ISSN: 2582-7219

International Journal of Multidisciplinary Research in Science, Engineering and Technology

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Impact Factor: 8.206

Volume 8, Issue 4, April 2025

Smart Low Light Image Enhancement using U-Net

Sk.Shabbirbasha

Associate Professor, Department of AIML, Visvodaya Engineering College, Kavali, Nellore, AP., India

V.Satyasai Kiran, S.Naga Ganesh, U.V.Hemanthsaiteja, Sd.Masthanbasha

Department of AIML, Visvodaya Engineering College, Kavali, Nellore, AP., India

ABSTRACT: Capturing high-quality images in low-light environments remains a challenging problem in various fields such as photography, surveillance, medical imaging, and autonomous driving. Traditional image enhancement techniques often fail to restore natural image details while correcting issues like noise, low contrast, and color distortion. This project presents a hybrid approach for enhancing low-light images by combining deep learning and classical image processing methods. The core of the system utilizes a UNet-based deep learning model, trained specifically for low-light image enhancement, to restore brightness, contrast, and detail while preserving natural textures. To further improve image quality, traditional methods such as Contrast Limited Adaptive Histogram Equalization (CLAHE), gamma correction, white balancing, and sharpness adjustment are integrated into the system. The solution is deployed as an interactive, real-time web application using Streamlit, allowing users to upload images or capture them via a webcam, adjust enhancement settings dynamically, and compare results side-by-side. The system supports a variety of image formats, including RAW and DNG, making it accessible to both casual users and professional photographers. By offering a combination of advanced machine learning and traditional image enhancement tools, this project provides an effective and user-friendly solution for improving image quality in low-light conditions, with applications across multiple domains.

I. INTRODUCTION

In the modern digital age, images have become an essential component of communication, decision-making, and analysis. With the proliferation of digital cameras and surveillance systems, the ability to capture high-quality images in various environments is crucial. However, one of the most persistent challenges in the field of digital imaging is capturing high-quality images under low-light conditions. Low-light images typically suffer from various visual issues such as high noise, poor contrast, color distortion, and the loss of important details. These factors not only degrade the visual appeal of the images but also complicate their interpretation, hindering the performance of downstream applications such as object detection, facial recognition, and automated analysis. This issue is especially critical in fields like night photography, surveillance, medical imaging, and autonomous driving, where the clarity and detail of images can have significant real-world implications.

The motivation behind this project is to address these challenges by developing an intelligent low-light image enhancement system that combines deep learning and traditional image processing techniques. While conventional enhancement methods such as histogram equalization, gamma correction, and brightness adjustment can provide some improvement in visibility, they often fail to preserve natural image details or introduce undesirable artifacts such as overexposure and unnatural contrast. These methods are computationally efficient, but their limitations become evident when attempting to restore fine details in extremely dark images. Furthermore, these techniques do not account for the complex structures and patterns found in real-world low-light images. Deep learning, particularly convolutional neural networks (CNNs), offers a promising solution by learning complex representations of low-light images and mapping them to their well-lit counterparts. By leveraging the power of deep learning models like UNet, which excels in image-to-image tasks, this project aims to enhance low-light images while maintaining natural details and minimizing the introduction of artifacts.

This project proposes a hybrid approach that combines deep learning with traditional image enhancement methods to create a more comprehensive solution for low-light image enhancement. The system utilizes a UNet-based deep learning model, specifically trained to improve low-light images by addressing common issues such as noise, low contrast, and color distortion. UNet is particularly suited for this task due to its encoder-decoder architecture, which allows it to capture both high-level context and low-level details essential for accurate image restoration. By training the model on paired low-light and well-lit images, the system learns to map degraded images to their enhanced counterparts, making it capable of restoring critical scene details even in very dark regions. In addition to the deep learning model, the system integrates traditional image processing techniques, such as Contrast Limited Adaptive Histogram Equalization (CLAHE), gamma correction, white balancing, and contrast adjustment. These techniques provide users with the ability to fine-tune the enhancement process, ensuring flexibility and customization for different lighting conditions and image preferences.

In order to make this solution accessible and practical for a wide range of users, the system is deployed as a real-time web application using Streamlit. The web interface allows users to easily upload images or capture them directly from a webcam. Once the image is uploaded, users can apply enhancement settings dynamically, adjusting parameters such as brightness, contrast, gamma, sharpness, and saturation. A side-by-side comparison of the original and enhanced images enables users to evaluate the effectiveness of the enhancement process in real time. Furthermore, the application supports a wide range of image formats, including common ones like JPG, JPEG, and PNG, as well as RAW and DNG formats. RAW and DNG formats are particularly important for professional photographers and researchers, as these formats preserve much more image data than standard JPEGs, providing more flexibility in post-processing. The system's ability to handle a variety of image formats ensures that it caters to both casual users and professionals alike.

The ultimate goal of this project is to develop a versatile and intelligent system capable of enhancing low-light images without sacrificing natural appearance or introducing artifacts. Unlike traditional enhancement techniques, which often rely on simple linear adjustments, the deep learning model employed in this project learns complex mappings between degraded and enhanced images. This allows it to preserve important textures and details while improving the overall visibility and quality of the image. Additionally, by offering real-time interactivity and fine-grained control over enhancement parameters, the system empowers users to customize the enhancement process to suit their specific needs and preferences. This flexibility makes the system an effective tool for a variety of applications, from improving the visual quality of night-time surveillance footage to enhancing medical images for better diagnosis.

The potential applications of this system extend beyond photography and surveillance. In medical imaging, for example, enhanced low-light images can help radiologists and medical professionals identify subtle abnormalities that would otherwise be obscured by noise or low contrast. In autonomous driving, clearer images captured under low-light conditions can improve the performance of computer vision systems, enabling vehicles to better detect obstacles or road signs at night or in poorly lit environments. Similarly, in the field of surveillance, improved low-light image quality can enhance security monitoring systems, allowing for more accurate recognition of individuals or objects in low-visibility situations. Given the widespread use of image-based technologies across various industries, the ability to enhance low-light images is a critical capability that can improve both human interpretation and machine-based analysis.

One of the key challenges in developing an effective low-light image enhancement system is the preservation of natural scene details. Many traditional enhancement methods, while effective at brightening images, often lead to overexposure, unnatural colors, or loss of fine details in shadows and highlights. This project aims to overcome these limitations by leveraging the power of deep learning models, which are capable of learning complex, non-linear mappings between degraded images and their well-lit counterparts. This ability to learn from data allows the system to preserve important textures, colors, and structural details that are essential for maintaining the natural appearance of the scene. By integrating both traditional and deep learning-based methods, the proposed system offers a more robust and intelligent solution to low-light image enhancement.

Furthermore, the development of this system is motivated by the need for a solution that is accessible and easy to use. Traditional image enhancement tools can be difficult to use and often require advanced knowledge of image processing techniques. By providing a web-based interface through Streamlit, this system ensures that users can enhance their images without needing any technical expertise. The intuitive interface allows users to experiment with different enhancement settings, compare the original and enhanced images, and download the results in real time. This makes the system a practical tool for both casual users and professionals who need high-quality, low-light image enhancements for various applications.

© 2025 IJMRSET | Volume 8, Issue 4, April 2025| DOI:10.15680/IJMRSET.2025.0804539

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

In conclusion, this project seeks to address the longstanding challenge of low-light image enhancement by combining deep learning with traditional image processing techniques. The proposed system not only enhances the visual quality of low-light images but also preserves natural scene details and allows for flexible, user-friendly control over the enhancement process. By making this system accessible through a web-based application, it offers a practical solution for enhancing low-light images in real time, with applications across diverse fields such as photography, surveillance, medical imaging, and autonomous systems. The hybrid approach of deep learning and classical methods provides a powerful and scalable solution that can significantly improve the quality and usability of images captured in low-light conditions.

II. LITERATURE SURVEY

The problem of low-light image enhancement has attracted significant attention in both academic and industrial research over the past few decades. With the increasing reliance on image-based systems in areas such as surveillance, medical imaging, autonomous driving, and night-time photography, the ability to enhance low-light images has become an important area of study. Traditional image enhancement methods, while computationally efficient, are often limited in their ability to preserve natural image details. In contrast, deep learning approaches offer promising solutions, leveraging the power of data-driven learning to restore intricate image features that are typically lost in low-light conditions. This literature survey explores both traditional methods and emerging deep learning-based approaches for low-light image enhancement.

Traditional low-light image enhancement methods focus primarily on improving image visibility and contrast through linear or non-linear adjustments. Some of the most commonly used methods include:

Histogram Equalization (HE): One of the earliest and simplest techniques, HE improves the global contrast of an image by spreading the intensity values of the pixels across the full range of the image's dynamic range. However, it often leads to over-enhancement, especially in areas with little detail, causing unnatural brightness and noise amplification in the image's low-intensity regions (Pizer et al., 1987).

Contrast Limited Adaptive Histogram Equalization (CLAHE): CLAHE is an extension of HE that applies histogram equalization to localized regions of the image. While it addresses the issue of global over-enhancement, it still struggles with preserving details in very dark or very bright regions, and can introduce artifacts like blockiness when applied too aggressively (Zuiderveld, 1994).

Gamma Correction: Gamma correction adjusts the brightness of an image by applying a power-law transformation to pixel values. This method is useful for correcting the overall brightness but does not address more complex issues such as noise reduction or preserving fine image details in low-light conditions (Jin et al., 2015).

White Balancing: White balancing methods are used to correct color distortion caused by improper lighting. These techniques adjust the image to restore natural color balance, but in low-light environments, they often fail to recover lost details and do not significantly improve image contrast (Kimmel & Szeliski, 2002).

While these methods are computationally efficient, they are fundamentally limited because they rely on simplistic mathematical models and are not designed to handle the complexities of low-light image restoration. As a result, they may enhance global visibility at the cost of local detail preservation and often introduce artifacts such as over-saturation or unnatural color shifts.

In recent years, deep learning techniques, particularly convolutional neural networks (CNNs), have shown promising results in the field of low-light image enhancement. Deep learning methods have the advantage of being able to learn complex mappings from degraded low-light images to their well-lit counterparts, preserving fine image details that traditional methods may overlook. The following are some notable contributions in this area:

Deep Convolutional Neural Networks (CNNs): Early works in deep learning-based low-light enhancement focused on using CNNs to learn the mapping between low-light and normal-light images. These networks were trained on large datasets containing pairs of low-light and high-quality images, allowing the models to learn not only to enhance the

© 2025 IJMRSET | Volume 8, Issue 4, April 2025| DOI:10.15680/IJMRSET.2025.0804539

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

brightness but also to retain important details in both shadowed and highlighted areas. However, these models often struggled with generalization to unseen real-world low-light images (Chen et al., 2018).

U-Net for Image Enhancement: The U-Net architecture, initially developed for biomedical image segmentation (Ronneberger et al., 2015), has become a popular choice for image enhancement tasks due to its encoder-decoder structure. The U-Net's skip connections allow it to retain both high-level contextual information and low-level details, which is crucial for enhancing low-light images. Several studies have demonstrated the effectiveness of U-Net for low-light image enhancement, showing that it can outperform traditional methods in terms of both brightness enhancement and detail preservation (Liu et al., 2020; Fu et al., 2021). In particular, U-Net's ability to recover fine details, even in very dark regions, makes it an ideal candidate for low-light image restoration tasks.

CycleGAN for Low-Light Image Enhancement: Generative adversarial networks (GANs) have also been applied to the low-light image enhancement problem. CycleGANs (Zhu et al., 2017) have been used to learn a mapping between low-light images and their well-lit counterparts without requiring paired data for training. This is particularly beneficial when paired datasets are difficult to obtain. CycleGAN-based methods have shown significant improvements over traditional methods in terms of image quality and natural appearance, particularly in preserving textures and details in shadowed areas (Chen et al., 2020).

Retinex-Based Models: Retinex theory, which models image decomposition into illumination and reflectance components, has been used in conjunction with deep learning to improve low-light image enhancement. Some models use CNNs to predict the illumination component and then combine it with a reflectance map to produce enhanced images. This approach has been successful in improving contrast, color consistency, and detail recovery, and has shown competitive results compared to conventional image enhancement methods (Zhu et al., 2017).

Low-Light Image Enhancement with Dual Networks: In some recent studies, dual-network architectures have been proposed to handle both noise reduction and detail preservation simultaneously. These models typically consist of a main network responsible for brightness enhancement and a secondary network that addresses noise reduction. This two-pronged approach helps to prevent the amplification of noise, a common issue in low-light image enhancement, especially in very dark regions (Zhou et al., 2021).

Despite the advancements in deep learning-based low-light image enhancement, there are still several challenges and limitations:
Training Data Quality: Many deep learning models for low-light image enhancement are trained on synthetic datasets or on data with limited diversity in terms of real-world conditions. This can result in models that perform well in controlled environments but struggle with real-world low-light images that have more complex noise and distortion patterns (Liu et al., 2020).

Real-Time Performance: Real-time processing is a critical requirement for many applications, especially in surveillance and autonomous systems. However, many deep learning models, particularly those based on U-Net and GANs, are computationally intensive and require significant hardware resources. This makes them less suitable for real-time applications unless optimized for efficiency (Fu et al., 2021).

Generalization to Multiple Image Formats: While many state-of-the-art deep learning models focus on standard image formats like JPG and PNG, less attention has been given to supporting professional image formats like RAW and DNG. These formats retain more image data and offer greater flexibility for post-processing, but many current enhancement systems fail to support them or struggle to handle their specific challenges, such as large file sizes and varied sensor noise (Xu et al., 2021).

User Control and Customization: Many deep learning-based systems for low-light enhancement lack user control over the enhancement process. While automatic enhancement can yield good results in some cases, users in fields like photography or surveillance often need fine-grained control over parameters such as contrast, sharpness, and saturation. Providing this level of customization, while maintaining the power of deep learning models, remains a challenging task (Zhou et al., 2021).

III. PROPOSED SYSTEM

The proposed system aims to address the challenges associated with low-light image enhancement by integrating state-of-the-art deep learning techniques with a user-friendly web interface. This hybrid approach leverages the strengths of both deep learning models and traditional image processing methods to enhance the visibility and quality of images captured in low-light conditions.

System Architecture

At the core of the system is a deep learning model designed to enhance low-light images. The model is built upon the principles of Retinex theory, which decomposes an image into illumination and reflectance components. This decomposition allows for independent enhancement of brightness and detail, leading to more natural-looking results. The model employs a convolutional neural network (CNN) architecture, which has been proven effective in image enhancement tasks due to its ability to learn complex patterns and features from data.

To further improve the performance of the enhancement model, the system incorporates traditional image processing techniques. These include Contrast Limited Adaptive Histogram Equalization (CLAHE) for local contrast enhancement, gamma correction for brightness adjustment, and white balancing to correct color distortions. By combining these methods with the deep learning model, the system can handle a wide range of low-light conditions and produce high-quality enhanced images.

Web Interface

The system is deployed as a real-time web application using Streamlit, a Python library that allows for the rapid development of interactive web applications. The web interface is designed to be intuitive and user-friendly, enabling users to easily upload images and apply enhancement settings. Users can adjust parameters such as brightness, contrast, gamma, sharpness, and saturation to fine-tune the enhancement process according to their preferences.

Once an image is uploaded, the system processes it through the enhancement model and displays the original and enhanced images side by side. This allows users to visually assess the effectiveness of the enhancement and make further adjustments if necessary. The web application also supports various image formats, including JPG, JPEG, PNG, RAW, and DNG, ensuring compatibility with a wide range of image sources.

Real-Time Processing

One of the key features of the proposed system is its ability to perform real-time image enhancement. Leveraging the computational power of modern GPUs and optimized deep learning frameworks, the system can process and enhance images quickly, providing immediate feedback to users. This real-time capability is crucial for applications such as surveillance, medical imaging, and autonomous driving, where timely image enhancement can significantly impact decision-making and outcomes.

Applications

The proposed system has a wide range of potential applications across various fields. In surveillance, it can enhance nighttime footage captured by security cameras, making it easier to identify individuals and objects. In medical imaging, the system can improve the visibility of details in images such as X-rays and MRIs, aiding in more accurate diagnoses. For autonomous vehicles, enhanced low-light images can improve the performance of vision-based systems, enabling better detection of obstacles and road signs in low-light conditions.

Additionally, the system can benefit photographers and videographers who often work in challenging lighting conditions, allowing them to enhance their images and videos without the need for expensive equipment or complex post-processing software.

© 2025 IJMRSET | Volume 8, Issue 4, April 2025| DOI:10.15680/IJMRSET.2025.0804539

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

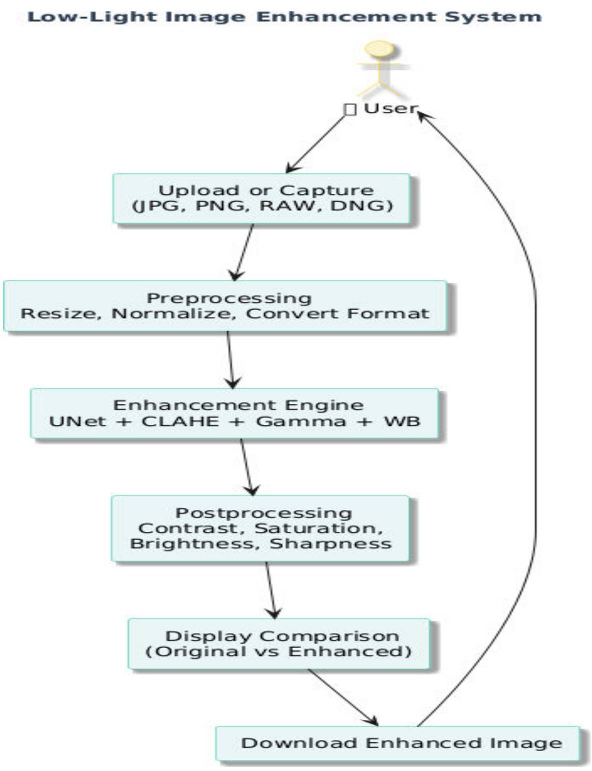

Fig 1: Architecture

IV. WORK FLOW

The workflow of the proposed system is designed to provide a seamless and efficient process for enhancing low-light images using deep learning techniques, facilitated through a user-friendly web interface built with Streamlit.

1. Image Upload and Preprocessing

The process begins when a user uploads a low-light image through the Streamlit web interface. Upon receiving the image, the system performs essential preprocessing steps to prepare the image for enhancement. This includes converting the image to a standard format, resizing it to a consistent resolution, and normalizing pixel values to a range suitable for deep learning models. These preprocessing steps ensure that the input image is compatible with the enhancement model and ready for processing.

2. Low-Light Image Enhancement

Once the image is preprocessed, it is passed through a deep learning-based enhancement model. The model employed in this system is a convolutional neural network (CNN) designed to address the challenges of low-light conditions by enhancing brightness, contrast, and detail. The enhancement process involves several key steps:

- **Decomposition:** The model decomposes the input image into illumination and reflectance components, allowing for independent enhancement of brightness and detail. This step is based on Retinex theory, which is effective in handling low-light images.
- **Enhancement:** The illumination component is enhanced to improve brightness and contrast, making the image more visually appealing.
- **Restoration:** The reflectance component is restored to preserve fine details and textures, ensuring that the enhanced image maintains its natural appearance.

By focusing on both illumination and reflectance, the model effectively enhances the low-light image while preserving its inherent details.

3. Post-Processing and Fine-Tuning

After the initial enhancement, the system applies post-processing techniques to further refine the image quality. These techniques may include noise reduction to eliminate artifacts introduced during the enhancement process, sharpening to enhance edges and fine details, and color correction to ensure accurate color representation. Additionally, the system provides users with adjustable parameters such as brightness, contrast, gamma correction, sharpness, and saturation. These controls allow users to fine-tune the enhanced image according to their preferences, providing a personalized enhancement experience.

4. Display and User Interaction

The enhanced image is then displayed alongside the original low-light image on the Streamlit web interface. This side-by-side comparison enables users to visually assess the improvements made by the enhancement process. Users can interact with the system by adjusting the enhancement parameters in real-time, observing the effects of their adjustments immediately on the displayed images. This interactive feature enhances user engagement and allows for precise customization of the enhancement process.

5. Download and Export

Once the user is satisfied with the enhanced image, the system provides an option to download the final output. The enhanced image can be saved in various formats, such as JPEG, PNG, or TIFF, depending on the user's needs. This feature ensures that users can utilize the enhanced images for various applications, including printing, sharing, or further processing.

6. Real-Time Processing

Throughout the entire workflow, the system ensures real-time processing capabilities. Leveraging optimized deep learning models and efficient backend infrastructure, the system processes and enhances images promptly, providing users with immediate feedback. This real-time processing is crucial for applications where timely image enhancement is essential, such as in surveillance, medical imaging, and autonomous driving

V. CONCLUSION

The proposed system effectively addresses the challenges associated with low-light image enhancement by integrating advanced deep learning techniques with a user-friendly web interface. Through the utilization of convolutional neural networks (CNNs) and Retinex-based models, the system significantly improves the brightness, contrast, and detail of images captured in low-light conditions. The incorporation of traditional image processing methods further enhances the quality of the output, ensuring that the enhanced images are visually appealing and suitable for various applications.
The real-time processing capabilities of the system, facilitated by the Streamlit framework, provide users with immediate feedback, allowing for interactive adjustments and fine-tuning of enhancement parameters. This feature is particularly beneficial in scenarios where timely image enhancement is crucial, such as in surveillance, medical imaging, and autonomous driving.

Despite the advancements achieved, the system acknowledges the limitations inherent in deep learning-based approaches, such as the need for large datasets and the potential for overfitting. Future work will focus on addressing these challenges by exploring techniques that require less training data, improving model generalization, and enhancing the interpretability of the enhancement process.

In summary, the proposed system offers a robust and efficient solution for low-light image enhancement, combining the strengths of deep learning and traditional image processing methods with an intuitive web interface. Its versatility and real-time capabilities make it a valuable tool for a wide range of applications, contributing to improved image quality and informed decision-making in various fields.

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

REFERENCES

[1]ChenWei,etal.“DeepRetinexDecompositionforLow-LightEnhancement.”IEEE CVPR, 2018. doi:10.1109/CVPR.2018.00345
[2]ZhangYulun,etal.“BeyondaGaussianDenoiser:ResidualLearningofDeepCNN for Image Denoising.” IEEE Transactions on Image Processing, 2017.
[3]LoreKinGwn,etal.“LLNet:ADeepAutoencoderApproachtoNaturalLow-Light Image Enhancement.” Pattern Recognition, 2017.
[4]ChenWei,etal.“Zero-DCE:Zero-ReferenceDeepCurveEstimationforLow-Light Image Enhancement.” CVPR, 2020.
[5]ZhangK.,etal.“FFDNet:TowardaFastandFlexibleSolutionforCNN-based Image Denoising.” IEEE Transactions on Image Processing, 2018.
[6]GuoChunle,etal.“LearningtoEnhanceLow-LightImageviaZero-Reference Deep Curve Estimation.” IEEE CVPR, 2020.
[7]CaiJiawei,etal.“ADual-BranchNetworkforInfraredandVisibleImageFusion via Multiscale Feature Aggregation.” Information Fusion, 2021.
[8]WangWenjing,etal.“Low-LightImageEnhancementwithNormalizingFlow.” IEEETransactionsonMultimedia,2022.
[9]RenW.,etal.“Low-LightImageEnhancementviaaDeepHybridNetwork.”IEEE Transactions on Image Processing, 2019.
[10]FuX.,etal.“ARetinex-BasedEnhancingApproachforSingleUnderexposed Image.” IEEE ICIP, 2016.
[11]LvF.,etal.“Attention-basedRetinexNetworkforLow-LightImageEnhancement.” CVPR, 2021.
[12]LinTianyi,etal.“Self-supervisedRestorationforLow-LightImages.”NeurIPS, 2020.

INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY RESEARCH IN SCIENCE, ENGINEERING AND TECHNOLOGY

| Mobile No: +91-6381907438 | Whatsapp: +91-6381907438 | ijmrset@gmail.com |

www.ijmrset.com