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Enhancing low-light images using U-Net Structure

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***Abstract*—The article designed an Enhancing Low-Light Image using U-Net Structure is a method to produce natural brightness and color for the pictures taken under low light conditions. Images captured in a low-light environment may cause poor image quality in terms of low visibility, low contrast, and color distortion. It refers to the process of improving the visual appearance of an image. This can involve adjustments to brightness, contrast, sharpness, color balance, and other attributes to bring out or correct imperfections. The objective is to create new images from the original image data to increase the amount of information. The proposed methodology uses a simple network with effective modules called the U-Net structure for enhancing low-light images.**

***Index Terms*—Enhancing Low-Light Image, U-Net Structure, Image Enhancement, Low Visibility, Contrast Enhancement, Color Correction, Brightness Adjustment, Sharpness Enhancement, Color Balance, Image Reconstruction.**

I. Introduction

Images with excessively low brightness not only impair human visual perception, but they also cause great distress to other computer vision tasks. For instance, poor lightning during nighttime surveillance video obstructs face recognition and traffic monitoring systems from identifying the offending vehicle’s license plate number. To some extent, the use of advanced camera equipment can eliminate the flaws oflow-quality photos. However, pictures taken with advanced cameras frequently display blurring, high noise, excessively dark images, and color deviation due to variables including exposure duration, weather, and scene light intensity. Furthermore, the cost of advanced camera gear adds to its limits. The original image’s brightness and contrast can be enhanced using the enhancing low-light image technique. The goal of light image enhancement is to achieve natural standard light images from images that is already captured in low lighting. The proposed method consists of three main tasks: preserving edges and textures, reducing noise and reproducing natural brightness and color [1], The effectiveness of region-based convolutional neural networks and region proposal techniques has led to recent advancements in object detection [2], It is said that region-based CNN method is a complex task with many challenges. Simple ELLI is a complex task with many challenges. Conventional ELLI methods build models to improve the illumination accuracy and obtain enhanced images. There is a good contrast enhancement technique for nature photos, medical imaging, and other initially nonvisual images is histogram equalisation[3], Applying the histogram equalisation mapping based on the pixels in a region around each pixel (i.e., its contextual region) to each pixel is the fundamental version of the approach. Put another way, the intensity of each pixel is mapped to be proportionate to its rank in the pixels around it. When a low-light image is enhanced, various information is lost such as illumination, color, structure, and contrast. Besides, the improved image has increased haze and noise. It may increase the contrast of background noise while decreasing the usable signal. Histogram fails when the input image has a large area low-intensity background. An efficient tool for improving low-light images is the Retinex-based model. It is predicated on the ability to dissect observed images into their lightning and reflectance [4], The basic purpose of image enhancement is to improve the quality of an image for human eyesight. Based on Retinex theory, it can be said that an image is a product of illumination and reflectance from the object. The theory examines the distribution of light and color information across the entire image. It takes the levels of illumination in various parts of the photo. By analyzing and adjusting the brightness and improving visibility. Pixel values are applied to the single logarithmic scale transformation and multi-scale retinex, each scale that applies Retinex separately. Both algorithms contribute to improving the quality of low- light images, just in slightly different ways. However, these models are complex and the processing time is very long. To accelerate the time of implementation we propose a simple end-to-end network structure [5]. Our suggested network was designed with a U-Net topology in mind, drawing inspiration from common image processing tasks.

II. Literature Survey

Matsui and Ikehara (2023): suggested a straightforward network structure for enhancing low-light images. The paper provides valuable information on low-light images and it also explores the architecture, techniques and results of the pro- posed network in the context of low-light image enhancement [1]. Ren, Shaoqing, et al. discussed real-time object detection by using region proposal networks in neural networks, Faster R-CNN is introduced with the goal of real-time object de- tection. The authors likely discuss the architecture, training process, and the improved efficiency of Faster R-CNN com- pared to previous methods in the field of computer vision [2]. Reza, Ali M. suggested contrast limited adaptive histogram equalisation (CLAHE) to improve in real-time images. In this paper the author explores the application of CLAHE, a histogram-based method, to improve the contrast of images while addressing limitations related to over-amplification of noise. The work contributes to the field of image processing and enhancement, specifically targeting real-time applications [3]. Wei, Chen, et al. The authors provide a decomposition method that effectively enhances performance by utilizing deep neural nets. Deep Retinex decomposition, a technique for improving low-light photos, is presented in this work. To enhance visibility in photos taken in low light, a deep-learning techniques is investigated [4]. Ronneberger, Olaf, Phillip Fischer, and Thomas Brox. This seminal paper introduces the U-net architecture, a convolutional neural network designed for biomedical image segmentation. The paper highlights its application in biomedical image analysis and has become a foundational model for various segmentation tasks in medical imaging [5]. Mao, Xintain, et al. suggested newly built block as Res FFT-ReLU Block which takes the advantages for both kernel-level pixel-level features through learning frequency-spatial dual-domain representations [6]. Woo, Sanghyun, et al. “Cbam: Convolutional block attention module.” In further research, scientists have expanded and studied CBAM, adding attention mechanisms to convolutional neural networks (CNNs) to enhance feature representation and model performance [7]. Shi, Wenzhe, et al. “Real-time single image and video super-resolution using an efficient sub-pixel convolutional neural network”. The paper focuses on real-time super-resolution using a sub-pixel convolutional network. The goal of study is to improve the resolution of photos and videos by expanding on the super-resolution techniques that already exist. The paper presents the idea of Sub-pixel convolution layers. This method is effective for real-world applications since it enables real-time processing [8]. Wang, Zhou, Eero P. Simoncelli, and Alan C. Bovik. “Multiscale structural similarity for image quality assessment.” Suggested a multiscale structural similarity index for image quality assessment. The likely discussed existing methods, highlighted the importance of assessing image quality, and explained the motivation behind developing a multiscale approach [9]. Li, Chongyi, et al. Research on deep learning techniques for improving low-light photos and movies can be found in publication “Low-light image and video enhancement using deep learning: A survey”. The paper, provides a thorough overview of methods in this field, including developments and approaches used to deal with low light [10]. Yang, Wenhan, et al. suggested a semi-supervised approach for enhancing low-light images, shifting focus from fidelity to perceptual quality. Presented at the IEEE/CVF conference on computer vision and pattern recognition in 2020, the paper explores methods to improve the visual quality of images captured in low-light conditions [11]. Zhai, Guangtao, and Xionguo Min. suggested a perceptual picture quality assessment is thoroughly reviewed in the work “Perceptual Image Quality Assessment: A Survey”. The study addresses a broad spectrum of issues regarding approaches, developments, and strategies for evaluating the perceived quality of photographs. The paper explores the different methodologies and measurements. The thorough analysis seeks to give readers a sophisticated grasp of the major advancements and difficulties in the evaluation of perceptual image quality [12].

III. Methodology

A. U-NET STRUCTURE

This study offers a method called LLIE for low-light images. U-Net architecture can be adapted for low-light image enhancement by training the network on a dataset of low-light images and their corresponding enhanced versions. The majority of CNN-based LLIE techniques feature intricate network architectures made up of many subnetworks. Our suggested network was built using a U-Net which was inspired by common image processing tasks [1]. U-Net can effectively capture an input low-light image’s global and local properties. Enhanced photos often appear blurry because low-light photographs have less information about edges and textures. We concatenate the edge-enhanced image and the input low-light image as an input to the U-Net. As the edge enhancement filter, we used an eight-neighbor Laplacian filter. Before applying the Laplacian, we used a blur filter and a Gaussian filter to prevent enhancing the noise in the low-light image. U-Net’s architecture is made up of a symmetric expanding path that allows for exact localization and a contracting path that captures context. The residual component in the final layer is the output that gives the network robustness for a variety of image types. The premise behind residual learning is that learning a residual relationship is less complicated than learning an output-to-input relationship directly. The residual learning strategy has been demonstrated to be effective for several image processing tasks in earlier research [13], [14], and [15]. To reduce the computational cost, we did not use a subnetwork similar to conventional methods. Instead, we take the strategy of focus on effective preprocessing and learning modules and the loss function.

B. PRE-PROCESSING

Enhanced images often appear blurry because low-light images have less information about edges and textures [1]. The Edge detection is one of the most fundamental computer vision tasks. An Edge detection filter is appropriate for Low-light image enhancement in order to address these problems, and they employed RCF. Edge-Enhanced Multi-Exposure Fusion Network to enhance extremely low-light images and recover realistic image details. Existing methods can be roughly categorized into three groups. The first one usually produces an edge map by designing various filters. Gaussian smoothing, for example, was first introduced in the method of removing the gradient from the photograph. The second category uses data-driven algorithms based on attributes that were created by humans to anticipate edges. Random decision forests are used in Structured Edges to determine the structure of edge patches. Third, deep learning techniques have made significant strides in their ability to extract intricate feature representations from unprocessed data.

- First, we applied a blur filter as follows:

S low, gray = slow, gray kblur

- Second, a Gaussian filter is applied as follows:

S low, gray = S low, gray kgauss
• Finally, we apply an eight-nearest-neighbor Laplacian filter, which can detect edges and textures not only in the horizontal and vertical directions but also in diagonal directions.
S low, gray = s low, gray klap8
• The combination of a blur filter and a Gaussian filter is effective for suppressing noise. An edge enhancement filter was added to a grayscale image to mitigate the network's excessive reliance on the colors. The Laplacian filter is a spatial filter used to extract contours from an image using a second derivative. The combination of a blur filter and a Gaussian filter is effective for suppressing noise. After the above edge enhancement process, the RGB image and filtered image are concatenated before inputting to U-Net.

C. MODULES

1) RES FFT-RELU BLOCK: To reduce noise the RES FFT-ReLU Block is a non-local processing block that handles global features to enhance high-frequency components. • First the image is transformed into a frequency domain by 2d real FFT
• Then two stacks of 1 × 1 convolution layers with a ReLU layer in between are applied.
• Then, an inverse 2d real FFT is performed to return the output to the image space.
• Two stacks of 3 × 3 convolution layers with a ReLU layer in between are applied.
• The output of the second 3x3 convolution layer is added element-wise to the original input signal.
• 1x1 convolution: this layer applies a filter of size 1x1 to the input, which essentially performs element-wise multiplication between the filter weights and the input signal. This can be used to learn linear transformations of the input.
• ReLU: The ReLU activation function sets all negative values to zero, effectively thresholding the output. This helps to introduce non-linearity into the network, which allows it to learn more complex features from the input.
• 3x3 convolution: this layer applies a filter of size 3x3 to the input, which can be used to learn spatial features from the image. RES FFT-ReLU Block removes the image broad characteristics, reducing noise and restoring overall lighting while also making object borders clear.

2) CHANNEL ATTENTION BLOCK: • Channel attention focuses on inter-channel relationships. It aims to understand the relative importance of each channel across the entire feature map, regardless of spatial location.
• Max and average pooling, commonly used in convolutional layers, operate along the spatial dimensions (width and height) of feature maps. They aggregate information from neighboring pixels within a channel, providing insights into local spatial patterns.
• The final layer in the sigmoid block usually applies a sigmoid activation function. Sigmoid squashes the output of the previous layers to the range [0, 1], effectively producing attention weights for each channel. These weights represent the importance of each channel relative to others.

3) PIXEL SHUFFLER: The U-Net decoder frequently uses upsampling and deconvolution. Pixel Shuffler is used to obtain high-resolution photos while lowering the running cost. It aims to increase the spatial resolution of an image by rearranging the pixels in feature maps obtained from convolutional layers. This rearrangement process facilitates the creation of higher-resolution feature maps, which can then be used for subsequent processing. By using pixel shuffler operation, we can generate high-resolution images from low-resolution inputs, or enhance the quality of images by increasing their spatial detail.

IV. Results and Discussions

The initial grayscale or dimly lit image undergoes an enhancement process to improve its quality or characteristics. Subsequently, the edge-enhanced version of the image is displayed in the Fig. 1

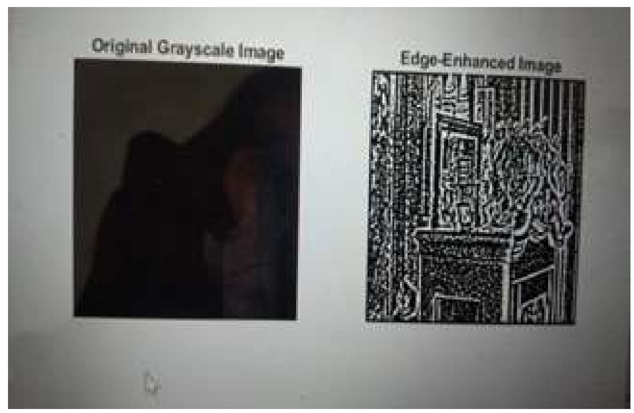

Fig. 1. Input Image and Enhanced

The enhancement of low-light images having problems such as loss of illumination, colour, and detail, and generation.The final result is shown in Fig. 2 It shows the proper image extracted from low dim light image.

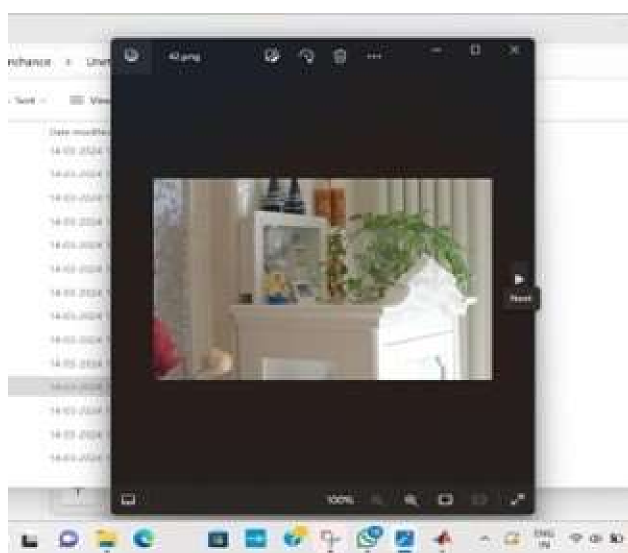

Fig. 2. Final Result

We train the model by using MATLAB. It is a proprietary multi-programming language and numeric computing environment developed by Mathworks.

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