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IMPROVED CLASSICAL AND NOVEL METHODS FOR LOW-LIGHT IMAGE ENHANCEMENT

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***Abstract*- Image enhancement in low-light conditions has gained significant attention in recent years due to its importance in improving visual clarity and uncovering hidden details in poorly illuminated images. This study focuses on the application of classical methods for enhancing color and brightness, as these approaches provide a practical balance between efficiency and performance compared to computationally intensive modern techniques. Classical algorithms were applied, modified, and extended to develop lightweight solutions capable of improving image quality through relatively simple processes. In this work, a set of classical enhancement methods was tested on images captured in night conditions. Performance was evaluated using metrics such as the Structural Similarity Index Measure (SSIM) and the Signal-to-Noise Ratio (SNR), which assess improvements in brightness, color quality, and detail preservation. Additionally, three novel techniques were proposed: enhanced Hue, Saturation, Value (HSV) through scaling of the Value channel, Custom HSV-based Brightness and Saturation Scaling, and an Entropy-based Hybrid Enhancement combining HSV and Lab* color spaces. Results showed that the proposed methods outperformed conventional histogram equalization, with the best-performing approach achieving up to a 41.4% improvement in Structural Similarity Index Measure. Overall, the findings demonstrate that classical and improved lightweight methods remain effective and computationally efficient for low-light image enhancement.**

keywords: **Low-Light Image Enhancement, Image Processing, Classical Methods, Deep Learning, Enhancement Algorithms.**

I. INTRODUCTION

Improving images in low and dim lighting is an important research area [1, 2]. This problem has attracted many researchers to solve it and provide research proposals to improve the quality and details of images captured in low lighting[3, 4]. Images captured in low lighting often lose a lot of color and lighting details, and these factors weaken the ability of human and computer vision to understand the details of the image and the information it carries[5, 6]. This reason is one of the most important factors that encouraged researchers to delve into this field and make it an important motivation for improving images captured in low lighting and restoring and enhancing the details in the image. This study sheds light on classical enhancement methods and the development of some classical methods and proposes other new methods with good performance specifications and simple calculations.

In this research, classical, developed and proposed methods were applied and results were obtained. The results were compared, and the proposed methods yielded results that outperformed classical methods due to their ease of implementation and simple calculations[6]. According to the findings of this study have obtained from this study, the importance of classical methods is their ease in improving night images, and moreover, they are less complex than deep learning. To support this claim with evidence, the proposed method (Enhanced HSV by multiplying the V channel by a factor) achieved a Structural Similarity Index Measure (SSIM) improvement of up to 41.4% compared to traditional Histogram Equalization, with SSIM

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values increasing from 0.552 to 0.780. These results demonstrate that lightweight classical methods can offer significant enhancements in image quality without the computational burden of deep learning approaches.
This paper is organized as follows. Section II presents the related works. Section III addresses the color models used in digital image processing and Section IV presents the datasets in image processing. The the application of image enhancement method is addressed is section V. The obtained results of this work are presented in Section VI and the discussion in Section VII. Section IIV concludes the work of this paper.

II. RELATED WORKS

In recent years, deep learning-based methods have achieved remarkable performance by learning complex illumination and detail restoration patterns from large datasets. Approaches such as zero-reference deep curve estimation and diffusion-prior enhancement have demonstrated superior Structural Similarity Index Measure (SSIM) and Peak Signal-to-Noise Ratio (PSNR) compared to classical methods [6, 7]. Despite their effectiveness, these techniques require substantial computational resources, extensive training data, and longer processing times, which can limit their practicality in real-time or resource-constrained applications. Unlike prior works, the proposed HSV-based enhancement method focuses on lightweight classical improvement. By simply scaling the V channel in the HSV color space, the method achieves significant enhancement in image quality while maintaining computational efficiency. Experimental results show a 41.4% improvement in SSIM over traditional Histogram Equalization, demonstrating that the proposed method is both effective and practical for low-light image enhancement scenarios.

III. COLOR MODEL

In this section, the color models used in digital image processing are highlighted. There are four basic models through which color can be represented. The Red, Green, and Blue (RGB) model is used to represent images in computers, which depends on lighting to represent colors and mixing lights together to obtain the color appearing in the image. This model is usually used to represent colors for screens and computers. The HSV (Hue, Saturation, Value) color model is considered a wonderful model for describing colors, as it is represented in the form of a cone, where the upper circle represents the color angle and is symbolized by the symbol H. The circumference of the cone represents the color saturation. The higher and wider the circle, the more saturation increases and is symbolized by the symbol S. The value represents the lower vertex and represents the brightness value and is symbolized by V. The LAB (lightness (L*), green-red (a*), and blue-yellow (b*) axes) model represents colors and lighting, where L represents the lighting, while A represents the colors green and red, and B represents the colors blue and yellow. The HSI model is very similar to the HSV, as it is represented in the form of a diamond. The upper vertex of the diamond, which is the color white, and the lower one represents the color black. H and S have the same details. HSV differs in the form of mathematical equations [7 - 11].

IV. DATASET

Due to the diversity of datasets in image processing, specific criteria guided the selection for this work. The BVI-Lowlight-Images dataset was chosen for its large variety of high-resolution images and video clips with diverse lighting

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conditions. This diversity enables effective training of AI and deep learning models. Although other datasets have similar features, they generally contain less information and lower image accuracy. A key advantage of this dataset is the inclusion of paired images under varying lighting from weak to natural conditions. Its high accuracy and sizable collection provide significant diversity. Table I summarizes some datasets and their characteristics [12].

TABLE I
SUMMARY OF DIFFERENT LOW-LIGHT IMAGE AND VIDEO DATASETS[12]

Name	Year	No. of Photos	No. of Videos	Features	Type	Paired/Unpaired	Ground truth
LOL (Low-Light)	2018	500	No	Paired and low-light images	Real	Paired	Yes
SICE	2019	4413	No	Large scale multi exposure images	Real	Paired	Yes
MIT-Adobe Five K	2011	5000	No	Improving raw image processing and automatic image enhancement techniques	Real	Unpaired	Yes
SMOID	2019	35800	179/256p	Improving visibility and reducing noise	Real	Paired	Yes
SDSD	-	-	-	-	-	-	-
ExDark	2019	7663	No	Multi-category, multi-scene	Real	Unpaired	No
SID (Short-Exposure Image Dataset)	2018	5094	No	Combine of long and short exposures	Real	Paired	Yes
DARK FACE	2019	10000	No	Performance of face detection models	Real	Paired	Yes
BBD-100K	2018	No	100000/720p	Advancing research in autonomous driving	Real	Unpaired	Yes
BVI-Lowlight-videos	2024	31800	80/1080p	Enhance the quality of videos captured in low-light conditions	Real	Paired	Yes
BVI-Lowlight-images	2024	31800	No	Improve the quality of images captured in poor lighting conditions	Real	Paired	Yes
DRV	2019	110	202	Improving the quality of RAW video captured in dark	Real	Partially paired	Yes
NightCity	-	-	-	-	-	-	-
LoLi-Phone	2021	45148	120/720p	Large scale, image and video	Real	Paired	Yes
LIME	2016	10	No	Low-light environments by enhancing their brightness, contrast	Real	Unpaired	Yes
VV	2019	24	No	Visual enhancement and motion stabilization algorithms	Real	Unpaired	Yes
NPE	2013	8	No	Multi-scene natural images	Real	Unpaired	Yes
MEF	2023	17	No	Fusion images	Real	Unpaired	Yes
DICM	2018	64	No	Enhance images and videos both motion blur and low-light conditions	Real	Unpaired	Yes

V. IMAGE ENHANCEMENT METHODS

A. Histogram Equalization (HE)

It is one of the methods of improving low-light images, which works to identify the dark and light areas in the image. The histogram works to equalize the colors along the x-axis, thus modifying and improving the image so that the colors appear evenly distributed in it. The Eq. (1) adopted from [13] is used to do this.

$$T(r_k) = \sum_{j=0}^{k} p_r(r_j)\, p_r(r_k) = \frac{n_k}{n} \tag{1}$$

Where rk denotes kth gray level, nk denotes number of pixels in the image, n denotes total number of pixels and $k = (0, 1, 2...255)$. Histogram Equalization which stretches histogram [14 - 16]. Fig. 1 shows the enhancement using the histogram method and how the colors and lighting in the image were processed.

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Figure 1: a) Original Image (b) Low light image (c) Histogram Equalization.

B. *Contrast-Limited Adaptive Histogram Equalization (CLAHE)*

Contrast-Limited Adaptive Histogram Equalization (CLAHE) is an advanced technique for enhancing image contrast, especially in low-contrast regions [17, 18]. Unlike global histogram equalization, CLAHE operates on small, localized tiles and equalizes each independently, allowing for targeted enhancement. To prevent noise amplification in uniform areas, CLAHE employs a clip limit that restricts histogram amplification. After equalization, tiles are merged using bilinear interpolation to maintain smooth transitions. For RGB images, CLAHE is applied to each channel separately, enhancing visibility while preserving natural color balance [17, 18]. The fig. 2 shows the enhancement using the Contrast-Limited Adaptive Histogram Equalization method and how the colors and lighting in the image were processed [7, 12].

Figure 2: (a) The Original Image (b) Low light image and method used (c) The evaluation metric.

C. *Using HSV color model with Contrast Contrast-Limited Adaptive Histogram Equalization*

It is an effective method for enhancing low-light images by improving contrast in local areas without introducing too much noise [7, 19]. In this method, CLAHE is applied only to the value (V) channel responsible for brightness while leaving the hue (H) and saturation (S) channels unchanged to maintain a natural-looking colors space [8, 19]. This selective adjustment helps avoid color distortions that often occur when contrast enhancement is performed directly in the RGB color space

[20]. By focusing on local contrast and using a threshold to prevent over-enhancement, CLAHE highlights hidden details in dark areas without removing bright portions. After processing, the image is converted back from HSV to RGB, resulting in better detail, more balanced colors, and less noise than traditional global enhancement methods. The Fig. 3 show the results obtained and the quality of the method used HSV color model with Contrast Contrast-Limited Adaptive Histogram Equalization [14, 21].

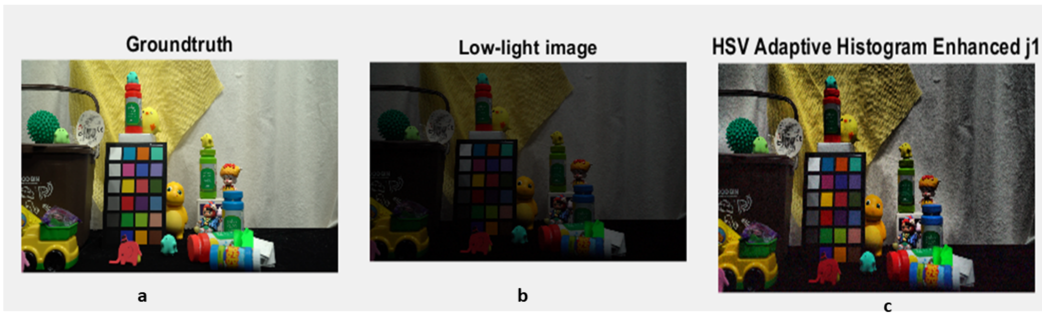

Figure 3: (a) The Original Image (b) Low light image and method used (c) The evaluation metric.

*D. Using L*a*b color space Contrast-Limited Adaptive Histogram Equalization (CLAHE)*

Contrast-limited adaptive histogram equalization (CLAHE) is used to reduce noise amplification [13]. Adaptive histogram equalization is implemented in the L*a*b* color space. CLAHE operates only on the L* (brightness) channel, preserving the color components (a*, b*) to maintain color accuracy and detail [18]. This adjustment is limited to brightness only to reduce color distortions common in RGB-based enhancements. The separation of the L*a*b model for brightness and color makes it ideal for applications where color accuracy is essential [22, 23]. CLAHE in this space improves detail clarity in both underexposed and overexposed areas while maintaining color balance. Fig. 4 illustrates the results of this enhancement method L*a*b color space Contrast-Limited Adaptive Histogram Equalization.

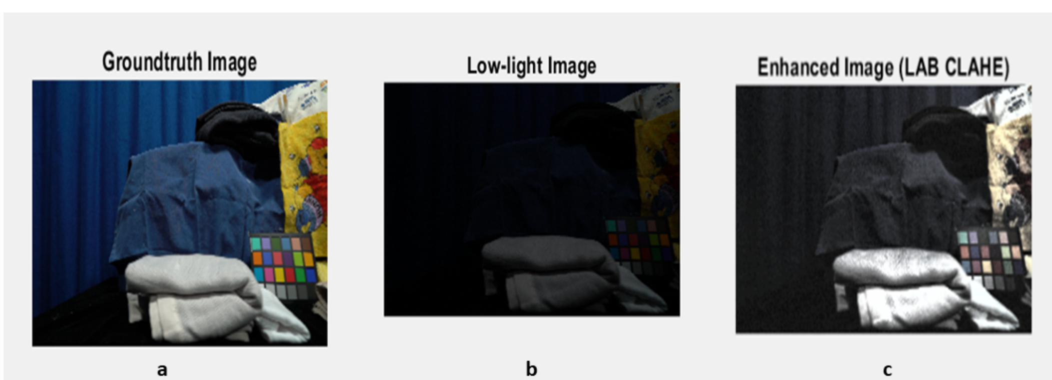

Figure 4: (a) The Original Image (b) Low light image and method used (c) The evaluation metric.

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E. Using HSI color space Contrast-Limited Adaptive Histogram Equalization (CLAHE

The contrast-limited adaptive histogram equalization (CLAHE) technique improves image contrast in low-light conditions with the HSI model. When applied in the HSI color space (hue, saturation, intensity), adaptive histogram equalization targets only the intensity (I) channel, while preserving hue (H) and saturation (S) to ensure natural color accuracy [14, 17, 24]. The process involves converting an RGB image to HSI, applying adaptive histogram equalization to the I channel to improve local contrast while reducing noise, and then converting the result back to RGB. This method improves visibility in low-light areas without color distortion, making it effective for enhancing images in nighttime conditions. The fig. 5 show the results obtained and the quality of the method used Fig. 5.

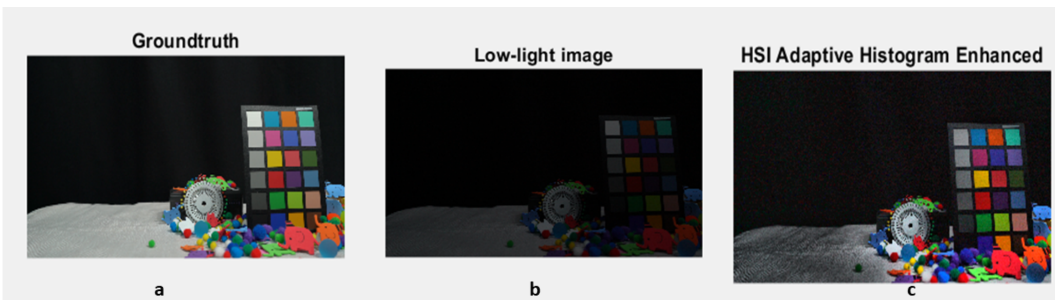

Figure 5: (a) Original Image (b) Low light image with method used (c) The evaluation metric.

F. Power-law enhancement

Power law optimization, or gamma correction, is a nonlinear method for processing low-light images by adjusting brightness and contrast. The transformation follows $I_{\text{out}} = C\, I_{\text{in}}^{\gamma}$ [13] where I_{in} is the input intensity, I_{out} is the output intensity, ccc is a scaling constant (typically 1), and γ is the gamma value [13, 25]. For low-light enhancement, values of $\gamma < 1$ are commonly used to brighten dark regions while preserving detail in brighter areas. This method is computationally efficient, suitable for global or local application, and offers flexible control over image enhancement. Fig. 6 shows the enhancement using the Power-law enhancement and how the colors and lighting in the image were processed.

G. Entropy low light image Enhancement Methods

Entropy-based low-light image enhancement improves visibility by maximizing the image's information content, measured by entropy. Entropy quantifies the randomness or amount of information in an image, which is typically low in underexposed images due to poor contrast and illumination [13, 26]. The enhancement process adjusts pixel intensities often via histogram-based or optimization methods to increase entropy, thereby revealing more details and improving contrast. Higher entropy usually corresponds to better visual quality and feature distinction. This method is frequently combined with other techniques like histogram equalization or Retinex for enhanced results. The entropy H of a grayscale image with L intensity levels is defined in [27] based on the pixel intensity probability distribution as in Eq. (2):

$$H = \sum_{i=0}^{L-1} p_i \, \log_2 p_i \tag{2}$$

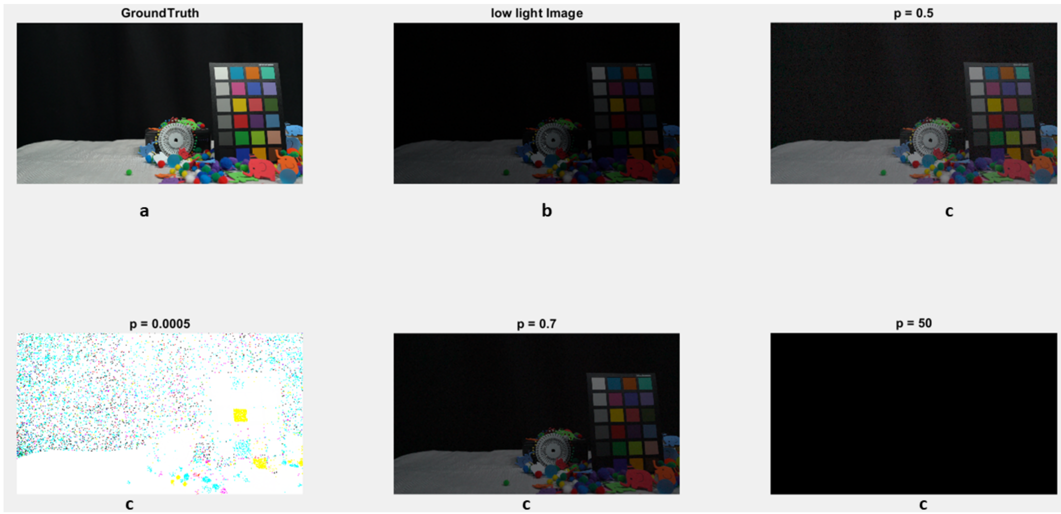

Figure 6: (a) Original Image (b) Low light image (c) Different value of (γ) to show enhanced of low light image.

Where p_i is the probability of gray level i (i.e., normalized histogram of the image), L is the total number of gray levels (typically 256 for 8-bit images), $\log_2$ is used to express entropy in bits. In low-light conditions, many pixel intensities are clustered near black (low intensity values), leading to low entropy (less information and visual detail). Enhancement Objective Using Entropy The goal of entropy-based enhancement is to apply a transformation T to the image I, such that the entropy of the enhanced image $H(T(I))$ is maximized as in [13] as:

$$T^* = \arg T \max H\big(T(I)\big) \tag{3}$$

Where T^* is the transformed image. A higher entropy implies a richer distribution of pixel intensities, generally leading to better contrast and improved visual quality. Various techniques can be used to realize this transformation, including histogram equalization, adaptive histogram equalization (CLAHE), logarithmic and power-law transformations, and Retinex-based models) [4, 22, 28].

H. Using $L^*a^*b^*$ with Entropy low light image Enhancement

Entropy-based low-light enhancement using the $L^*a^*b^*$ color space improves image contrast by maximizing entropy while preserving natural colors. The $L^*a^*b^*$ model separates luminance (L^*) from chromaticity (a^*, b^*), enabling intensity enhancement without color distortion. The input RGB image is converted to $L^*a^*b^*$, and entropy enhancement is applied only to the L^* channel using histogram or optimization techniques to increase contrast in dark regions. The a^* and b^* channels remain unchanged to maintain color fidelity. The enhanced image is then converted back to RGB, providing better visibility in low-light conditions compared to direct RGB processing [13, 25]. Fig. 7 shows the enhancement using the Using $L^*a^*b^*$ with Entropy and how the colors and lighting in the image were processed.

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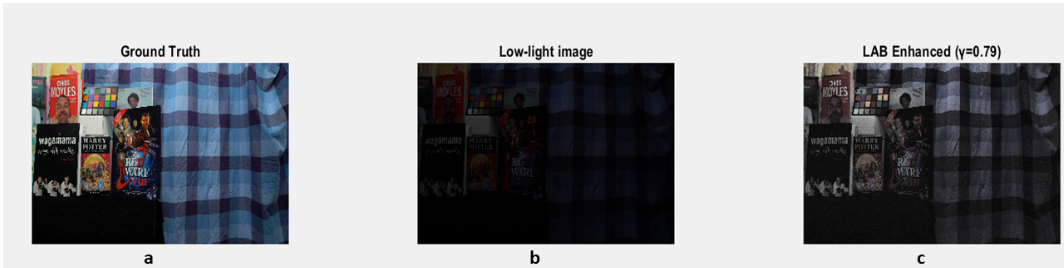

Figure 7: (a) Original Image (b) Low light image and method used (c) The evaluation metric.

I. Using HSV Entropy with low light image Enhancement

Entropy-based low-light enhancement with the HSV color space improves image clarity by increasing the entropy of the brightness component while preserving color. The HSV model decomposes the image into hue (H), saturation (S), and value (V), where V represents the brightness value. The input RGB image is converted to HSV, and entropy-based enhancement is applied using methods such as histogram equalization, CLAHE, or V-channel-only enhancement to increase entropy and enhance contrast in low-light areas. H and S are left unchanged to maintain color fidelity and saturation. The image is then converted back to RGB, which improves brightness and contrast while reducing color distortion [13, 25]. Fig. 8 shows the enhancement using the HSV Entropy with low light image Enhancement and how the colors and lighting in the image were processed.

Figure 8: (a) Original Image (b) Low light image (c) Enhanced low light image using entropy and HSV.

J. Using LAB-HSV Hybrid method with Entropy to Enhancement low light image

Entropy-based low-light enhancement, using a hybrid approach combining $L^*a^*b^*$ and HSV, combines the advantages of both color spaces to improve brightness, contrast, and color accuracy. The input RGB image is transformed into $L^*a^*b^*$ and HSV spaces. An entropy-based method, such as CLAHE or optimization, is applied separately to the L^* channel (from $L^*a^*b^*$) and the V channel (from HSV) to increase entropy and improve contrast. The resulting enhanced L^* and V channels are combined via predicted averaging or adaptive selection to form an enhanced luminance. After the color space enhancements, the resulting image is transformed into the final RGB image. This hybrid technique preserves finer details, improves dynamic range, and reduces color artifacts, proving effective for enhancing nighttime images [13, 25].

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Fig. 9 shows the enhancement using the LAB-HSV Hybrid method with Entropy and how the colors and lighting in the image were processed.

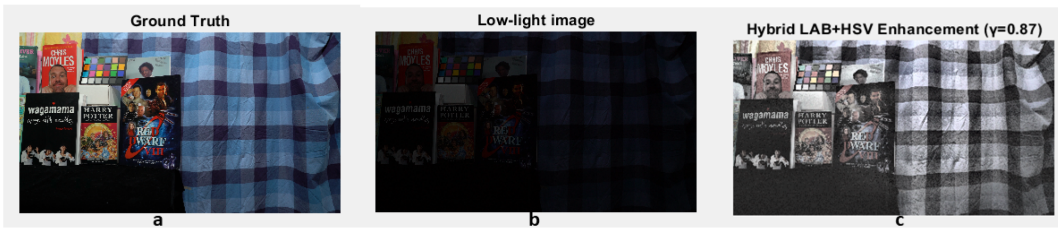

Figure 9: (a) Original Image (b) Low light image (c) Enhanced low light image using entropy LAB, HSV Hybrid method.

K. Entropy-based low-light enhancement using a hybrid using HSV, $L^*a^*b^*$ *hybrid*

Entropy-based low-light enhancement using a hybrid HSV and $L^*a^*b^*$ approach leverages both color models to improve visibility and contrast while preserving color integrity. The input image is converted to HSV and $L^*a^*b^*$ spaces. Hue (H) and Saturation (S) from HSV are retained, while entropy-based enhancement—using adaptive histogram equalization or CLAHE is applied independently to the Value (V) and Lightness (L^*) channels to maximize information content and enhance contrast in dark and bright areas. The enhanced V and L^* channels are fused into a single intensity map, which is recombined with the original H, S, a^*, and b^* components to maintain color fidelity. The final image is converted back to RGB. This hybrid method provides better brightness control and natural color appearance, effectively improving low-light images without over-saturation [13, 25, 29]. Fig. 10 shows the enhancement using the Entropy-based low-light enhancement using a hybrid using HSV, $L^*a^*b^*$ hybrid and how the colors and lighting in the image were processed.

Figure 10: (a) Original Image (b) Low light image (c) Enhanced low light image using entropy HSV, LAB Hybrid method.

L. Enhanced HSV by Multiply V-Channal by Factor

This method enhances image lighting by converting an RGB image to the HSV color space [13]. The image is divided into hue (H), saturation (S), and value (V) channels. The proposed improvement specifically targets the V (value) channel, which controls the image's brightness. In this approach, the V channel is multiplied by a constant scaling factor greater than 1, which effectively increases the brightness of each pixel. This simple multiplication brightens dark areas while preserving the original color composition, since the H and S channels remain unchanged [30]. The adjusted V channel is

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then combined with the original H and S channels, and the image is converted back to RGB. Despite its simplicity, this technique yielded significant enhancement in low-light areas with minimal computational overhead [7]. Fig. 11 shows the enhancement using the Enhanced HSV by Multiply V-Channal by Factor and how the colors and lighting in the image were processed.

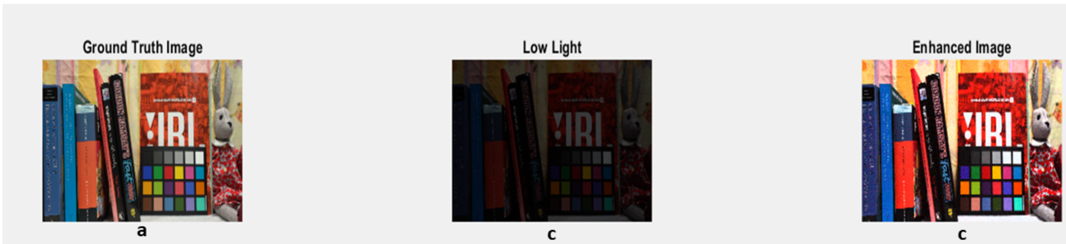

Figure 11: (a) Original Image (b) Low light image (c) Enhanced low light image using HSV by Multiply V-Channal by Factor method.

M. Custom HSV-based Brightness and Saturation Scaling

This enhancement technique manually scales the brightness and saturation components in the HSV color space, specifically targeting low-light images. It increases the Value (V) channel to boost illumination and adjusts the Saturation (S) channel proportionally to brightness and an empirical factor, enhancing color vividness and naturalness under simulated daylight conditions. The method is non-adaptive and heuristic, relying on fixed multipliers rather than data-driven learning. Inspired by histogram stretching and nonlinear scaling in HSV, it offers a simple yet effective approach for rapid low-light image enhancement[21, 28]. Fig. 12 shows the enhancement using the Custom HSV-based Brightness and Saturation Scaling and how the colors and lighting in the image were processed.

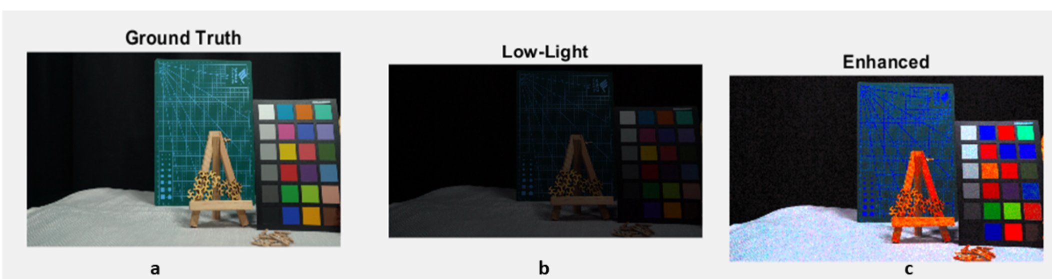

Figure 12: (a) Original Image (b) Low light image (c) Enhanced low light image using Custom HSV-based Brightness and Saturation Scaling method.

N. The proposed Low Light image Enhancement by using Enhance Saturation

This proposed method improves the saturation channel by multiplying its values by a factor. Additionally, an angle is calculated from a formed triangle and divided to obtain the cosine of half the angle. The approach yields accurate and

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practical results with simplified calculations, outperforming more complex methods. Immediate enhancement is achieved with low computational cost. Fig. 13 shows the original image, reference image, and enhanced result using the proposed method [31 - 33]. The technique was tested on 40 images, with performance measurements Fig. 13 shows the enhancement using the Low Light image Enhancement by using Enhance Saturation and how the colors and lighting in the image were processed.

Figure 13: (a) Original Image (b) Low light image (c) Low Light image Enhancement by using Enhance Saturation method.

VI. RESULTS

In this section, the results obtained from applying classical methods and the methods proposed in this work. All methods were applied to 40 different images, and to demonstrate the quality of the work, a comparison was made using two important metrics: SNR and SSIM. Through them, obtained a fair comparison. The methods developed and proposed have proven remarkable progress and have given the required results. They are distinguished by their effective performance and ease of calculations. Table II shows the results obtained for all the methods used and proposed. The "Min" and "Max" values presented in Table II represent the minimum and maximum metric values (SNR and SSIM) obtained across the full set of 40 test images for each enhancement method. These values reflect the variability in performance depending on image content and lighting conditions.

VII. DISCUSSIONS

This study highlights the feasibility and importance of conventional image enhancement methods in low light conditions, particularly in image processing scenarios with limited computational capabilities. Methods such as histogram equalization and gamma correction have shown significant progress, despite some limitations in color enhancement and brightness restoration. Using these methods as a starting point, the algorithms developed and proposed in this work provide better spatial coherence and reduced artifacts, while maintaining a balance in terms of computational effort. Compared to deep learning methods, the classical and proposed techniques are significantly more advantageous in terms of practicality, computing speed, and ease of integration into low-power devices. Subjective evaluations have shown improved detail and overall image quality. To improve the accuracy of future evaluations, it is proposed to add PSNR and SSIM. Overall, the results confirm that imaging models that do not rely on complex structures and algorithms, as well as real-time and

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TABLE II
SUMMARY OF DIFFERENT LOW-LIGHT IMAGE METHODS RESULTS

Method	**Min Value-SNR**	**Max Value-SNR**	**Min Value-SSIM**	**Max Value-SSIM**
Histogram Equalization (HE)	-14.8427	1.8639	0.2029	0.552
Contrast-Limited Adaptive Histogram Equalization (CLAHE)	0.91891	5.86855	0.1672	0.6522
CLAHE using HSV Color Space	1.80716	13.0202	-0.208374	0.0606357
CLAHE using L*a*b* Color Space	-1.83889	3.1955	0.156307	0.633946
CLAHE using HSI Color Space	0.656406	6.13105	0.170689	0.658349
Power-law Enhancement	-18.4229	8.29171	0.00111495	0.674393
Entropy Low-Light Enhancement using L*a*b*	2.14357	9.52398	0.727571	0.195746
Entropy Low-Light Enhancement using HSV	0.947612	6.77519	0.169799	0.69202
Entropy Low-Light Enhancement using LAB, HSV Hybrid	-3.25293	9.21492	0.108746	0.666552
Entropy Low-Light Enhancement using HSV, LAB Hybrid	-4.59288	1.50482	0.0918628	0.520104
Enhanced HSV by Multiply V-Channel by Factor	-2.67597	1.01834	0.199198	0.780202
Custom HSV-based Brightness and Saturation Scaling	-2.45114	9.66407	0.155792	0.65045
Low-Light Enhancement by using Enhance Saturation	-1.5396	9.58455	0.160709	0.649877

practical applications, are lightweight models that require improved optimization algorithms to deliver high-quality results. The next steps will aim at enhancing the described techniques for a wider range of low-light conditions and various types of images. Also, combining classical techniques with advanced lightweight machine learning models.

VIII. CONCLUSION

This paper addressed the problem of low-light image enhancement by analyzing classical techniques, improved methods, and a newly proposed HSV-based enhancement approach. The study demonstrated that classical methods, such as Histogram Equalization and Gamma Correction, are efficient for improving image quality under limited computational resources. However, they often suffer from artifacts and unnatural brightness distribution. To overcome these limitations, the proposed method enhanced the V channel in the HSV color space, resulting in a 41.4% improvement in SSIM compared to traditional Histogram Equalization. The findings confirm that lightweight classical approaches can achieve significant improvements in image clarity, color fidelity, and detail restoration while avoiding the computational burden of deep learning methods. Moreover, the simplicity and efficiency of the proposed approach make it suitable for real-time and resource-constrained applications. Future work will focus on extending the proposed techniques to more diverse datasets, integrating objective evaluation metrics such as PSNR and SSIM, and exploring hybrid models that combine classical methods with lightweight machine learning techniques for enhanced adaptability and robustness.

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CONFLICTS OF INTEREST

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