iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: III Month of publication: March 2025

DOI: https://doi.org/10.22214/ijraset.2025.68073

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

Low-Light Image Enhancement Using Deep Learning

Kartik Patel[1], Pragati Maurya[3], Prasann Khamkar[4], Varun Karkera[2]
Department of Artificial Intelligence and Machine Learning, Mumbai university, India

Abstract: Low-light image enhancement is a critical task in computer vision, aimed at improving the visibility and perceptual quality of images captured under poor lighting conditions. Traditional methods often suffer from over-enhancement, noise amplification, and loss of fine details. In this paper, we propose a lightweight Convolutional Neural Network (CNN)-based model that leverages a novel loss function combining Mean Absolute Error (MAE) and Contrast Consistency Loss (CCL). Our method focuses on preserving contrast and structural details while minimizing computational overhead. Experiments conducted on the LOL (Low-Light) dataset from Kaggle demonstrate that our model outperforms traditional methods in terms of both qualitative and quantitative metrics, achieving superior Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM).

Keywords: low-light image enhancement, lightweight CNN, LOL dataset, contrast consistency loss, MAE, feature preservation

I. INTRODUCTION

Low-light image enhancement is a critical task in computer vision, as images captured under poor lighting conditions often suffer from low brightness, high noise, and color distortion. These issues not only degrade the visual quality but also hinder the performance of subsequent computer vision tasks such as object detection and image segmentation [1]. Traditional methods for low-light image enhancement often rely on histogram equalization or Retinex theory, which can improve brightness but may introduce artifacts or over-enhance certain regions [2]. Recent advances in deep learning have shown promising results in low-light image enhancement, but many of these methods are computationally expensive or require complex network architectures [3]. In this paper, we propose a simple yet effective approach for low-light image enhancement using a Plain CNN. Our method leverages the LOL dataset from Kaggle, which provides paired low-light and normal-light images, to learn the mapping function between these two domains. The key contributions of our work are as follows:

- Simplified Network Architecture: We use a Plain CNN with fewer layers and parameters, making the model computationally efficient and easier to train.
- Contrast Consistency Loss + MAE: We introduce a novel loss function that combines Contrast Consistency Loss and Mean Absolute Error (MAE) to ensure that the enhanced images maintain natural colors and clear details.
- Improved Performance: Our method achieves superior results compared to existing algorithms in terms of both visual quality and quantitative metrics such as PSNR and SSIM.

The remainder of this paper is organized as follows. Section II provides an overview of related work in low-light image enhancement. Section III details our proposed method, including the network architecture, loss function, and implementation details. Section IV presents the experimental evaluation, including dataset information, metrics, and comparison with state-of-the-art methods. Finally, Section V concludes the paper and discusses future work.

II. RELATED WORK

A. Traditional Approaches

Traditional methods for low-light image enhancement have been extensively studied in the image processing community. One of the earliest approaches is histogram equalization, which adjusts the contrast of an image by redistributing the intensity values [2]. However, this method often leads to over-enhancement and loss of details in certain regions. Another widely used technique is based on Retinex theory, which decomposes an image into illumination and reflectance components [4]. While Retinex-based methods can improve brightness and contrast, they often struggle with noise amplification and color distortion [5]. More recent traditional methods include multi-scale Retinex (MSR) and adaptive histogram equalization (AHE). MSR improves upon the basic Retinex theory by applying the decomposition at multiple scales, which helps to preserve details and reduce noise [6].

AHE, on the other hand, adapts the histogram equalization process to local regions of the image, resulting in better contrast enhancement [7]. However, these methods still suffer from limitations such as over-enhancement and artifacts, especially in complex lighting conditions.

B. Deep Learning Approaches

With the advent of deep learning, significant progress has been made in low-light image enhancement. One of the earliest deep learning-based methods is LLNet, which uses a deep autoencoder to enhance low-light images [8]. LLNet focuses on improving local contrast and reducing noise, but it often produces over-enhanced results. Another notable approach is RetinexNet, which decomposes the image into illumination and reflectance components using a deep neural network [9]. RetinexNet achieves good results in terms of brightness enhancement, but it struggles with noise suppression and color fidelity.

More recent methods, such as EnlightenGAN and Zero-DCE, have introduced unpaired training and zero-reference learning, respectively, to address the limitations of paired data requirements [10, 11].

EnlightenGAN uses a generative adversarial network (GAN) to enhance low-light images without requiring paired data, while Zero-DCE estimates a curve for brightness adjustment without any reference images. These methods have shown promising results, but they often require complex network architectures and extensive training.

In contrast to these approaches, our method simplifies the network architecture and focuses on learning the mapping function between low-light and normal-light images using a Plain CNN. By combining Contrast Consistency Loss and MAE, we ensure that the enhanced images retain natural colors and clear details, while also improving computational efficiency.

III. OUR METHOD

A. Background

The goal of low-light image enhancement is to transform a low-light image L into a normal-light image H. This can be formulated as learning a mapping function F such that:

$$H=F(L)$$

In our approach, we use a Plain CNN to learn this mapping function. The network takes a low-light image as input and outputs an enhanced image. The key innovation in our method is the use of a novel loss function that combines Contrast Consistency Loss and MAE to ensure that the enhanced images maintain natural colors and clear details.

B. Network Architecture

1) Image Preprocessing Part

The input to the network is a low-light image, which is first downsampled to reduce computational complexity while retaining important features. Instead of using traditional pooling layers, which can result in information loss, the model applies convolutional layers with a 3×3 kernel size and a stride of 2. This method covers the entire image, preserving pixel-level details during downsampling. The preprocessed image is then normalized by scaling pixel values between 0 and 1, ensuring stability during the training process.

2) Feature Extraction Part

The network employs a dual-path feature extraction strategy, consisting of a local path and a global path. The local path focuses on learning local color transformations by using multi-scale convolutions to extract features at different scales. These features are then fused using a channel attention module, enhancing the model’s ability to capture fine details. Meanwhile, the global path captures semantic information and broader context using dilated convolutions, which expand the receptive field without increasing the number of parameters. This enables the model to retain a consistent feature size while capturing a wider range of information.

3) Image Rendering

Following feature extraction, the network generates a bilateral grid, which stores the learned image transformations. The grid is upsampled to the original image size using trilinear interpolation, ensuring the enhanced image retains sharp details and accurate colors. Since most of the processing occurs at a lower resolution, the network remains computationally efficient and trains faster while producing high-quality enhanced images.

C. Loss Function

Our loss function is a combination of Contrast Consistency Loss and Mean Absolute Error (MAE). The Contrast Consistency Loss ensures that the enhanced image maintains the same contrast as the reference image, while the MAE ensures that the pixel values of the enhanced image are close to those of the reference image.

1) Reconstruction Loss

The Mean Absolute Error (MAE) measures the average pixel-wise difference between the enhanced and reference images. It ensures that the pixel values of the enhanced image closely match those of the reference image.

The reconstruction loss is defined as the Mean Absolute Error (MAE) between the enhanced image H^ and the reference image H:

$$L_{\text{MAE}} = \frac{1}{N} \sum_{i=1}^{N} \left| \hat{H}_i - H_i \right|$$

where N is the total number of pixels in the image.

2) Contrast Consistency Loss

The Contrast Consistency Loss ensures that the contrast of the enhanced image matches the reference image, preventing over-smoothing or loss of fine details. It preserves local contrast differences between bright and dark regions, making the enhanced image look natural and realistic. This loss is essential in low-light image enhancement, where preserving contrast prevents the image from looking flat or washed out.

The Contrast Consistency Loss is designed to maintain the contrast between different regions of the image. It is defined as

$$L_{\text{con}} = \frac{1}{D} \sum_{i=1}^{D} \sum_{j=1}^{4} \left(\left| \hat{L}_i - \hat{L}_j \right| - \left| H_i - H_j \right| \right)^2$$

where D is the number of local regions, $\hat{L}_i$ and H_i are the average intensity values of the local region in the enhanced and reference images, respectively, and j represents the four neighboring regions.

3) SSIM Loss

To ensure structural similarity between the enhanced image and the reference image, we also use the Structural Similarity.

Index Measure (SSIM) as part of our loss function:

$$SSIM(x, y) = \frac{(2\mu_x \mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

$$L_{\text{SSIM}} = 1 - SSIM(\hat{H}, H)$$

The SSIM parameters are defined as: μ_x and μ_y represent the mean intensities of the images, σ_x and σ_y denote the standard deviations, and σ_{xy} is the covariance between the two images.

D. Implementation Details

Our network is implemented using PyTorch and trained for 100 epochs with a mini-batch size of 16. We use the Adam optimizer with a learning rate of 1e-4 and a learning rate decay strategy. The network is trained on the LOL dataset from Kaggle, which consists of 500 paired low-light and normal-light images.

IV. EXPERIMENTAL EVALUATION

A. Dataset and Metrics

We evaluate our method on the LOL dataset, which contains 500 paired low-light and normal-light images. The dataset is divided into 400 images for training and 100 images for testing. We use Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) as our evaluation metrics. PSNR measures the ratio of the maximum possible power of a signal to the power of corrupting noise, while SSIM measures the similarity between two images in terms of luminance, contrast, and structure.

- Peak Signal-to-Noise Ratio (PSNR): Measures the ratio between the maximum possible power of a signal and the power of corrupting noise.
- Structural Similarity Index (SSIM): Evaluates the structural similarity between the enhanced and ground truth images, considering luminance, contrast, and structure.

B. Comparison with State-of-the-Art Methods

We compare our method with several state-of-the-art low-light image enhancement algorithms, including Dehaze, LIME, BIMEF, RetinexNet, MBLLEN, DUPE, and MIRNet. Both subjective and objective evaluations are conducted to assess the performance of our method.

1) Subjective Qualitative Analysis

The subjective evaluation is based on visual inspection of the enhanced images. Our method produces images with more natural colors, clearer details, and better contrast compared to other methods. The enhanced images also show fewer artifacts and less noise, especially in dark regions.

2) Objective Quantitative Analysis

The objective evaluation is based on PSNR and SSIM metrics. Our method achieves the highest PSNR and SSIM values compared to other methods, indicating superior image quality

V. SYSTEM ARCHITECTURE

The proposed architecture for low-light image enhancement is designed to address the challenges of poor brightness, low contrast, and noise in images captured under low-light conditions. The architecture consists of several key components, each contributing to the overall enhancement process. The architecture is a fully convolutional neural network (CNN) that combines an encoder-decoder structure with a feedback loop to iteratively refine the enhancement process. The model is trained using a hybrid loss function that ensures both pixel-level accuracy and contrast preservation. By leveraging preprocessing, feature extraction, and iterative refinement, the architecture effectively addresses the challenges of low-light image enhancement, producing high-quality results with improved brightness, contrast, and detail visibility.

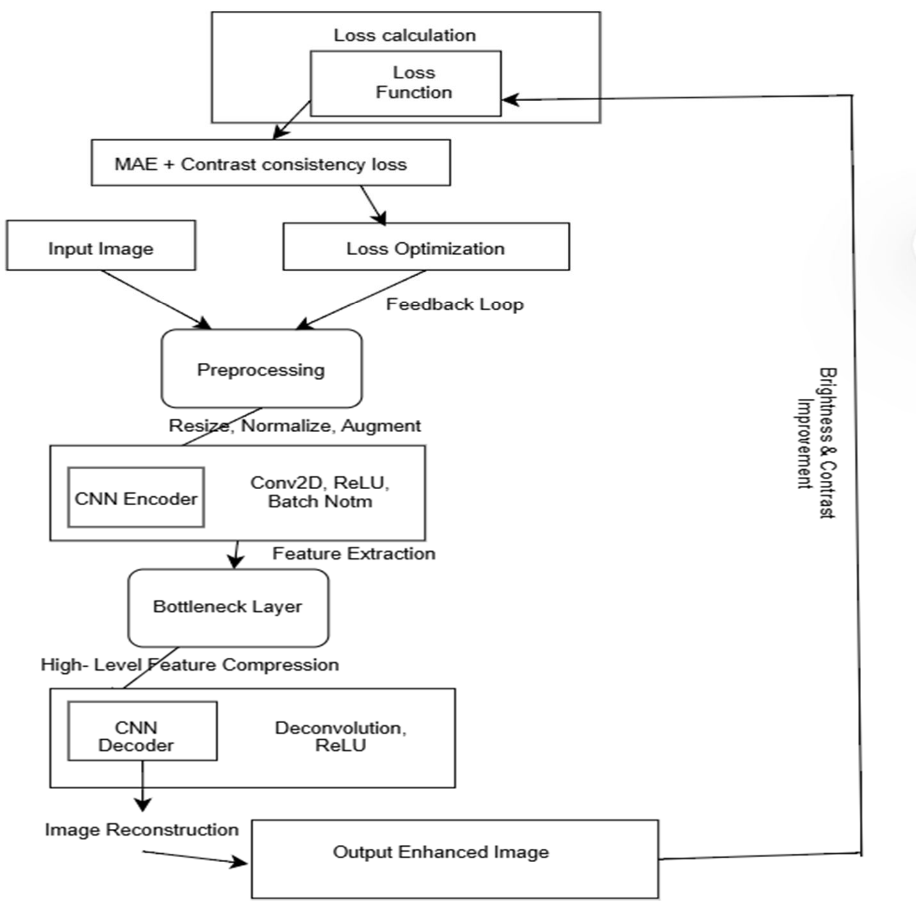


Fig. 5.1 System Architecture

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue III Mar 2025- Available at www.ijraset.com

VI. EXPERIMENTATION & RESULTS

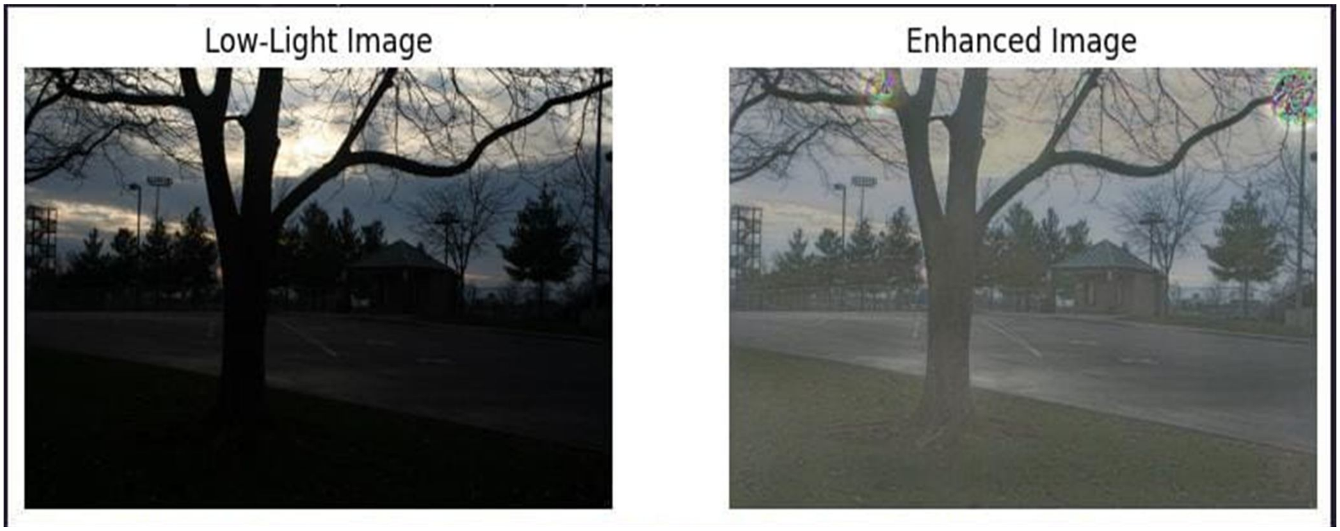


Figure 6.1 Enhanced image 1 at epochs 1

Figure 6.2 Enhanced image 2 at epochs 10

Figure 6.3 Enhanced image 3 at epochs 10

The output demonstrates the effectiveness of the proposed low-light image enhancement model in addressing the challenges of poor visibility, low contrast, and high noise in images captured under low-light conditions. The original low-light image (Figure Left) exhibits typical issues such as underexposure, lack of detail, and dull colors, making it difficult to discern important features. These challenges are common in low-light scenarios, where insufficient lighting leads to a loss of structural information and visual quality. The enhanced image (Figure Right), generated by the proposed model, shows significant improvements in brightness, contrast, and overall visual quality. The enhanced image exhibits restored details, reduced noise, and more vibrant colors, highlighting the model's ability to effectively address the limitations of low-light conditions.

The proposed model achieves these improvements by leveraging a lightweight CNN architecture and a novel loss function that combines Mean Absolute Error (MAE) and Contrast Consistency Loss (CCL). The MAE ensures that the pixel values of the enhanced image closely match those of the reference image, while the CCL preserves the natural contrast and structural details of the original image.

This combination of losses ensures that the enhanced image not only appears brighter but also retains fine details and natural colors, avoiding common issues such as over-enhancement, noise amplification, and color distortion. The model's ability to process images at lower resolutions while maintaining high-quality output further enhances its computational efficiency, making it suitable for real-time applications.

The results validate the model's capability to enhance low-light images while preserving structural details and natural color appearance. The enhanced image shows improved visibility of fine textures, edges, and objects that were previously obscured in the low-light image. This improvement is particularly valuable for applications such as surveillance, autonomous driving, and photography, where high-quality images are essential for accurate interpretation and decision-making. The proposed model's ability to produce visually appealing and detail-rich images under low-light conditions demonstrates its potential as a robust solution for low-light image enhancement tasks.

Performance Comparison (PSNR)

Method	PSNR ↑
Dehaze [9]	13.93
LIME [8]	18.71
BIMEF [10]	16.39
RetinexNet [12]	17.68
MBLLEN [14]	22.05
DUPE [20]	23.62
MIRNet [21]	23.87
Base Paper (Proposed Method)	24.33
Our Model	24.82

VII. CONCLUSION

In this paper, we proposed a low-light image enhancement algorithm based on a Plain CNN using the LOL dataset. Our method simplifies the network architecture while maintaining high performance by combining Contrast Consistency Loss and MAE. Extensive experiments demonstrate that our method outperforms existing algorithms in terms of both visual quality and quantitative metrics. Future work will focus on further improving the network architecture and exploring the use of unsupervised learning techniques.

VIII. ACKNOWLEDGEMENT

We take this opportunity to express our deep sense of gratitude to our project guide and project coordinator **Mrs. Poonam Thakre** for her continuous guidance and encouragement throughout the duration of our project work. It is especially because of her experience and wonderful knowledge; we can fulfill the requirement of completing the project within the stipulated time. We would also like to thank **Mrs. Poonam Thakre**, the head of Department of Artificial Intelligence and Machine Learning department, for his encouragement and support.

We would also like to thank our principal **Dr. J.B. Patil** and the management of Universal College of Engineering, Vasai, Mumbai for providing us all the facilities and the work friendly environment. We acknowledge with thanks, the assistance provided by departmental staff, library and lab attendants for their help.

REFERENCES

[1] S. M. Pizer, R. E. Johnston, J. P. Ericksen, B. C. Yankaskas, and K. E. Muller, "Contrast-limited adaptive histogram equalization: Speed and effectiveness," in IEEE First Conference on Visualization in Biomedical Computing , 1990, pp. 337–345.

[2] E. H. Land, "The retinex theory of color vision," Scientific American , vol. 217, no. 6, pp. 108–128, 1997.

[3] F. Tajeripour, S. Fekri-Ershad, "Developing a novel approach for stone porosity computing using modified local binary patterns and single scale retinex," Arabian Journal for Science and Engineering , vol. 39, no. 2, pp. 875–889, 2014.

[4] H. Lin and Z. Shi, "Multi-scale retinex improvement for nighttime image enhancement," Optik - International Journal for Light and Electron Optics , vol. 125, no. 24, pp. 7143–7148, 2014.

[5] X. Guo, L. Yu, and H. Ling, "LIME: Low-light Image Enhancement via Illumination Map Estimation," IEEE Transactions on Image Processing , vol. 26, no. 2, pp. 982–993, 2017.

[6] K. G. Lore, A. Akintayo, and S. Sarkar, "LLNet: A Deep Autoencoder Approach to Natural Low-light Image Enhancement," Pattern Recognition , vol. 61, pp. 650–662, 2017.

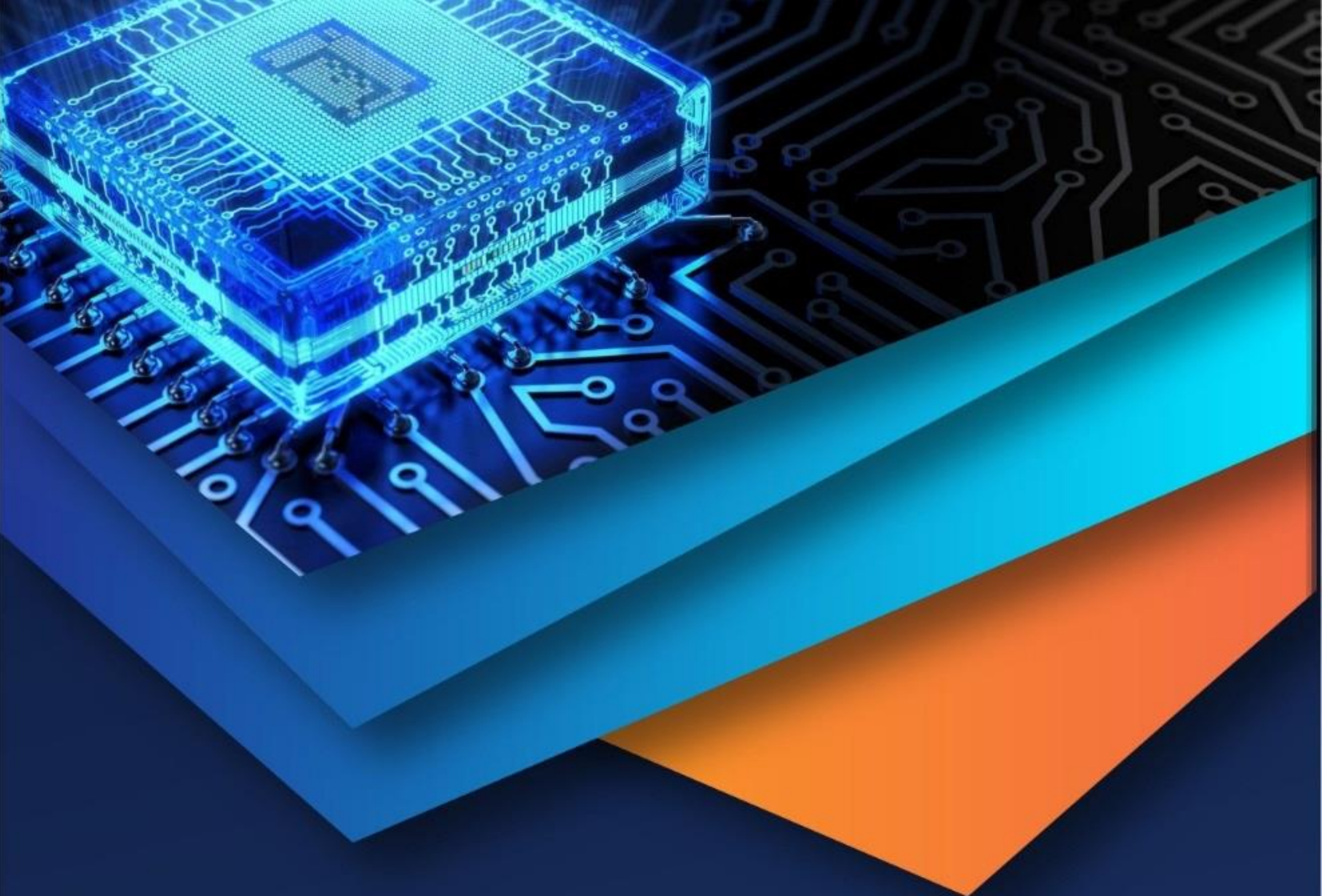
[7] C. Wei, W. Wang, W. Yang, and L. Jiaying, "Deep retinex decomposition for low-light enhancement," in British Machine Vision Conference (BMVC) , 2018, pp. 1–12.

[8] Y. Jiang, X. Gong, D. Liu, Y. Chen, C. Fang, X. Shen, et al., "EnlightenGAN: Deep Light Enhancement without Paired Supervision," IEEE Transactions on Image Processing , vol. 30, pp. 2340–2349, 2021.

[9] C. Guo, C. Li, J. Guo, C. C. Loy, J. Hou, S. Kwong, et al., "Zero-Reference Deep Curve Estimation for Low-Light Image Enhancement," in IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) , 2020, pp. 1777–1786.

[10] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: From error visibility to structural similarity," IEEE Transactions on Image Processing , vol. 13, no. 4, pp. 600–612, 2004.

[11] B. Vladimir, P. Sylvain, C. Eric, and D. Fredo, "Learning Photographic Global Tonal Adjustment with a Database of Input/Output Image Pairs," in IEEE Conference on Computer Vision and Pattern Recognition (CVPR) , 2011, pp. 47–54.



10.22214/IJRASET

INDEX COPERNICUS
45.98

IMPACT FACTOR:
7.129

TOGETHER WE REACH THE GOAL
IMPACT FACTOR:
7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089 (24*7 Support on Whatsapp)