Unet architecure produces high yeild because it is straight forwarded. It allows end-to-end training which means the entire network can be trained in a single step. Skip connections are used to preserve spatial information.Unet achieves good results without needing many parameters so it saves resources. The discussion encourages further exploration of modules capturing spatial and semantic features, as well as the exploration of alternative network architectures beyond Convolutional Neural Networks (CNNs) to achieve even greater improvements in LLIE performance.

5. Conclusion

In conclusion, this study proposes a streamlined approach to Low-Light Image Enhancement that attains comparable performance to conventional networks while addressing prevalent issues such as illumination loss, color distortion, and detail degradation, as well as noise and haze generation during enhancement. The pre-processing steps, including an edge enhancement filter, coupled with modules like Res FFT-ReLU, Channel Attention, and Pixel Shuffler, contribute to the network's simplicity and efficiency. While achieving comparable or superior Image Quality Assessment values to conventional methods, the proposed network significantly reduces processing time. Acknowledging limitations in handling scenarios like backlit images with varying brightness, future directions involve incorporating modules capturing spatial and semantic features.

6. Reference

1. Matsui, Takuro, and Masaaki Ikehara. "Low-light image enhancement using a simple network structure." IEEE Access (2023).
2. Zhang, Feng, et al. "Unsupervised low-light image enhancement via histogram equalization prior." arXiv preprint arXiv:2112.01766 (2021).
3. Liu, Fangjin, et al. "Dual UNet low-light image enhancement network based on attention mechanism." Multimedia Tools and Applications 82.16 (2023): 24707-24742.
4. J. Hai, Z. Xuan, R. Yang, Y. Hao, F. Zou, F. Lin, and S. Han, ‘‘R2RNet: Low-light image enhancement via real-low to real-normal network,’’ J. Vis. Commun. Image Represent., vol. 90, Feb. 2023, Art. no. 103712
5. Gasparyan, H., Hovhannisyan, S., Babayan, S., & Agaian, S. (2023). Iterative Retinex-Based Decomposition Framework for Low Light Visibility Restoration. IEEE Access.
6. Zhang, Zhijia, et al. "Continuous learning deraining network based on residual FFT convolution and contextual transformer module." IET Image Processing 17.3 (2023): 747-760.
7. H. Tang, H. Zhu, L. Fei, T. Wang, Y. Cao, and C. Xie, ‘‘Low-illumination image enhancement based on deep learning techniques: A brief review,’’ Photonics, vol. 10, no. 2, p. 198, Feb. 2023.
8. Su, Y., Wu, M., & Yan, Y. (2023). Image Enhancement and Brightness Equalization Algorithms in Low Illumination Environment based on Multiple Frame Sequences. IEEE Access.
9. Wang X, Chen L (2018) Contrast enhancement using feature-preserving bi-histogram equalization. Signal Image Video Process 12(4):685–692
10. Yu, W., Zhao, L., & Zhong, T. (2023). Unsupervised Low-Light Image Enhancement Based on Generative Adversarial Network. Entropy, 25(6), 932.
11. C. Wei, W. Wang, W. Yang, and J. Liu, ‘‘Deep Retinex decomposition for low-light enhancement,’’ 2018, arXiv:1808.04560.

12. Zhang, Q., Zou, C., Shao, M., & Liang, H. (2023). A Single-Stage Unsupervised Denoising Low-Illumination Enhancement Network Based on Swin-Transformer. IEEE Access.

13. Zhang, D., Huang, Y., Xie, X., & Guo, X. (2023). A variational Retinex model with structure-awareness regularization for single-image low-light enhancement. IEEE Access.

14. Liu, X., Zhang, C., Wang, Y., Ding, K., Han, T., Liu, H., ... & Ju, M. (2022). Low Light Image Enhancement Based on Multi-Scale Network Fusion. IEEE Access, 10, 127853-127862.

15. Garg, A., Pan, X. W., & Dung, L. R. (2022). LiCENt: Low-light image enhancement using the light channel of HSL. IEEE Access, 10, 33547-33560.