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MULTI-SCALE RETINEX-UNET FOR ENHANCEMENT OF LOW LIGHT WEAK CONTRAST IMAGES

MUDDAPU HARIKA[1*], GOTTAPU SASIBHUSHANA RAO[2], RAJKUMAR GOSWAMI[3]

[1]Research Scholar, Dept. of ECE, Andhra University, Visakhapatnam, India

[2]Senior Professor, Dept. of ECE, Andhra University, Visakhapatnam, India

[3]Professor, Dept. of ECE, Gayatri Vidya Parishad College of Engineering for Women, Visakhapatnam, India

E-mail: [1]jalluharika427@gmail.com , [2]sasigps@gmail.com, [3]rajkumargoswami@gmail.com

ABSTRACT

The enhanced quality of images is crucial in the realm of image processing applications. However, images captured in low-light environments often suffer from poor contrast and noise, leading to a loss of detailed information. To address this challenge, we propose a Multi-Scale RETINEX-UNET (MSR-UNET) model for low-light weak contrast (LLWC) image enhancement. This novel approach integrates a modified U-Net architecture with an improved multi-scale Retinex (IMSR) model, aiming to preserve natural colors while enhancing visual quality. The proposed model is validated using the Renoir dataset, and its effectiveness is measured through PSNR (34.3 dB) and SSIM (99%). Compared to conventional enhancement techniques, our model outperforms existing methods by effectively reducing noise while maintaining structural details. This study advances deep learning-based image enhancement and sets a new benchmark for LLWC image processing.

Keywords: *Image Enhancement, Convolutional Neural Networks, Grey Level Co-occurrence Matrix, U-Net, Multi-Scale Retinex, Deep Learning.*

1. INTRODUCTION

The ability to process and enhance images is fundamental to various real-world applications, including video surveillance, medical imaging, and remote sensing. However, low-light conditions and weak contrast significantly degrade image quality, making it challenging to extract meaningful information. Traditional histogram equalization-based approaches improve brightness but often fail to retain natural color tones. Similarly, deep learning techniques, such as CNN-based models, enhance structural details but suffer from overexposure and noise artifacts. This study aims to bridge the gap by introducing a novel hybrid model (MSR-UNET), which integrates CNN-based feature extraction with Retinex-based enhancement for superior visual quality.

Processing of Images to have a significant role in daily life. Images may be used for a variety of purposes, such as improving surveillance, conducting computer vision research, snapping selfies, and more [1]. All the tasks need high-quality photographs. However, low lighting, low contrast, noise, and blurring severely affect photos shot in low light. Sometimes it becomes quite difficult to interpret a picture captured in a noisy environment. For instance, it might be exceedingly challenging to identify a person in a nighttime CCTV camera image. Nevertheless, several factors, like poor weather, dim lighting, a side that is completely black and the other partially illuminated, haze, fog, etc., can adversely influence the quality of a picture. Figure 1 displays an example of low-light photos [2].

One of the fundamental stages in processing images and videos in fields like medical image analysis, video analytics, and video surveillance is image enhancement. The algorithm used to design the enhancement of image models is to get enhanced clarity in a picture by highlighting important elements that may be obscured by varying lighting conditions. For instance, the lighting of a scene can be greatly affected by the surrounding surroundings. The sequence of videos or images may be excessively bright or dark, with uneven background lighting, depending on the surrounding conditions. This might cause a partial loss of clarity and negative impact on the analysis's findings. This study first reviews some of the most advanced low light poor contrast picture enhancing approaches and gives a quick overview of the research that has been done. Since various studies are conducted with a focus on various situations, they may employ various testing parameters. We will give a quick overview of the dataset, the methodology, and the testing outcomes for the strategies in this study. Enhancing images aims to improve their quality without losing any important features. In most computer vision tasks, it serves as a pre-processing stage [3]. It simply implies creating a picture from a noisy, low-light photograph that is like a fresh image acquired in a less noisy setting. Improving low light images has long been a well-known topic in the field of computer vision. Various researchers have occasionally offered a wide range of methodologies.

Fig.1. Sample images of Low light images

Deep learning (DL) is an AI technique that is now upending computer vision and image counting systems [4]. The author plans to use deep learning specifically for poor contrast low-light picture enhancement and image filtering. In many applications DL is used for solving complicated problems in patter recognition systems. One example is structuring of human brain for recognition of brain features. The most common use of convolutional neural networks (CNNs), a class of deep neural systems in deep learning, is the analysis of visual symbols. The Department of Computer Vision at the University of Freiburg, Germany, developed U-Net, a CNN. The contracting method is a standard convolutional structure consisting of re-used convolutions, each followed by a maximum pooling activity and a Rectified Linear Unit (ReLU). The spatial size of the feature map reduces during the contracting path and grows during the expanding path.

The Retinex algorithm was developed because of Edwin Land's 1977 model, which explained how the apparent hue and brightness are altered by the visionary system of humans for objects to address the issue of uneven lighting. Numerous image improvement methods, including the Single Scale Retinex (SSR) algorithm, Multi-Scale Retinex (MSR) algorithm, Multi-Scale Retinex with Color Restoration (MSRCR), and others, have been documented in the literature since then and are based on the theory of Retinex in RGB color space [5–10].

The paper designed and proposed model is as follows:

a. Generation weak contrast image and obtaining RGB level features using CNN
b. Converting image to grey scale and obtaining GLCM features.
c. Enhancement of image using U-Net and MS-Retinex model
d. In terms of assessment indexes and visual perception, the suggested strategy outperforms the existing methods for enhancing low-light poor contrast photographs substantially.

This paper's remaining content is divided into sub sections. A summary of the study and its literature review is provided in section 2. The design flow of the suggested technique is discussed in Section 3. In section 4, results and discussion are found. Finally, the summary of the work is portrayed.

2. RELATED WORK

Several deep learning-based methods have been developed to enhance low-light images. Histogram equalization (HE) methods such as CLAHE and AHE improve brightness but introduce artifacts. Retinex-based models (MSR, MSRCR) preserve natural colors but often result in color distortion in extreme low-light conditions. U-Net-based architectures have shown promise in image restoration tasks, but their enhancement capabilities for LLWC images remain unexplored.

Several methods have been put out to improve photos taken in low light. Histogram equalization-based algorithms have produced several different results, including dynamic histogram equalization (HE), adaptive histogram equalization (AHE) [11], and contrast-limited adaptive histogram equalization (CLAHE) [12]. HE is a technique that uniformly distributes an image's grey range, increasing contrast. To perform histogram equalization processing, AHE splits the picture into many tiny blocks. This can boost the image's local contrast and produce superior enhancement outcomes. To avoid the potential blocky effect created by AHE, CLAHE establishes a threshold level and the averages of the required area that exceeds the threshold to each grey level. The SSR, MSR [13], and MSRCP [14] are the principal traditional Retinex-based techniques. Filters, which are intended to filter an image's multiple channels, are used in SSR. After that, they are employed to produce lighting images. To produce the enhancement effect, the illumination picture and the low-light image are logarithmically processed and removed. MSR may be thought of as the weighted total of several SSRs, or the equivalent of stacking numerous SSRs. MSRCP enhances multi-scale MSR findings with color balancing, normalization, and other features. Low-light picture enhancement based on dehazing involves processing the low-light image by applying the dehazing algorithm to its reflection image. The final enhancement effect is then obtained by inverting the image after processing.

A technique for training a self-encoder with a fictitious picture dataset is presented by LLNet [15]. It improves the image while achieving noise reduction. The author of [16] suggested a network that uses the unsupervised LE-GAN model to improve low-light photos. To filter out background noise and extract different characteristics, the network makes use of a light-aware attention module. Additionally, they presented a loss function that may be applied to overcome overexposure. A self-calibrating lighting framework with crowd-share and a lighting learning method was presented by the author in [17] for improvement goals. On the other hand, the suggested self-calibrating lighting framework may accomplish quick processing and save a large amount of computing expenses. In [18], the author presented RetinexNet, a method that uses BM3D to reduce noise in the reflectance picture and enhance the illumination image in low-light photographs by combining the theory of Retinex with CNN. To improve component outcomes, R2RNet builds a residual module (RM) and adds it to its Decom-Net, network with noise reduction, and network augmentation. R2RNet is also built on Retinex and deep learning networks. Retinex is used with zero-shot networks, such RRDNet, in some methods [19]. Based on the principle of Retinex, RRDNet employs a method of noise reduction by breaking down lower visual quality pictures into good quality, reflection, and noise free images. The technique lowers the coupling between the illumination and reflection pictures by transforming the Decom-Net into a generative network.

The author in [20] created CNN architecture for picture enhancement in low light. In this research, they suggested a LightenNet-based approach for feature improvement and patch extraction. An end-to-end mapping between bright and dimly lit pictures was created by architecture. They achieved better results than state-of-the-art research from the past, but the model is flawed with poor quality, poorly lit photographs. Deep Renement Network (DRN) for enhancement of images with natural low light in Symmetric Pathways was created by the author in [21].

To make use of the complicated spatial and organizational properties recorded in the training set, the author of [22] presented a novel augmentation approach based on picture registration. The dataset is expanded using the novel augmentation approach to train U-net-based deep networks. The outcomes demonstrate that the novel augmentation method improves performance without compromising processing speed. Based on the data augmentation technique, the author in [23] suggested an enhanced framework for the U-Net network for autonomous pancreatic segmentation of CT images. By thoroughly upgrading the input pictures of several segmentation channels, the author of [24] greatly enhanced the diagnostic capacity of convolutional neural networks (CNNs) for lymph node metastatic identification in breast cancer patients. The author of [25] enhanced the U-Net model's performance by substantial data augmentation. Two data augmentation techniques (AutoReplace and AutoMove) were suggested by the author in [26] to address the issue of data efficiency. In [27], the author used the CNN of the U-Net architecture to create a significant data augmentation technique based on medical procedures. To eliminate the issues related to weak contrast images and to enhance the visuality quality of LLWC images U-Net and improved multi-scale Retinex models are implemented in this paper. The designed model is discussed in section 3.

Research Problem Statement

Existing enhancement methods either fail to generalize across different lighting conditions or struggle to retain fine structural details while enhancing contrast. To address these gaps, this study proposes the Multi-Scale RETINEX-UNET model, leveraging CNN-based feature extraction with a Retinex-inspired enhancement module for superior contrast enhancement while minimizing unnatural color shifts.

Difference from Prior Work

Unlike previous single-modality enhancement methods, our work introduces a multi-modal fusion of deep learning (U-Net) and color enhancement (Retinex) techniques. Key differences include:

1. Integration of CNN and Retinex for dual enhancement.
2. Preserving both color and contrast while reducing overexposure.
3. Optimized for real-world low-light conditions, ensuring better generalizability.
4. Lower computational complexity compared to conventional GAN-based enhancement models.

This hybrid approach ensures balanced enhancement, making it superior to conventional methods that either over-enhance contrast or introduce artifacts.

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3. METHODOLOGY

The proposed MSR-UNET model follows a structured pipeline consisting of:

- Data Acquisition: Using the Renoir dataset for low-light image enhancement.
- Preprocessing: Standardizing image dimensions, applying noise reduction, and histogram equalization.
- Feature Extraction using CNNs: Extracting RGB and texture features using a modified U-Net architecture.

- Retinex-Based Enhancement: The IMSR module applies multi-scale filtering to retain natural colors.
- Evaluation Metrics: PSNR, SSIM, and NCC are used for quantitative analysis.

.3.1 Dataset

RENOIR is the dataset that was used to assess the effectiveness of the suggested approach. Renoir is a dataset that includes both spatially and intensity-aligned low noise photos of the same scenery together with color images tainted by natural noise resulting from poor light. The dataset consists of around 120 scenes, and each scene has above 500images. The images in the dataset are captured using three different devices, among which two use digital camera and one using smartphone. The raw image size using S90 device is 3684×2760, T3i device is 5250×3465 and Mi3 device is 4208×3120 [28]. The total size of data captured from each device is elaborated in table 1.

Table 1. Renoir dataset details

Device/Data	Sensor Type	Aligned Data	Raw Data
Cannon T3i	Mid-Size sensor	4.9Gb	4.5Gb
Cannon S90	Larger Sensor	2.6Gb	1.8Gb
Xiaomi Mi3	Smaller sensor	2.1Gb	2.5Gb

3.2 Preprocessing

Preprocessing is the crucial step for processing images in the dataset. The images in the database are of different sizes and external noise is added while capturing the images. In this step all the images will be resized to a standard form i.e., $1080 \times 1080 \times 5$. This will help to improve the training model's performance. A median filter is applied to the resized image to remove the minute noises which are portrayed in the images.

3.3 Features extraction

The dataset consists of low light images, from which images with weak contrast are generated for the pre-processed images. The weak contrast image is generated by varying the attenuation factor while changing the pixel values. The change in image is represented as,

$$\overline{IP}(x,y) = (1-k).\left(IP(x,y) - IP_{avg}\right) + IP\_avg \tag{1}$$

Where, $IP(x,y)$ is the value of pixel in x-row and y-column of the original image. $\overline{IP}(x,y)$ is the new pixel value of the generated image w.r.t original image. $k \in [0,1]$ is the coefficient of attenuation. Higher the value of k, contrast of image becomes weak. IP_avg is the mean value of the pixel and is given as,

$$P_{avg} = \left(\sum IP(x,y)\right)/n \tag{2}$$

Here n is the total count size of pixels that are available in the image.

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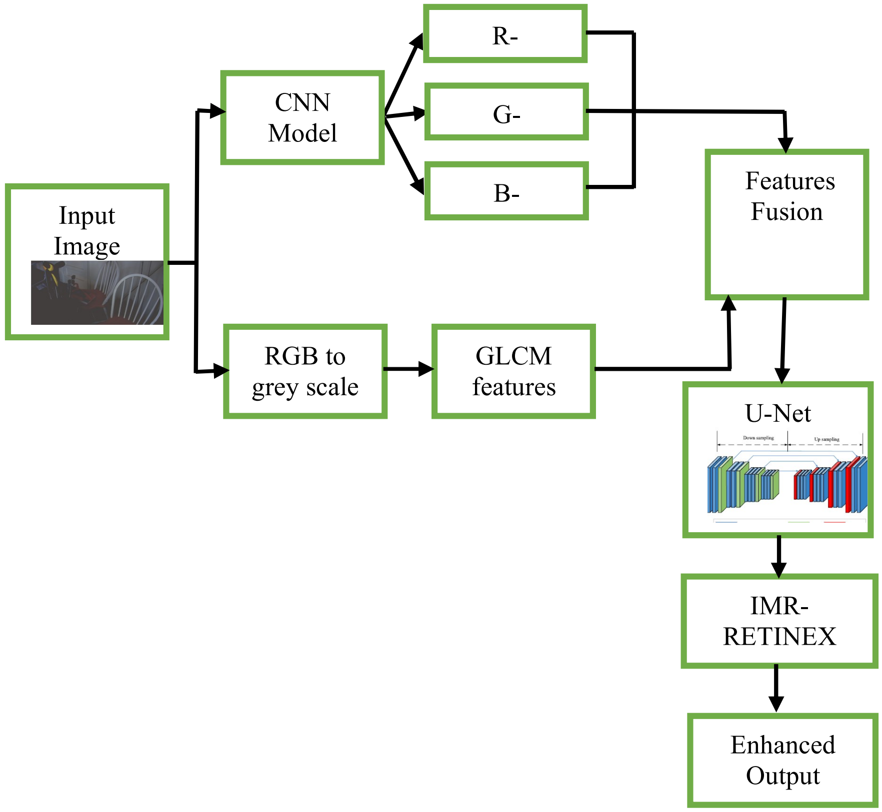
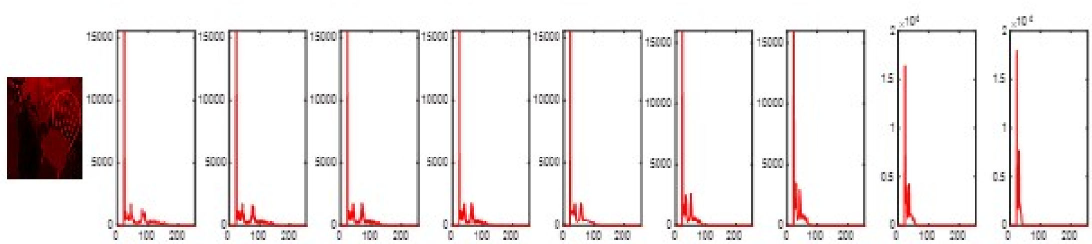
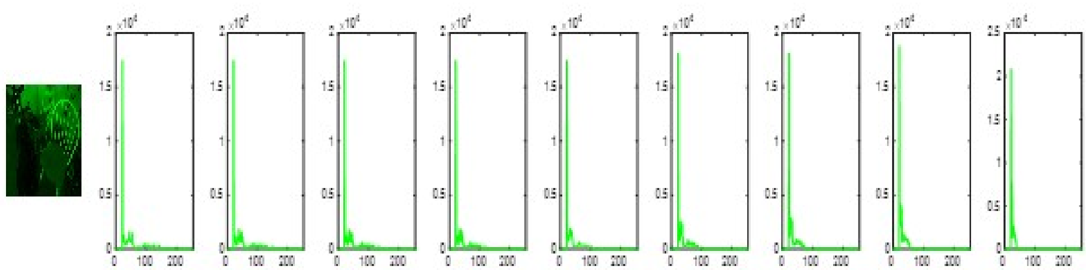


Fig.2. Framework of proposed model

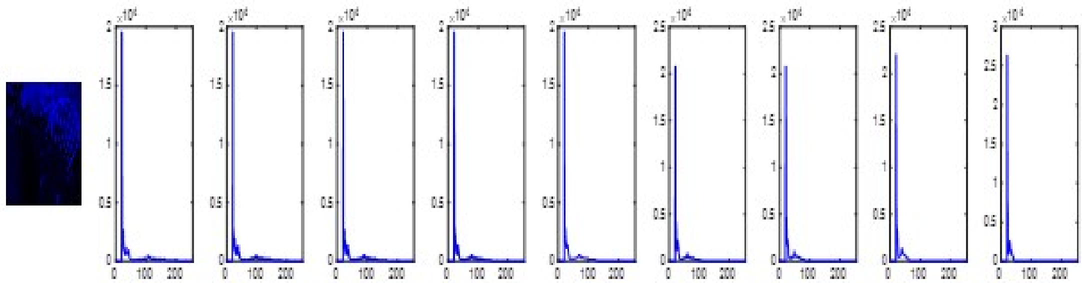
The images generated with weak contrast have RGB channels. The characteristic features of the three channels, i.e., R,G,B channel traits are extracted and used for training of network models which is considered for enhancement of images. Initially the histogram is used to analyze the features of the image. The histogram analysis for given input image in RGB channels is shown in figure 3.



(a)



(b)



(c)

Fig.3. Histogram analysis (a) R-Channel (b) G-Channel (c) B-Channel

The model created to extract the characteristics of the image in the RGB channels is CNN. The Conv2d layer is the central component of a CNN that extracts important layers. These characteristics act as building blocks to assist the network in deciphering the content of the image. The Conv2d layer analyses the picture using filters, sometimes referred to as kernels. These filters scan the picture one little area at a time as they glide over it. They convert the unprocessed pixels into meaningful representations as they travel, extracting pertinent information along the way. It can identify edges, forms, and other significant aspects of the picture by using this method. The characteristics are extracted using basic CNN architecture. The way CNN operates is by turning one image into a series of ever more representations. It consists of a sequence of operations that progressively construct from the unprocessed pixels more intricate features:

- Conv2d layers: These are the crucial steps. From the supplied image, they extract the most important characteristics. Using its kernels, the Conv2d layer convolves the input picture to create feature maps that depict various patterns.
- ReLU (Rectified Linear Unit): This activation function gives the model non-linearity. By enabling the network to approximate any function, it guarantees that it can learn intricate patterns.
- MaxPool2d: The spatial dimensions of the feature maps are reduced using MaxPool2d, much as when you step back to see the view. It lessens computing strain while preserving the most crucial information.
- Flattening: The network flattens the feature maps into a one-dimensional tensor following feature extraction. The data is ready for the final categorization in this stage.

All the features extracted using CNN model are fused with GLCM feature. The input image is converted into grey level image and extracted GLCM features. GLCM features help to obtain texture features of the image. The features extracted are contrast, energy, homogeneity, entropy, dissimilarity.

3.4 Design of U-Net

The U-Net model is intended to improve the characteristics that are extracted even further. A low-resolution, noisy, and deteriorated picture is the input used by U-Net. To provide a clearer, better image in the output, all noise characteristics are eliminated and only features of higher quality are used. This contributes to a decrease in computing complexity and time. The capacity to extract features has been enhanced. Figure 4 displays the U-Net architecture that was used for the project.

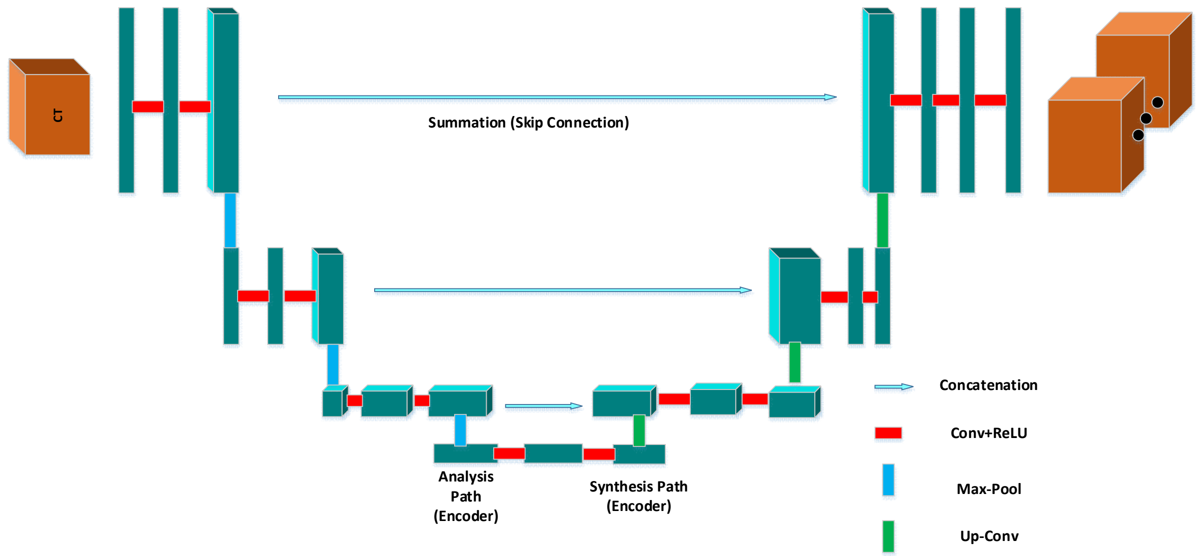


Fig.4. U-Net Model

The encoder and decoder components make up the U-Net model. Figure 5 depicts the module's design. An encoder is made up of many convolutional layers. These layers will decrease the image's spatial dimensions, increasing the number of feature channels. The data is down-sampled in the encoder portion and up-sampled in the decoder portion.

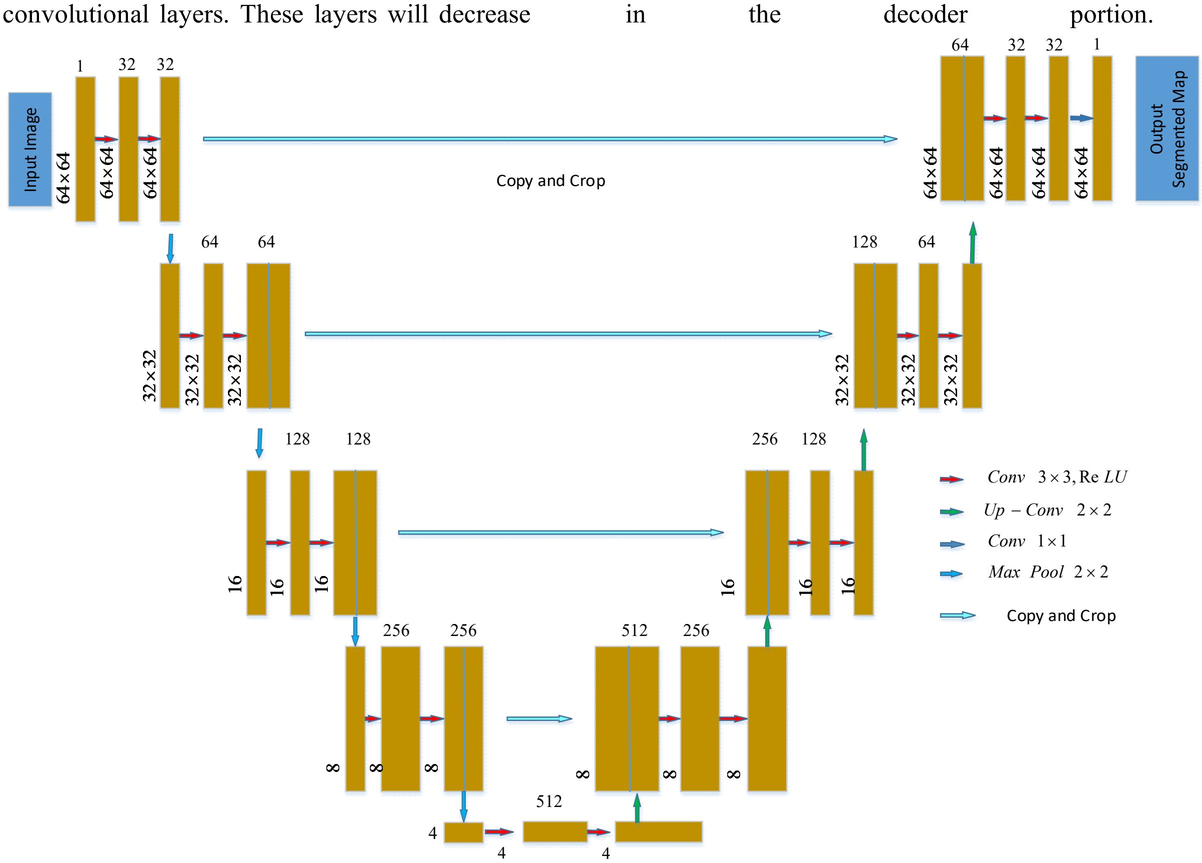


Fig. 5. Process of encoding and decoding

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Two 3x3 convolutions are applied repeatedly in the encoder section. Batch normalization and a ReLU come after each conversion. The spatial dimensions are then decreased by doing a 2x2 max pooling procedure. Once more, we reduce the spatial dimensions by half while doubling the channel features for every step of down-sampling. The expanding path of the decoder part consists of up sampling the feature map and then performing a 2x2 transpose convolution, which reduces the total number of multichannel features by half, for each iteration. Following a ReLU, the contracting route often provides us with a 3x3 convolution and an accumulation with the matching map of features. A 1x1 convolution is applied in the last layer to convert the channels into the necessary count of categories.

The size of convolutional kernel for each channel is adjusted to extract the features from the RGB channels. Since the information of weak edge in the feature graph can be easily disregarded, we use the activation layer's convolution network to map the final layer's acquired features to a more sensitive feature space. This increases the network's nonlinear characteristics and allows for the acquisition of more edge information. By mapping one higher dimension vector to another higher dimensional vector, the higher dimensional mapping layer enhances the nonlinear properties of the network. This can improve the expressiveness of the network and facilitate its convergence. Every channel's output contains several mappings thanks to the convolution layer above. After the improved image is created, the final image generating network must be constructed to obtain the pixel values for the R, G, and B channels. Using this U-Net, a noise map that is close to the actual picture size is produced. The LLWC picture may be improved by taking off the noise map. Using U-Net, the picture's comprehensive information is built, and the quality of the image is improved. U-Net's design makes it a flexible tool for picture enhancement jobs since it can record and recreate comprehensive information.

To further enhance the quality of image, multi scale retinex model is designed.

3.5 Improved Multi-scale Retinex

The multiscale retinex model improves the visible quality of the image by maintaining natural colors which are present in the image. The input image is convolved with different sizes of gaussian filters. Different spatial frequencies are achieved for each scale. The retinex output is evaluated at each scale using equation (3)

$$I_{MSR}(x,y) = log(I(x,y) - log(F(x,y) * I(x,y)) \tag{3}$$

$I(x,y)$ is the input image function, the gaussian filter for each scale is $F(x,y)$, $*$ is the convolution factor. If the image has a mixture of various colors and gray dominance, then retinex model needs to be improved. The improved multiscale retinex model introduces a color restoration function and is shown in figure 4.

$$I_{IMSR}(x,y) = \beta \log\left(\alpha \frac{I_i(x,y)}{\sum_{j=1}^{3} I_j(x,y)}\right) \tag{4}$$

The multiscale approach helps enhance details across different spatial frequencies. Final output is a contrast-enhanced image with improved visibility of details.

4. RESULTS AND DISCUSSION

4.1 System Environment

The experimental evaluation is performed using MATLAB 2021a. The system configuration utilized is 32gm RAM, intel i7 core OS, NVIDIA graphic card, and 500Gb storage space. The network is trained using $1080 \times 1080 \times 5$ sized images. The image enhancement model is designed using U-Net and Improved MSR.

4.2 Parameters Evaluated

The parameters are evaluated to estimate the performance of the designed model. The parameters like mean square error (MSE), Peak signal to noise ratio (PSNR), Structural similarity index measure (SSIM), Normalized Cross-Correlation (NCC), Mean Absolute Error (MAE), Feature Similarity Index method (FSIM), Entropy (N), Entropy (E), Correlation coefficient.

a. MSE

The average of the squares of the mistakes, or the average squared difference between the predicted values and the actual value, is the mean squared deviation (MSD) of an estimator. Since MSE shows the predicted value of the squared error loss, it is a risk indicator. Eq. 5 contains the MSE.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2 \quad (5)$$

b. PSNR

PSNR refers to the relationship between the signal's maximum potential intensity and the amount of noise which is corrupted and that reduces representational accuracy. Since many of the signals have a large dynamic range, the logarithmic decibel scale is typically used to describe the value of PSNR. PSNR is found in equation 6.

$$PSNR = 10\log_{10}\left(\frac{255 \times 255}{MSE}\right) \quad (6)$$

c. SSIM

A method for forecasting the perceived quality of digital films, television shows, and other digital pictures and media is called SSIM. A tool for comparing two drawings' similarity is called SSIM. Eq. 7 has SSIM information.

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (7)$$

Where, μ_x is the pixel samples mean of x; μ_y is the pixel sample mean of y; c_1, c_2 are constants; σ_x^2 variance of x; σ_y^2 variance of y; σ_{xy} covariance of x and y.

d. Normalized cross-correlation

Image registration can also be accomplished by normalized cross-correlation (NCC) between pixel intensities. NCC determines the best match by calculating the degree of similarity between the reference and target images with a window size that is equal to the template image.

e. Mean Absolute Error

The mean absolute distance between a pixel in one picture and its matching pixel in another image is called the Mean Absolute Error (MAE). You may easily evaluate the MAE as follows as it is the total of the (L1-norm) discrepancies between corresponding pixels in your two pictures, x and y, divided by the number of pixels.

$$MAE = \frac{\sum_{i=1}^{n}|y_i - x_i|}{n} \quad (8)$$

f. Feature Similarity Index Method

Index of Feature Similarity The process maps the characteristics of two photos and calculates their similarity. Two criteria need to be clarified to fully characterize FSIM. Phase congruency (PC) and gradient magnitude (GM) are the two. Between the reference picture and the deformed image, these two aspects must be weighed.

$$FS_{pc} = \frac{2.PC_1.PC_2 + C_1}{PC_1^2 + PC_2^2 + C_1} \quad (9)$$

$$FS_{gm} = \frac{2.GM_1.GM_2 + C_2}{GM_1^2 + GM_2^2 + C_2} \quad (10)$$

Here C_1 and C_2 are constantly functioning. In case of any divisions by zero will be avoided.

g. Entropy

An image's degree of uncertainty or unpredictability is measured by its entropy. The mathematical definition of it is as follows:

$$En = -\sum_{i=0}^{L-1} p(i)\log_2 p(i) \quad (11)$$

In the above formula, $p(i)$ is the probability associated with the gray-level i and L possible intensity levels of the image. This formula determines an image's global entropy. Discrete entropy is a metric used in image processing that expresses how many bits are needed to encode a picture. A picture will have greater detail the higher its entropy value.

h. Correlation Coefficient (CC)

The range of CC varies from -1.0 to 1.0. When there is a perfect match between the pixel values in two photographs, the correlation coefficient is 1.0. When there is a complete discrepancy in the pixel values of the two pictures, the correlation coefficient is -1.0.

4.3 Design Implementation

We shall conduct a thorough analysis of the algorithm's performance in this portion of the study. To produce the improved picture, the trained network is first utilized to acquire the noise map. The network's viability and ability to provide high-quality visual outcomes are confirmed by the image. The benefits of the suggested approach are then illustrated using quantitative techniques by comparing it with various parameter types. crucial factors, such as image SSIM and PSNR.

Image1.

From the renoir dataset image 326 is considered and processed with out prosposed model. The output achieved is shown in figure 6. The param*-eters evaluated is shown in table 2.

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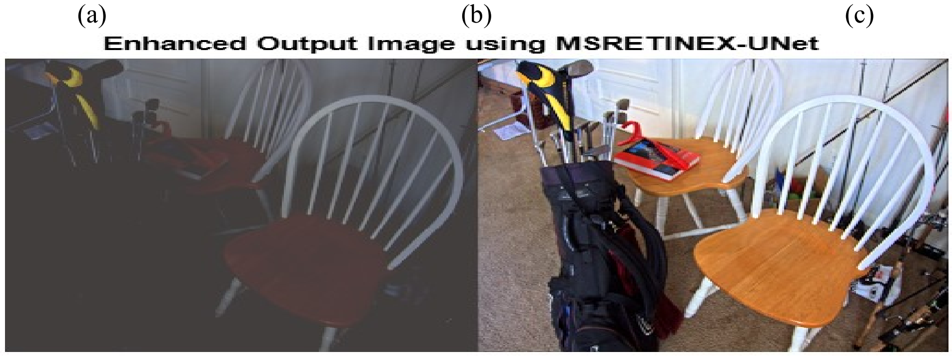
(a) (b) (c)



(d)

Fig.6. (a) Input Image (b) Grey Color Image (c) Enhanced image using Multi-layer CNN (d) Enhanced using UNet- Improved Multiscale Retinex

Table 2. Parametric Results comparison for Image1

Technique/ Parameter	PSNR	SSIM	MSE	NCC	MAE	FSIM	Entropy (N)	Entropy (E)	Corr-Coeff
Multi Scale CNN	33.32	0.92	0.018	0.938	0.128	0.99	0.79	0.64	0.99
U-Net + IMSR	33.56	0.94	0.016	0.948	0.118	0.99	0.817	0.754	0.99

The result shown in table 2 indicates that the proposed model achieved better results. The output of multi-scale CNN method looks like image have some unnatural deviations in color, when compared to the outcome of improved MSR-UNet model. The noise factor reduced by combining U-Net and IMSR. Dual enhancement of output provides more visual quality. The model is tested on different images and outcomes are shown in figures 7 to 10. The parameters evaluated for every image are shown in table 3-table 6.

Image2.

In figure 7, the input image is 426 number images of the dataset. The output achieved is shown. The parameters are recorded in table 3.

In figure 7, the 405 image is considered from the Renoir dataset. The evaluated parameters are shown in table 3. The PSNR value is improved using the proposed model. The SSIM is improved by 0.2% by combining U-Net and IMSR.

Image3.

In figure 8, the input image is 484 number images of the dataset. The output achieved is shown. The parameters are recorded in table 4.

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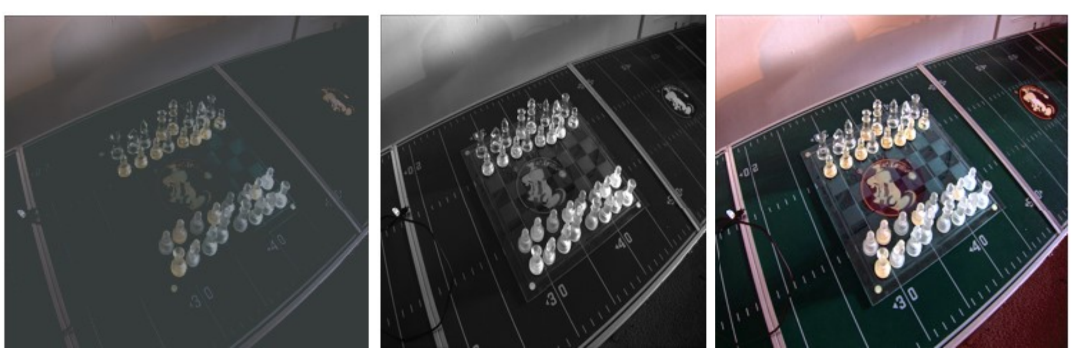
(a) (b) (c)

(d)

Fig.7. (a) Input Image (b) Gey color image (c) Enhanced image using Multi-layer CNN (d) Enhanced using UNet- Improved Multiscale Retinex

Table 3. Parametric Results comparison for Image2

Technique/ Parameter	PSNR	SSIM	MSE	NCC	MAE	FSIM	Entropy (N)	Entropy (E)	Corr-Coeff
Multi Scale CNN	33.36	0.88	0.010	0.94	0.095	0.99	0.499	0.410	0.99
U-Net + IMSR	34.93	0.90	0.009	0.952	0.085	0.99	0.525	0.517	0.99



(a) (b) (c)

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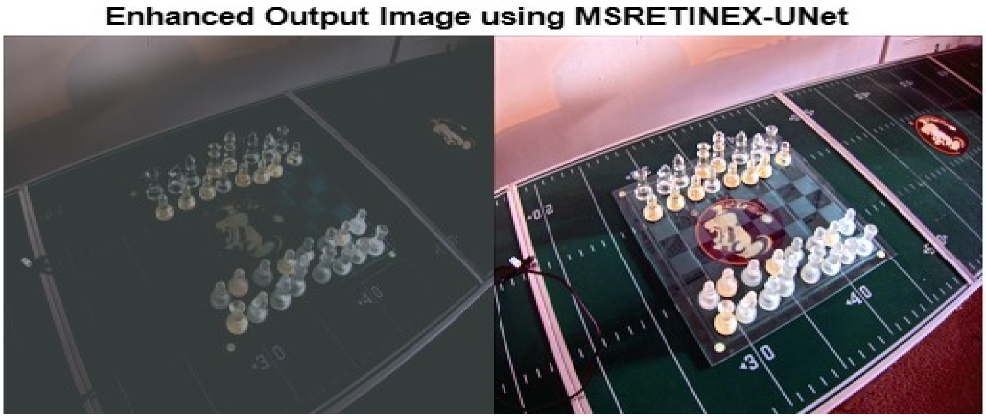

(d)

Fig. 8. (a) Input Image (b) Grey Color image (c) Enhanced image using Multi-layer CNN (d) Enhanced using U-Net – Improved Multiscale Retinex

Table 4. Parametric Results comparison for Image3

Technique/ Parameter	PSNR	SSIM	MSE	NCC	MAE	FSIM	Entropy (N)	Entropy (E)	Corr-Coeff
Multi Scale CNN	33.35	0.883	0.012	0.943	0.112	0.99	0.678	0.495	0.99
U-Net + IMSR	34.94	0.899	0.0113	0.953	0.102	0.99	0.704	0.603	0.99

From table 4, in this case the improvement of SSIR is about 0.016% when compared the proposed model to traditional model.

In figure 9, the input image is 506 number images of the dataset. The outputs achieved is shown. The parameters are recorded in table 5.

Image4.

(a) (b) (c)

(d)

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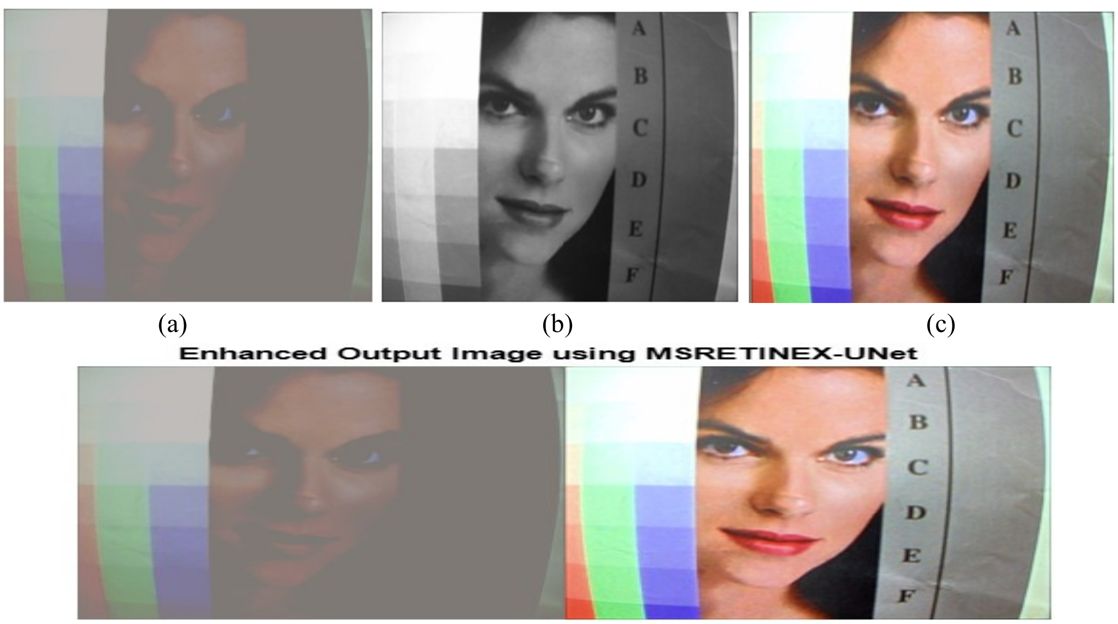
Fig.9. (a) Input Image (b) Grey Color Image (c) Enhanced image using Multi-layer CNN (d) Enhanced using UNet-Improved Multiscale Retinex

Table 5. Parametric Results comparison for Image4

Technique/ Parameter	PSNR	SSIM	MSE	NCC	MAE	FSIM	Entropy (N)	Entropy (E)	Corr-Coeff
Multi Scale CNN	33.36	0.893	0.017	0.944	0.102	0.99	0.620	0.483	0.99
U-Net + IMSR	34.83	0.909	0.0094	0.954	0.092	0.99	0.646	0.590	1.00

Image5.

In figure 10, the input image is 664 number images of the dataset. The output achieved is shown. The parameters are recorded in table 6.



(a) (b) (c)

(d)

Fig.10. (a) Input Image (b) Grey Color Image (c) Enhanced image using Multi-layer CNN (d) Enhanced using U-Net - Improved Multiscale Retinex

Table 6. Parametric Results comparison for Image5

Technique/ Parameter	PSNR	SSIM	MSE	NCC	MAE	FSIM	Entropy (N)	Entropy (E)	Corr-Coeff
Multi Scale CNN	33.29	0.977	0.0303	0.938	0.153	0.99	0.986	0.982	0.98
U-Net + IMSR	33.52	0.99	0.029	0.948	0.143	0.99	1.012	1.089	0.986

By observing the results from figure 7- 10, and table 3 to 6 the proposed model performance is good when compared to the general CNN model. We employed the two primary features that are highly valued in image-quality metrics—SSIM and PSNR as shown in Table 7 to ensure a fair qualitative comparison. We used the actual extreme LLWC photos together with the output result from our training model for this comparison. In addition to achieving excellent performance, UNet-IMSR also demonstrated strong double enhancement model performance.

Table 7. Comparison of PSNR and SSIM parameters

Author	Technique	PSNR	SSIM
P.P Banik et al., [29]	Retinex	8.26	0.12
W. Wang et al., [30]	Glad-Net	10.96	0.18
C. Li et al., [31]	Lighten-Net	11.96	0.63
F. Lv et al., [32]	MBLLEN	17.65	0.93
C. Wei et al., [33]	Retinex-Net	17.39	0.91
Y. Jiang et al., [34]	Enlighten GAN	17.53	0.91
S. Lim et al., [35]	DSLR	14.93	0.83
L. Zhang et al., [36]	ExcNet	16.39	0.9
A. Shu et al., [19]	RRD-Net	10.87	0.51
B. Guo et al., [37]	Zero DEC	14.86	0.82
C.Li et al., [38]	Zero DEC++	14.68	0.85
J. Hai et al., [18]	R2R Net	18.17	0.89
C. Chen et al., [39]	U-Net	28.64	0.79
L. Shen et al., [40]	MSR-Net	19.5	0.92
H. Jiang et al., [41]	LL-Net	22.58	0.63
Proposed	U-Net+ IMSR	34.94	0.99

The proposed model (MSR-UNET) was evaluated using multiple low-light images from the Renoir dataset. Performance was compared against existing models like HE, CLAHE, and GAN-based enhancement methods.

Discussion of Limitations

While the model outperforms conventional methods, certain limitations exist:

1. **Computational Overhead:** The U-Net architecture increases processing time, making real-time applications challenging.
2. **Dataset Dependency:** The model is optimized for Renoir dataset images, requiring fine-tuning for other datasets.
3. **Potential Color Shifts:** While minimized, slight color distortion may occur in extreme low-light conditions.

5. CONCLUSION

This study introduced MSR-UNET, a hybrid model integrating CNN-based feature extraction with Retinex-inspired enhancement, to address the limitations of existing low-light image enhancement techniques. Our experimental findings validate the superior performance of MSR-UNET over traditional methods, achieving a PSNR of 34.3 dB and SSIM of 99%.

The study confirms that combining deep learning with Retinex-based color correction provides a balanced enhancement without significant artifacts. Future research will focus on real-time implementation and applying the model to diverse datasets.

The proposed approach significantly improves low-light image enhancement, making it a promising solution for medical imaging, surveillance, and night-time photography applications.

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