ISSN: 2178-7727

Low-Contrast Color Image Enhancement with Improvised Histogram Equalization based on Spatial Contextual Information

B. Shoba Rani[1*], Seetharam Khetavath[2]

[1]Scholar, Department of ECE, Chaitanya Deemed to be University, Hanmakonda, India. Email: shobarani.research@gmail.com
[2]Professor & Head, ECE Department, Chaitanya Deemed to be University, Hanmakonda, India. Email: seetharamkhetavath@gmail.com
Corresponding author: B. Shoba Rani

ABSTRACT
Enhancement of Color images plays a vital role in applications like medical imaging, remote sensing, and surveillance by improving visual quality by adjusting brightness, contrast, and sharpness. However, traditional techniques often suffer from noise amplification, over-enhancement, and loss of detail, particularly in low-exposure images with poor visibility. To address these challenges, this paper introduces Exposure-Based Sub Histogram Equalization with Spatial Contextual Information (RS-ESIHE-E), a novel approach that replaces conventional histograms with an Energy Curve derived from spatial contextual information, enabling more precise contrast enhancement while preserving critical details. The proposed methodology combines the advanced technique, Recursive Symmetric Exposure-based Sub-image Histogram Equalization (RS-ESIHE), and the concept of Spatial Contextual Information, in which the histogram is replaced by an energy curve, which independently enhances different exposure regions. This method was tested on low-contrast color images and compared against established techniques. Performance was evaluated using metrics such as AMBE (brightness preservation), PSNR & MSE, Entropy (information richness), SSIM & FSIM (perceptual quality). Results demonstrate that the proposed techniques outperform existing methods, providing superior enhancement while minimizing artifacts and maintaining natural appearance. This research presents a robust framework for adaptive image enhancement, particularly effective in low-light conditions, making it valuable for applications requiring high precision and clarity.

KEYWORDS: Color Image Enhancement, Image Exposure, Low Contrast Image, Spatial Contextual Information, Energy Curve

INTRODUCTION
Even though there is an improvement in camera technology for capturing images, normal pictures are still impacted by low light in open area situations, which leads to the generation of low-contrast images. The low coverage of a picture results in the brilliance or dimness of the picture. Numerous picture upgrades or enhancement algorithms are used to enhance or upgrade the images after the generation of pictures, depending on the nature of the image. Progressively, various histogram adjustments or enhancement techniques are used to upgrade the images. Hertzsprung equalization (HE) is a commonly employed contrast enhancement technique due to its ease of use and simplicity in implementation. An image enhancement method called histogram equalization increases a picture's contrast by dispersing the pixel intensity values over the full range of potential values. The image histogram's dynamic range is stretched and flattened throughout this procedure, producing a more even distribution of intensities. The enhanced image reveals more details in dark and bright regions, making features more distinguishable. Because of the simplicity of HE, directly applying it to a normal picture can adjust its mean brightness to the normal level of the dark level; different methods or strategies based on histogram equalization are proposed, in which issues are being discussed at different levels. The figures, Figure 1 and Figure 2, illustrate the examples of image enhancement with histogram equalization of gray–scale and color images.

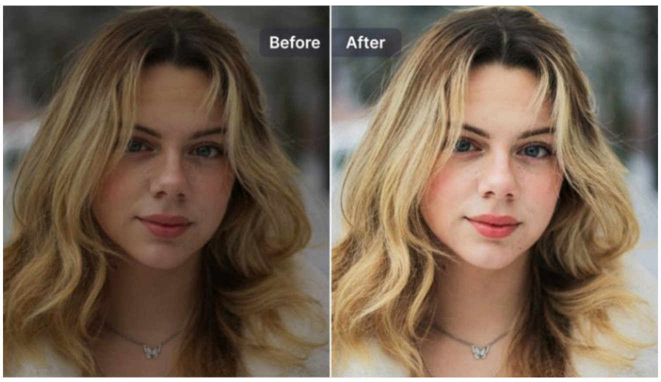
Image enhancement has diverse applications across various fields, significantly improving visual quality and usability. Medical imaging aids in better diagnosis by clarifying details in MRI and X-ray images. In satellite imagery, enhanced images provide clearer views for environmental monitoring and urban planning. Security and surveillance improve the clarity of footage, aiding in identifying and analyzing activities. Additionally, image enhancement is crucial in photography and

Before After

Figure 1: Example of Image Enhancement of a gray-scale image before and after enhancement

Cinematography for aesthetic improvements and in scientific research, where detailed image analysis is necessary. Overall, it enhances images' functional and aesthetic value across different domains.

Image enhancement faces several challenges, including balancing noise reduction with preserving crucial details, managing varying lighting conditions, and dealing with low-resolution or blurred images. Techniques must also be flexible to various images and contexts, such as medical scans versus security footage, each requiring specific enhancements. Despite these challenges, image enhancement is critically important in real life as it improves the accuracy and efficiency of visual information interpretation. In healthcare, it leads to more accurate diagnoses; in security, it aids in clearer surveillance; in photography and media, it ensures higher quality visual content; and in scientific research, it facilitates more precise data analysis. This makes overcoming the challenges of image enhancement essential for its effective application across various fields. The need for image enhancement methods arises from the inherent limitations and imperfections in image acquisition and display processes. Factors such as low resolution, poor lighting, noise, and motion blur often degrade the quality of images captured by cameras, scanners, or other imaging devices. Additionally, there are varying requirements for different applications. Therefore, image enhancement methods are essential to compensate for these deficiencies, ensuring that images are functional and visually appealing across diverse contexts.



Before After

Figure 2: Example of Image Enhancement of a color image before and after enhancement

Histogram equalization is a widely used method for improving the visual quality of images, and several

ISSN: 2178-7727

variations and related methods have been developed to address specific needs and limitations. This paper will discuss different types of image enhancement algorithms or methods depending on histogram equalization.

APPLICATIONS OF IMAGE ENHANCEMENT

Color image enhancement plays a pivotal role in improving visual data across multiple industries, ensuring better clarity, accuracy, and usability. Below are 10 key applications where this technology is extensively utilized:

Table 1: Evaluation parameters with required mathematical equations

S.No	Parameters	Mathematical Expression
1	Peat to Signal Ratio (PSNR)	$PSNRV = 20log_{10}\left(\frac{255}{MSE}\right)dB$
2	Mean Square Error (MSE)	$\sqrt{\frac{\sum_{i=1}^{R_0}\sum_{j=1}^{C_0}\left(I(i,j)-I^s(i,j)\right)}{R_0 \times C_0}}$ $I(i,j)$ is the input image, $I^s(i,j)$ is the final image
3	Structural Similarity Index (SSIM)	$\frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_{2)}}{\left(\mu_x^2 + \mu_y^2 + c_1\right)(\sigma_x^2 + \sigma_y^2 + c_2)}$ $\mu_x and \mu_y$ are mean values of input and output images. σ_x^2 and σ_y^2 are the standard deviation of images.
4	Feature Similarity Indexing Method (FSIM)	$FSIM = [S_{PC}(x)]^{\alpha}.[S_G(x)]^{\beta}$ $S_{PC} = \frac{2PC_1PC_2 + T_1}{PC_1^2 + PC_2^2 + T_1}$ PC is the Phase Congruency maps extracted from two images, T1, a positive constant. $S_G = \frac{2G_1G_2 + T_2}{G_1^2 + G_2^2 + T_2}$ G indicates the gradient of the image, and T2 is the appropriate constant.
5	Absolute Mean Brightness Error (AMBE)	$AMBE(I,O) = \frac{1}{1 + \lvert E(I) - E(O) \rvert}$ I and O are input and output images, E represents the mean (expectation)

2.1 Medical Imaging & Diagnostics:

- Enhances MRI, CT scans, and X-rays for better detection of tumors, fractures, and vascular structures.
- Improves dermatological imaging for skin cancer analysis.

2.2 Satellite & Remote Sensing

- Sharpens satellite imagery for agriculture, deforestation tracking, and urban planning.
- Enhances hyperspectral images for mineral exploration and disaster monitoring.

2.3 Surveillance & Forensic Analysis

- Refines low-light CCTV footage for criminal investigations.

- Enhances facial recognition and license plate detection in traffic monitoring.

2.4Autonomous Vehicles & Robotics

- Improves object detection in varying lighting for self-driving cars.
- Enhances real-time navigation for drones and industrial robots.

2.5 Digital Photography & Social Media

- Powers photo-editing tools (e.g., Adobe Lightroom, Instagram filters).
- Corrects over-/underexposed images automatically in smartphone cameras.

2.6 Entertainment & Gaming

- Enhances CGI and VFX in movies for realistic visuals.
- Optimizes VR/AR environments for immersive experiences.

2.7 Historical & Art Restoration

- Digitally restores faded paintings, manuscripts, and old photographs.
- Reconstructs damaged archaeological artifacts for preservation.

2.8 Industrial Quality Control

- Enhances microchip and PCB inspection in manufacturing.
- Improves defect detection in textile and automotive industries.

2.9 Retail & E-Commerce

- Adjusts product images for accurate color representation in online shopping.
- Enhances virtual try-on features for fashion and cosmetics.

2.10 Astronomy & Space Exploration

- Processes telescopic images to reveal clearer details of celestial bodies.
- Enhances Mars rover images for geological analysis.

Key Techniques Used

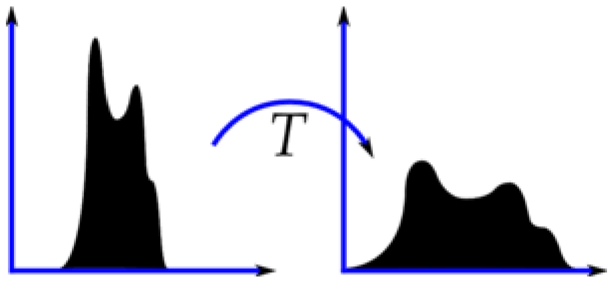
From healthcare to entertainment, color image enhancement drives innovation, ensuring clearer, more accurate visual data for decision-making and automation. Would you like a deeper dive into any specific application?

LITERATURE REVIEW

The camera's inability to produce high-quality photographs in low light, low exposure, and underwater situations leads to post-processing requirements like image enhancement. With current image processing techniques in low light and underwater situations, more comfortable vision and reduced noise in images are not possible. Low exposure and submerged conditions were too difficult for the earlier enhancement methods like CLAHE and BBHE. Despite significant advancements in image-capturing technology, low-exposure issues still arise when taking natural underwater or low-light photographs. Consequently, images taken in settings with a high dynamic range frequently display underexposure artifacts in the shadow areas [1,2]. When shooting in low light, an image may suffer from low exposure due to the camera's imperfect aperture and shutter speed settings. Each element's brightness or blackness in an image is determined by its exposure [2]. The figure, Figure 3 depicts the histogram of an image before and after enhancement. After enhancement, the histogram expands to the entire gray scale range.

When shooting in low light, an image may suffer from low exposure due to the camera's imperfect aperture and shutter speed settings. Each element's brightness or blackness in an image is determined by its exposure [2]. Because of its simplicity and convenience, histogram equalization (HE) is the widely used contrast enhancement algorithm [3-5]. Increasing contrast in an image by adjusting its pixel value ranges is referred to as the contrast enhancement approach. The HE is an established method for improving images, particularly for low-contrast medical and satellite images. It can also recognize objects, perform speech recognition, and perform other applications. Although HE has several benefits, there are drawbacks as well.

ISSN: 2178-7727



Before After

Figure 3: Example of Histogram of an Image before and after histogram equalization for enhancement

This technique preserves the values of average pixels before and after the HE process, which can lead to enhanced images that are either over-saturated or under-saturated.

Bi-histogram equalization (BHE)[4-5], a novel model of histogram equalization, is applied as a remedy for this issue by splitting the histogram into two sub-regions known as sub-histograms.On low-brightness and dimly lit images, the Brightness Preserving Bi-Histogram Equalization (BBHE) [4–6, 10] functioned. BBHE is another method for equalizing a histogram; it divides the histogram according to average brightness and then equalizes it. This method affects the average brightness of the picture.

By segmenting the image into discrete areas known as tiles and executing histogram equalization on each, contrast-limited Adaptive Histogram Equalization (CLAHE) enhances or improves image contrast. To eliminate noise enhancement while giving better visibility of picture features, CLAHE [7-10, 18-21] limits contrast amplification. This prevents over-enhancing and noise artifacts that are frequent in standard histogram equalization[22-24].

An image processing method called Dualistic Sub-Image Histogram Equalization (DSIHE) [11-14] divides an image's histogram into two equal sections at the median intensity level and then equalizes each sub-histogram separately to improve contrast. This technique preserves tiny features while enabling localized contrast enhancement by ensuring that every sub-histogram has an identical number of pixels. Instead of over-enhancement and detail loss frequently connected with standard histogram equalization, DSIHE creates a final image with increased overall contrast and balanced intensity distribution by recombining the equalized sub-histograms. Nevertheless, the aforementioned approach has several problems and limitations, making it unsuitable for use in specific circumstances, such as low-exposure and underwater settings.

The lack of post-handling problems [14-15] may lead to intriguing restrictions on captured photographs since low contrast degrades the image's perceived quality. Contrast enhancement creates a very appealing image to verify additional visual information. Contrast enhancement techniques are applied to enhance the contrast of low-exposure and inadequate light photos. An adaptive histogram leveling technique that enhances contrast on individual image tiles rather than the entire image. The scattered scope of values coordinates the tiles; in the end, all the image pixels are used and generate better images with more contrast through a bilinear interpolation.

To improve low-exposure photographs, Singh and Kapoor presented the exposure-based subsub-image histogram equalization (ESIHE) [11-13,16–17] technique, which divides images based on their image exposure threshold. Pictures taken at low exposure have a narrow dynamic range, giving them a low contrast.

Minimal-intensity exposure photographs have histogram bins oriented toward the lower portion of the darker gray levels. In contrast, high-intensity exposure images have histogram bins oriented toward the upper portion of the brighter section. Both types of images show minimal contrast. Various existing techniques to address the particular issue of contrast enhancement, low-exposure image enhancement, remain a relatively unexplored field. Two ESIHE [16, 25-26] extensions are put forth in this work.

ISSN: 2178-7727

First, Recursive Exposure-based sub-image histogram equalization (R-ESIHE) is proposed as a recursive technique to extend the ESIHE [1-3,17]. The suggested technique applies ESIHE[26-28] to the image iteratively until the variation in exposure values amongst iterations is smaller than a predetermined threshold. The second technique is recursively separated Exposure-based sub-image histogram equalization (RS-ESIHE) [1-2,16]. In contrast to the R-ESIHE, the second algorithm divides the histogram into two or more sub-histograms according to separate exposure thresholds. Following that, all of the sub-histograms undergo a histogram equalization. To prevent over-enhancement, the two recommended approaches include histogram clipping.

DEVELOPING EFFECTIVE ENHANCEMENT METHODS

The problem brought up by the earlier procedure might be resolved, and the suggested approach could handle the various conditions more skillfully. An Energy Curve [3] is utilized in the recommended procedures in place of a histogram. The approaches will perform better on the Energy Curve since only the histogram equalization technique will be used.

4.1 Proposed method

This work operates a recursive symmetric histogram utilizing the image's energy curve. The proposed method is Recursive Symmetric Exposure-based Sub-image Histogram Equalization based on Energy Curve (RS-ESIHE-E). The recursive approaches are evaluated based on the average of the image histogram. There is no visualization and an unsatisfactory natural energy curve in the raw photos.

4.2 Computation of Exposure of Image

$$\mathbf{exposure} = \frac{\sum_{K=0}^{L-1} E(K)K}{L\sum_{K=0}^{L-1} E(K)} \tag{1}$$

Where the total number of gray scales is represented by L and the energy curve by E. The boundary value divides an exposed image into underexposed and overexposed areas upon exposure. The exposure level starts at 0, and an image is considered underexposed if the value is lower than 0.5 or down and overexposed if it is higher than 0.5.

$$X_i = L(1 - exposure) \tag{2}$$

4.3 Energy Curve (E)

The energy curve computer the energy of each pixel value, which is different from the histogram [2] Let I be an image $= x(i, j)$, i and spatial coordinates, where $i = 1$ to N and $j = 1$ to M, the size of an image is M X N and, image I is defined by N of order d, for an image (i, j) as $N_{ij}^{d} = \{(i+u, j+v), (u, v) \in N^{d}\}$. The subsystems are used to compute the energy curve of an image,i.e.,$(u, v) \in \{(\pm 1, 0), (0, \pm 1), (1, \pm 1), (-1, \pm 1)\}$.First, calculate each pixel's energy for the entire grayscale range and generate a binary matric.

$B_x = \{b_{ij}, 1 \le i \le M, 1 \le j \le N\}$,the $b_{ij} = 1$if $X_{ij} > x$;else $b_{ij} = -1$.let $C = \{c_{ij}, 1 \le i \le M, 1 \le j \le N\}$ other matric is $c_{ij} = 1, \forall (i, j)$.At each pixel X, the energy value E(K) oIis shown below [2] The $[t_1, t_2]$represents the pixel range

$$E(K) = -\sum_{i=1}^{M}\sum_{j=1}^{N}\sum_{pq \in {N^2}_{ij}} b_{ij}b_{pq} + \sum_{i=1}^{M}\sum_{j=1}^{N}\sum_{pq \in {N^2}_{ij}} c_{ij}c_{pq} \tag{3}$$

of an image I, for $x = t_1$, B_x= 1. As the X value increases for a few elements matrix B_x be -1, if $x = t_2$, then the $B_x$be -1. The energy curve is computed throughout the grayscale range of 0 to 255, or E(K), once the

ISSN: 2178-7727

original image has been modified based on the range. This curve performs better than a histogram and has qualities that are comparable to those of a histogram because it considers the spatial contextual information of picture pixels with their nearby pixels.

4.4 Energy curve of image

The E computes the image's energy curve, which is then utilized to clip the image and determine the threshold. The grayscale image is computed into a 2-dimensional matrix, and the binomial image's values are aggregated. The threshold values are compared, and the mean energy values are calculated using Xpdf.

$$T_c = \frac{1}{L}\sum_{K=0}^{L-1} E(K) \qquad (4)$$

$$E_c(K) = \begin{cases} E(K), E(K) < T_c \\ T_c, \quad E(K) \geq T_c \end{cases} \qquad (5)$$

4.5 Sub-division and equalization

Based on the exposure threshold valueX_i, the natural image is separated into WL and WU from a grayscale of 0 to X_i-1 and $X_i$to L-1.Equations 6 and 7 of $P_L(K)$ and $P_U(K)$ define the PDF of sub-images.

$$P_L(K) = {E_c(K)}/{N_L} \; for\ 0 \leq K \leq X_i\text{- }1 \qquad (6)$$

$$P_U(K) = {E_c(K)}/{N_U} \; for\ X_i \leq K \leq L\text{ - }1 \qquad (7)$$

where the sum of the pixels is represented by where N_L and N_U. Equations 8 and 9 then define the CDF of individual images as CL(K) and CU(K).

$$C_L(K) = \sum_{K=0}^{X_i-1} P_L(K) \qquad (8)$$

$$C_U(K) = \sum_{K=X_i}^{L-1} P_U(K) \qquad (9)$$

Using the transfer function as a guide, equalize and combine four sub-images into one.

$$F_L = X_i C_L \qquad (10)$$

$$F_U = (X_i + 1) + (L - X_i + 1)C_U \qquad (11)$$

Where F_L and F_U are transfer functions.

4.6 Computation of Exposure of Image

From equation 3,X_i is computed. In the next process, more exposure values are calculated on two sub-images X_{iL} and X_{iU}.

$$X_{iL} = L\left[\frac{X_i}{L} - \frac{\sum_0^{X_i-1} E(K)K}{L\sum_0^{X_i-1} E_c(K)}\right] \qquad (12)$$

$$X_{iU} = L\left[1 + \frac{X_i}{L} - \frac{\sum_{X_i}^{L-1} E(K)K}{L\sum_{X_i}^{L-1} E_c(K)}\right] \qquad (13)$$

4.7 Sub-division and equalization

Equation (2) X_i is used to compute the image's exposure. Based on individual exposure X_{iL} and X_{iU}, the individual total images are divided into smaller sub-images.

The sub-divided images range as W_{Ll},W_{Lu},W_{Ul} and W_{Uu} for gray level 0 to X_{iL} - 1,X_{iL} to X_i - 1,X_i to X_{iU} - 1,X_{iU} to L - 1.The PDF are $P_{Ll}(K)$,$P_{Lu}(K)$,$P_{Ul}(K)$ and $P_{Uu}(K)$ equation 14,15,16 and 17.

$$P_{Ll}(K) = {}^{E_c(K)}/_{N_{Ll}} \text{ for } 0 \leq K \leq X_{iL} - 1 \tag{14}$$

$$P_{Lu}(K) = {}^{E_c(K)}/_{N_{Lu}} \text{ for} X_{iL} \leq K \leq X_i - 1 \tag{15}$$

$$P_{Ul}(K) = {}^{E_c(K)}/_{N_{Ul}} \text{ for} X_i \leq K \leq X_{iu} - 1 \tag{16}$$

$$P_{Uu}(K) = {}^{E_c(K)}/_{N_{Uu}} \text{ for} X_{iU} \leq K \leq L - 1 \tag{17}$$

The number of pixels is indicated byN_{Ll}, N_{Lu}, N_{Ul} and N_{Uu} for in sub-images.

The CDFs of individual sub-images are defined as $C_{Ll}(K)$,$C_{Lu}(K)$,$C_{Ul}(K)$ and $C_{Uu}(K)$ equations 18 to 21.

$$C_{Ll}(K) = \sum_{K=0}^{X_i - 1} P_{Ll}(K) \tag{18}$$

$$C_{Lu}(K) = \sum_{K=X_{il}}^{X_i - 1} P_{Lu}(K) \tag{19}$$

$$C_{Ul}(K) = \sum_{K=X_i}^{X_i - 1} P_{Ul}(K) \tag{20}$$

$$C_{Uu}(K) = \sum_{K=X_{iu}}^{L - 1} P_{Uu}(K) \tag{21}$$

The transfer function can be used to equalize 4 sub-images

$$F_{Ll} = X_{il} C_{Ll} \tag{22}$$

$$F_{Lu} = (X_{il} + 1) + (X_i - X_{il} + 1)C_{Lu} \tag{23}$$

$$F_{Ul} = (X_i + 1) + (X_{iu} - X_i + 1)C_{Ul} \tag{24}$$

$$F_{Uu} = (X_{iu} + 1) + (L - X_{iu} + 1)C_{Uu} \tag{25}$$

Where F_{Ll},F_{Lu},F_{Ul} and F_{Uu} are transfer functions.

4.8 Algorithm of Proposed Method (RS-ESIHE-E**)**

- Determine the image's energy curve E(K).
- Determine the threshold value X_i and the exposure.
- Clip the energy $E_c(K)$ and clip based on the threshold T_c.
- Utilizing the threshold X_i., diverge the curve to two sub-sectors.
- Divide the sub-images X_{iL} and X_{iU} according to a decomposed threshold, then compute their exposure.
- On each sector, apply histogram equalization.
- Combine smaller images into a single larger one.

RESULTS ANALYSIS

The images for experimentation are given in Figure Fig.3. The consequences of tsevenimage enhancement algorithms experimented on six low-exposure color images named Img.1 to Img.6 are given in Tables Table 2 to Table 7. the histogram and energy Curve of images Img.1 toImg.3 are given in the first and second rows of Figure Fig.4, in the exact figure the third row depicts the histogram of enhanced images with RS_ESIHE_Energy method, from that it is clear that the histogram is expanded among all the pixel ranges

ISSN: 2178-7727

from 0 to 255. In Figure 5, the enhanced images of six images are shown with seven different methods. The five comparative metrics [29-32] are considered for evaluating all these techniques as given in the Table.1, along with the required mathematical expressions. They are Absolute mean brightness error (AMBE) [18-19], PSNR, mean square error (MSE), Structural Similarity Index (SSIM) [22], and Feature Similarity Indexing Method (FSIM) [20-21]. The seven different image enhancement techniques used in sequence are HE, CLAHE, DSIHE, ESIHE, R_ESIHE, RS_ESIHE, and the proposed method(RS_ESIHE_E) in sequence. Results are compared on average values of comparative metrics of each image with seven different image enhancement methods.

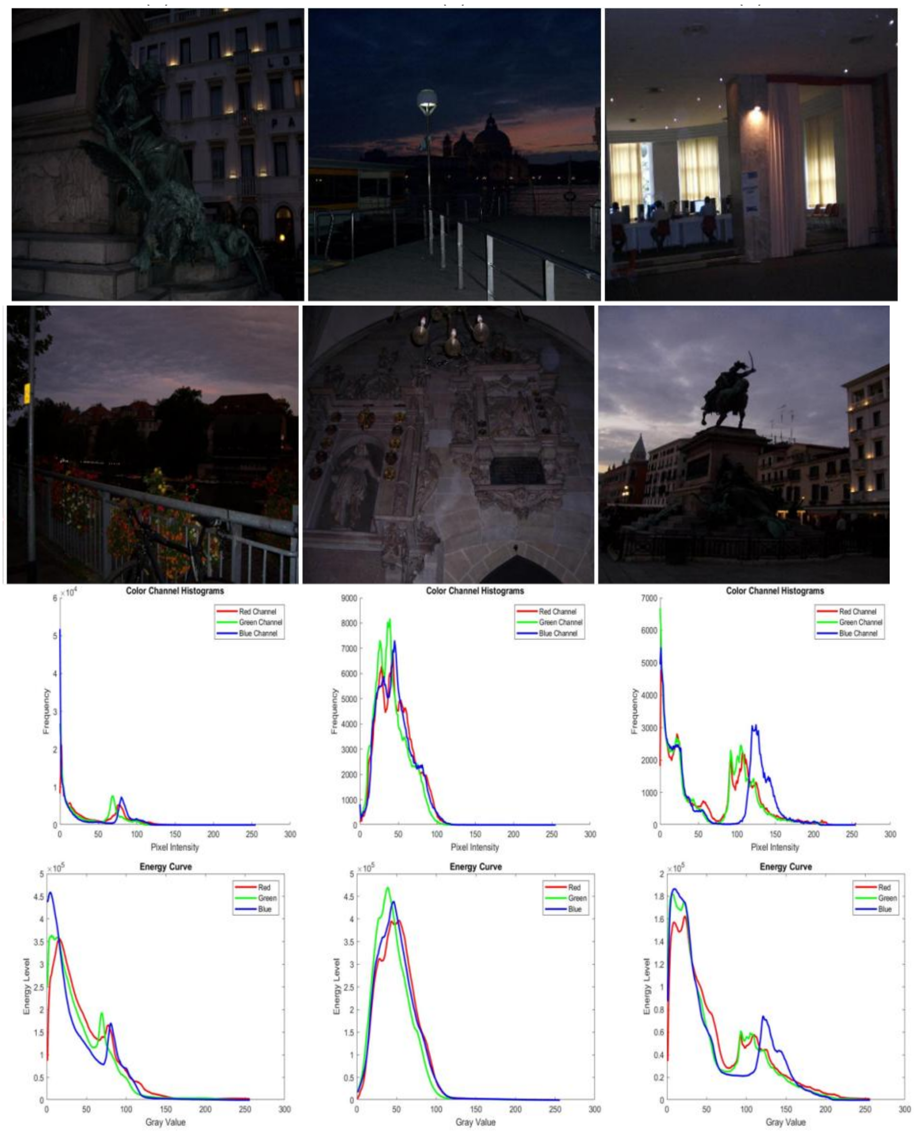


Figure 4: Input Images considered for experimentation, third row: Histograms of images in second row, Fourth row: Energy Curves of Images in Second row

The ten different image enhancement techniques evaluated on six low-exposure color images are as mentioned above. Five comparative metrics were used: AMBE, PSNR, MSE, SSIM, and FSIM.

Starting with AMBE, which measures the difference in brightness between the original and enhanced images, the proposed method stands out with the lowest AMBE value of 28.60046. This indicates that the proposed method preserves the brightness of the input images exceptionally well, making the enhanced images look natural and visually appealing. R_ESIHE_Energy also performs well in terms of brightness preservation with

ISSN: 2178-7727

an AMBE of **38.3164**. On the other end of the spectrum, HE has the highest AMBE value of **84.3531**, indicating poor brightness preservation, which can result in unnatural-looking images.

Table 2: Comparison of AMBE of images Img.1 to Img 6

S.No	Image Name	HE	CLAHE	DSIHE	ESIHE	R-ESIHE	RS-ESIHE	Proposed
1	Img.1	101.7992	25.49628	93.77086	62.78829	57.53405	77.6935	59.65868
2	Img.2	106.7140	20.50247	55.19949	45.08672	43.32902	89.4079	40.99574
3	Img.3	65.73050	61.5748	32.01041	30.54826	28.76206	23.810	0.069764
4	Img.4	87.60568	39.5578	90.98304	36.09309	37.33548	49.4336	32.40011
5	Img.5	80.69124	46.40651	52.69482	44.7771	47.80344	34.8576	23.61659
6	Img.6	63.57824	63.71691	60.09712	15.52144	15.13432	11.6622	14.8619
	Average	**84.3531**	**42.875**	**64.12596**	**39.13582**	**38.3164**	**47.8108**	**28.60046**

Table 3: Comparison of PSNR with different images

S.No	Image Name	HE	CLAHE	DSIHE	ESIHE	R-ESIHE	RS-ESIHE	Proposed
1	Img.1	6.7860	18.14915	6.8726	10.3238	10.0025	9.3347	11.16987
2	Img.2	6.7634	17.47751	7.7171	11.6022	11.7052	9.12063	13.8959
3	Img.3	9.6128	10.40695	13.6313	16.0182	16.1264	16.7371	32.00479
4	Img.4	8.0965	13.91258	8.5749	14.299	14.0372	12.5450	14.59487
5	Img.5	8.2281	14.25309	10.594	13.330	12.4959	14.5140	16.23458
6	Img.6	11.3334	9.655806	11.7103	23.2111	22.1067	20.5256	21.41152
	Average	**8.47003**	**13.9758**	**9.8500**	**14.7973**	**14.4123**	**13.7961**	**18.21859**

Table 4: Comparison of MSE with different images

S.No	Image Name	HE	CLAHE	DSIHE	ESIHE	R-ESIHE	RS-ESIHE	Proposed
1	Img.1	4578.51035	333.3038	4204.376	1802.076	1755.624	2594.012	1664.24142
2	Img.2	4896.88447	329.1616	2212.406	1085.927	1062.872	3299.135	802.009889
3	Img.3	2145.90539	2268.857	1041.725	452.5088	415.8713	338.8879	7.32395048
4	Img.4	3125.08265	969.6262	3262.254	724.8658	853.7919	919.6991	525.899593
5	Img.5	3112.79664	883.138	2134.477	911.4757	1175.438	610.2498	365.751303
6	Img.6	1594.75956	2267.951	1407.274	105.6544	130.1018	89.69516	105.710671
	Average	**3242.323**	**1175.34**	**2377.085**	**847.0846**	**898.9498**	**1308.613**	**578.4895**

Table .5: Comparison of SSIM with different images

ISSN: 2178-7727

S.No	Image Name	HE	CLAHE	DSIHE	ESIHE	R-ESIHE	RS-ESIHE	Proposed
1	Img.1	0.208017	0.065111	0.221616	0.300532	0.288407	0.331439	0.413343
2	Img.2	0.169741	0.041773	0.250124	0.398237	0.203867	0.376868	0.458796
3	Img.3	0.40527	0.008401	0.569942	0.734543	0.65982	0.750092	0.905599
4	Img.4	0.259295	0.151476	0.291009	0.618617	0.30991	0.600071	0.483525
5	Img.5	0.416069	0.013447	0.530939	0.609372	0.590885	0.634299	0.629614
6	Img.6	0.406799	0.059014	0.53037	0.702943	0.602559	0.686341	0.707235
	Average	**0.31086**	**0.05653**	**0.3990**	**0.56070**	**0.44257**	**0.56318**	**0.5996**

Table.6: Comparison of FSIM with different images

S.No	Image Name	HE	CLAHE	DSIHE	ESIHE	R-ESIHE	RS-ESIHE	Proposed
1	Img.1	0.5780	0.6863	0.5772	0.6657	0.6685	0.6984	0.71115
2	Img.2	0.6075	0.6883	0.6685	0.7690	0.6759	0.7781	0.81406
3	Img.3	0.69073	0.6083	0.7658	0.8987	0.8637	0.8968	0.98364
4	Img.4	0.74151	0.6089	0.7444	0.8623	0.8389	0.8805	0.86688
5	Img.5	0.6620	0.6395	0.7000	0.7768	0.8154	0.828	0.83782
6	Img.6	0.7855	0.6193	0.7892	0.9550	0.9196	0.9543	0.90947
	Average	**0.67754**	**0.641767**	**0.707517**	**0.82125**	**0.7970**	**0.83935**	**0.853837**

Table 7: Comparison of Time (in seconds) required for the images

S.No	Image Name	HE	CLAHE	DSIHE	ESIHE	R-ESIHE	RS-ESIHE	Proposed
1	Img.1	2.31	2.312	2.067	2.18	2.154	2.129	2.104
2	Img.2	2.853	1.827	1.682	1.654	1.728	1.679	1.841
3	Img.3	2.289	1.897	1.722	1.734	1.816	1.7939	1.621
4	Img.4	2.343	2.655	2.1	2.172	2.217	2.189	2.254
5	Img.5	2.901	2.996	2.094	2.257	2.201	2.238	2.214
6	Img.6	4.313	1.887	1.726	1.724	1.863	1.7898	1.797
	Average	2.834833	2.262333	1.8985	1.9535	1.9965	1.969783	1.971833

The Higher PSNR values indicate better noise reduction and preservation of image details. The proposed technique achieves the highest PSNR value of **18.21859**, indicating superior noise reduction and detail preservation among the techniques. The comparison of PSNR for different methods for image enhancement is illustrated in Table 3 and Figure 6. Conversely, HE has the lowest PSNR value of **8.47003**, indicating inadequate noise reduction and potential loss of image details.

The MSE quantifies the average of the squares of the errors between the original and enhanced images. Lower MSE values are preferable as they indicate fewer errors and better fidelity to the original image. RS-ESIHE-E excels in this metric with the lowest MSE value of **578.4895**, reflecting minimal errors introduced during enhancement. R_ESIHE (**898.9498**) and ESIHE (**847.0846**) also perform well, indicating lower errors. In contrast, HE shows the highest MSE value of **3242.323**, reflecting significant errors and deviations from the original images.

ISSN: 2178-7727

The original and improved images' structural similarity is compared using the SSIM. Better preservation of structural information and visual quality is indicated by higher SSIM scores. The proposed enhancement technique leads with the highest average SSIM value of **0.5996**, indicating excellent preservation of structural details. RS_ESIHE (**0.56318**) also shows strong performance in maintaining structural similarity. HE, however, has the lowest SSIM value of **0.31086**, indicating poor structural retention and potential visual degradation.

Figure 5: Input images and enhanced images with different histogram equalization methods, finally, resultant images with the proposed method (last row)

The FSIM evaluates the similarity between images based on features that are important to human visual

ISSN: 2178-7727

perception. Higher FSIM values suggest better retention of important features. The proposed method demonstrates the highest FSIM value of **0.853837**, indicating the best feature retention among the techniques. RS_ESIHE (**0.83935**) and ESIHE (**0.82125**) also perform well, showing strong feature preservation. HE, with the lowest FSIM value of **0.67754**, indicates poor feature retention and potential loss of important visual details.

In summary, RS-ESIHE_E consistently performs the best across multiple metrics, particularly excelling in noise reduction (PSNR), error minimization (MSE), structural preservation (SSIM), and feature retention (FSIM). The RS_ESIHE and ESIHE also show strong performance across various metrics, making them reliable choices for image enhancement. Conversely, HE consistently underperforms, particularly in brightness preservation (AMBE), noise reduction (PSNR), and structural and feature retention (SSIM and FSIM), making it the least effective technique among the ten compared.

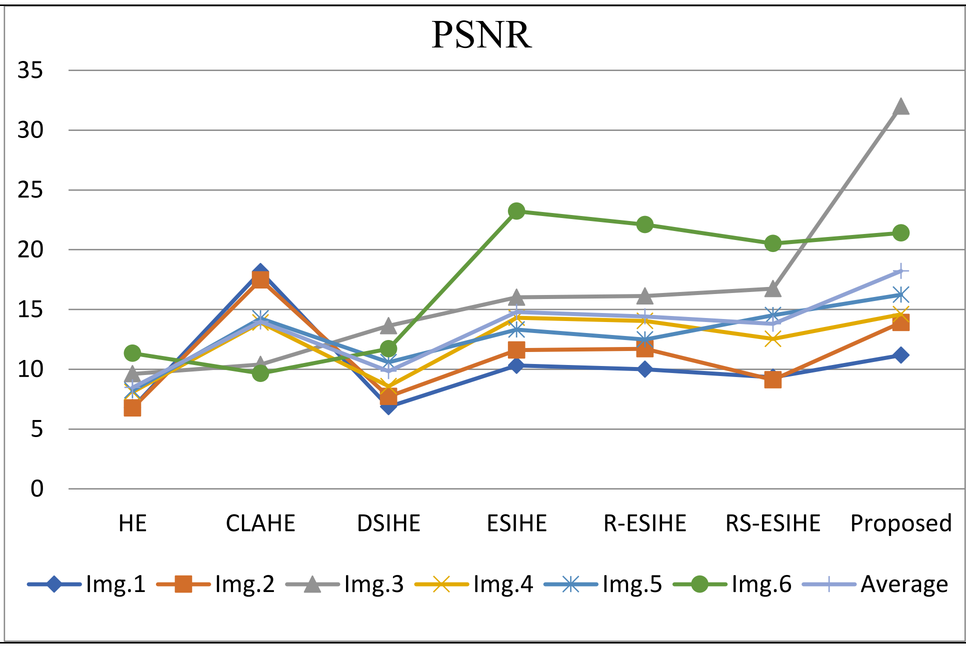


Figure 6: Comparison of PSNR value of various images with the Proposed Method

CONCLUSION

With the aid of an energy curve, the suggested method applies an effective histogram equalization methodology to the experimental result. Effective image processing underwater and in low-light circumstances is currently not possible, nor can it reduce noise in the image for more pleasant viewing. To overcome these problems, the suggested approach offers effective outcomes and aids in resolving the low-exposure mystery. The comparative analysis of ten image enhancement techniques on eight low-exposure color images using six metrics (AMBE, PSNR, MSE, SSIM, and FSIM) reveals that RS-ESIHE-E consistently outperforms other methods. It excels in noise reduction, error minimization, and preserving structural and feature details, making it the most effective technique for image enhancement. The ESIHE and RS_ESIH also demonstrate strong performance across various metrics, indicating their reliability. Conversely, HE performs the worst, with significant deficiencies in brightness preservation, noise reduction, and structural retention. These findings highlight the superior capabilities of energy curve-based enhancement methods, particularly for improving low-exposure images while maintaining visual fidelity.

REFERENCES

1. K. Singh, R. Kapoor, S.Kr. Sinha, Enhancement of low Exposure Images via Recursive Histogram Equalization Algorithms, Optik - International Journal for Light and Electron Optics (2015),https://dx.doi.org/10.1016/j.ijleo.2015.06.060.

2. Kuldeep Singh, Rajiv Kapoor, Image enhancement using Exposure based Sub Image Histogram Equalization, Pattern Recognition Letters, Volume 36, 15 January 2014, Pages 10-14, ISSN 0167-8655, http://dx.doi.org/10.1016/j.patrec.2013.08.024.
3. Jarjish Rahaman, Mihir Sing, An efficient multilevel thresholding based satellite image segmentation approach using a new adaptive cuckoo search algorithm, Expert Systems with Applications, Volume 174, 2021, 114633, ISSN 0957-4174, https://doi.org/10.1016/j.eswa.2021.114633.
4. Mingzhu Wu, Qiuyan Zhong, Image enhancement algorithm combining histogram equalization and bilateral filtering, Systems and Soft Computing, Volume 6, 2024, 200169, ISSN 2772-9419, https://doi.org/10.1016/j.sasc.2024.200169.
5. Abhisek Paul, Paritosh Bhattacharya, Santi P. Maity, Histogram modification in adaptive bi-histogram equalization for contrast enhancement on digital images, Optik, Volume 259, 2022, 168899, ISSN 0030-4026, https://doi.org/10.1016/j.ijleo.2022.168899.
6. Boyina Subrahmanyeswara Rao, Dynamic Histogram Equalization for contrast enhancement for digital images, Applied Soft Computing, Volume 89, 2020, 106114, ISSN 1568-4946, https://doi.org/10.1016/j.asoc.2020.106114.
7. Y.-T. Kim, ‘‘Contrast enhancement using brightness preserving bihistogram equalization,’’ IEEE Trans. Consum. Electron., vol. 43, no. 1, pp. 1–8, Feb. 1997.
8. Arriaga-Garcia, Edgar & Sanchez-Yanez, Raul & Garcia-Hernandez, Ma. (2014). Image enhancement using Bi-Histogram Equalization with adaptive sigmoid functions. CONIELECOMP 2014 - 24th International Conference on Electronics, Communications and Computers. 28-34. 10.1109/CONIELECOMP.2014.6808563.
9. Chao Wang and Zhongfu Ye, "Brightness preserving histogram equalization with maximum entropy: a variational perspective," in *IEEE Transactions on Consumer Electronics*, vol. 51, no. 4, pp. 1326-1334, Nov. 2005, doi: 10.1109/TCE.2005.1561863.
10. Junwon Mun, Yuneseok Jang, Yoojun Nam, Jaeseok Kim, Edge-enhancing bi-histogram equalisation using guided image filter, Journal of Visual Communication and Image Representation, Volume 58, 2019, Pages 688-700, ISSN 1047-3203, https://doi.org/10.1016/j.jvcir.2018.12.037.
11. Kuldeep Singh, Rajiv Kapoor, Image enhancement via Median-Mean Based Sub-Image-Clipped Histogram Equalization, Optik, Volume 125, Issue 17, 2014, Pages 4646-4651, ISSN 0030-4026, https://doi.org/10.1016/j.ijleo.2014.04.093.
12. Majid Zarie, Hassan Hajghassem, Abdollah Eslami Majd, Contrast enhancement using triple dynamic clipped histogram equalization based on mean or median, Optik, Volume 175, 2018, Pages 126-137, ISSN 0030-4026, https://doi.org/10.1016/j.ijleo.2018.08.082.
13. S. H. Majeed and N. A. M. Isa, "Iterated Adaptive Entropy-Clip Limit Histogram Equalization for Poor Contrast Images," in *IEEE Access*, vol. 8, pp. 144218-144245, 2020, doi: 10.1109/ACCESS.2020.3014453.
14. G. Mageshwari, M. Chandralekha and D. Chaudhary, "Underwater image re-enhancement with blend of Simplest Colour Balance and Contrast Limited Adaptive Histogram Equalization Algorithm," *2023 International Conference on Advancement in Computation & Computer Technologies (InCACCT)*, Gharuan, India, 2023, pp. 501-508, doi: 10.1109/InCACCT57535.2023.10141807.
15. K. Ezhilraja and P. Shanmugavadivu, "Contrast Enhancement of Lung CT Scan Images using Multi-Level Modified Dualistic Sub-Image Histogram Equalization," *2022 International Conference on Automation, Computing and Renewable Systems (ICACRS)*, Pudukkottai, India, 2022, pp. 1009-1014, doi: 10.1109/ICACRS55517.2022.10029217.
16. D. Abin and S. D. Thepade, "Illumination Inconsistency Reduction in Video Frames using DSIHE with Kekre's LUV Color Space," *2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV)*, Tirunelveli, India, 2021, pp. 1056-1060, doi: 10.1109/ICICV50876.2021.9388567.
17. Zarie, Majid & Hajghassem, Hassan & Eslami Majd, Abdollah. (2018). Contrast Enhancement

Using Triple Dynamic Clipped Histogram Equalization Based on Mean or Median. Optik. 175. 10.1016/j.ijleo.2018.08.082.
18. Himanshu Singh, Anil Kumar, L.K. Balyan, G.K. Singh, Swarm intelligence optimized piecewise gamma corrected histogram equalization for dark image enhancement, Computers & Electrical Engineering, Volume 70, 2018, Pages 462-475, ISSN 0045-7906, https://doi.org/10.1016/j.compeleceng.2017.06.029.
19. Sonali, S. Sahu, A. K. Singh, S. P. Ghrera, and M. Elhoseny, "An approach for de-noising and contrast enhancement of retinal fundus image using CLAHE," Opt. Laser Technol., vol. 110, pp. 87–98, Feb. 2019.
20. Minghua Zhao, Xiangdong Qin, Shuangli Du, Xuefei Bai, Jiahao Lyu, Yiguang Liu, Low-light stereo image enhancement and de-noising in the low-frequency information enhanced image space, Expert Systems with Applications, Volume 265, 2025, 125803, ISSN 0957-4174, https://doi.org/10.1016/j.eswa.2024.125803.
21. Mousa Alhajlah, Underwater Image Enhancement Using Customized CLAHE and Adaptive Color Correction, Computers, Materials and Continua, Volume 74, Issue 3, 2022, Pages 5157-5172, ISSN 1546-2218, https://doi.org/10.32604/cmc.2023.033339.
22. Muhammad Tahir Rasheed, Daming Shi, Hufsa Khan, A comprehensive experiment-based review of low-light image enhancement methods and benchmarking low-light image quality assessment, Signal Processing, Volume 204, 2023, 108821, ISSN 0165-1684, https://doi.org/10.1016/j.sigpro.2022.108821.
23. K. S. Sim, C. P. Tso and Y. Y. Tan, Recursive Sub-Image Histogram Equalization Applied to Gray Scale Images, Pattern Recognition Letters 28 (2007) 1209-1221.
24. M. Jordanski, A. Arsic and M. Tuba, "Dynamic recursive subimage histogram equalization algorithm for image contrast enhancement," *2015 23rd Telecommunications Forum Telfor (TELFOR)*, Belgrade, Serbia, 2015, pp. 819-822, doi: 10.1109/TELFOR.2015.7377591.
25. S. F. Tan and N. A. M. Isa, "Exposure Based Multi-Histogram Equalization Contrast Enhancement for Non-Uniform Illumination Images," in *IEEE Access*, vol. 7, pp. 70842-70861, 2019, doi: 10.1109/ACCESS.2019.2918557
26. K. Srinivas, A. K. Bhandari and A. Singh, "Exposure-Based Energy Curve Equalization for Enhancement of Contrast Distorted Images," in IEEE Transactions on Circuits and Systems for Video Technology, vol. 30, no. 12, pp. 4663-4675, Dec. 2020, doi: 10.1109/TCSVT.2019.2960861.
27. Zhan Jingchun, Goh Eg Su, Mohd Shahrizal Sunar, Low-light image enhancement: A comprehensive review on methods, datasets, and evaluation metrics, Journal of King Saud University - Computer and Information Sciences, Volume 36, Issue 10, 2024, 102234, ISSN 1319-1578, https://doi.org/10.1016/j.jksuci.2024.102234.
28. S. D. Chen, A New Image Quality Measure for Assessment of Histogram Equalization-Based Contrast Enhancement, Digital Signal Processing 22 (2012) 640–647.
29. M. Kalhor, A. Kajouei, F. Hamidi and M. M. Asem, "Assessment of Histogram-Based Medical Image Contrast Enhancement Techniques; An Implementation," *2019 IEEE 9th Annual Computing and Communication Workshop and Conference (CCWC)*, Las Vegas, NV, USA, 2019, pp. 0997-1003, doi: 10.1109/CCWC.2019.8666468.
30. Soong-Der Chen, 2014. A Statistical Evaluation of Image Quality Analyzer for Assessment of Histogram Equalization-based Contrast Enhancement Methods. Journal of Applied Sciences, 14: 18-25. DOI: 10.3923/jas.2014.18.25
31. Ashish Kumar Bhandari, Immadisetty Vinod Kumar, A context sensitive energy thresholding based 3D Otsu function for image segmentation using human learning optimization, Applied Soft Computing, Volume 82, 2019, 105570, ISSN 1568-4946, https://doi.org/10.1016/j.asoc.2019.105570.
32. Singh, Navdeep & Kaur, Lakhwinder & Singh, Kuldeep. (2019). Histogram equalization techniques for enhancement of low radiance retinal images for early detection of diabetic retinopathy. Engineering Science and Technology, an International Journal. 22. 10.1016/j.jestch.2019.01.014.

ISSN: 2178-7727