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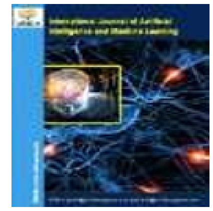

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Metaheuristic-Optimized Exposure-Based Sub-Image Histogram Equalization for Low-Contrast Color Image Enhancement

[1*]Farheen Fathima ,[2]Rangu Srikanth, [3]Kalagadda Bikshalu

[1*]Dept. of Electronics and Communication Engineering, Kakatiya University, Warangal, Telangana 506009, India.
E-mail: farheenfathima794@gmail.com
[2]Dept. of Electronics and Communication Engineering, Kakatiya Institute of Technology and Science, Warangal, Telangana, 506009, India.
E-mail: rangu.srikanth@gmail.com
[3] Dept. of Electronics and Communication Engineering, Kakatiya University, Warangal, Telangana 506009, India.
E-mail:kalagaddaashu@gamil.com

Abstract

Low-contrast images often suffer from poor visibility, loss of structural details, and reduced perceptual quality, affecting human interpretation and subsequent image analysis tasks. Histogram-based enhancement techniques improve contrast but may cause over-enhancement, brightness distortion, and unnatural appearance due to improper histogram partitioning. To address these limitations, an optimized low-contrast color image enhancement framework based on Exposure-based Sub-Image Histogram Equalization (ESIHE) is proposed. ESIHE is used as the core technique to preserve brightness and exposure characteristics, while optimization algorithms determine the histogram division threshold. Harmony Search Optimization (HSO), Grey Wolf Optimization (GWO), Whale Optimization Algorithm (WOA), Firefly Algorithm (FA), Grasshopper Optimization Algorithm (GOA), and hybrid Grey Wolf–Particle Swarm Optimization (HGWPSO) are employed to determine the optimal threshold. Experimental results show that optimized ESIHE with HSO outperforms non-optimized ESIHE, achieving an average PSNR of 19.44 and an SSIM of 0.844, compared with 16.50 and 0.5707, respectively. Entropy reaches 6.04, with improved edge preservation and lower NIQE scores.

Keywords: Low-Contrast Image Enhancement; Exposure-Based Histogram Equalization; Optimization Algorithms; Adaptive Threshold Selection; Image Quality Metrics; Contrast Enhancement

1 Introduction

Image enhancement is a broad term that covers all techniques that try to improve an image's quality or transform it into an appropriate form for human interpretation or processing. Unlike image restoration, which attempts to reconstruct an image based on a specific degradation model, image enhancement is largely subjective and application-dependent. The primary goals of enhancement include improving contrast, preserving important details, suppressing noise, and sharpening edges. Depending on the application, the enhancement methods may be focused on revealing detailed information in medical images, improving visibility in low-light images, or improving texture and edge information in computer vision and machine learning tasks. Depending on the domain in which the enhancement operations are performed, the techniques of image enhancement can be broadly classified into the frequency domain method and the spatial domain method, each having its own advantages and limitations depending on the image and the outcome to be achieved.

Spatial domain techniques work directly on the pixel values of an image, unlike frequency domain methods, modifying intensity values to improve visual quality and highlight structural features. These methods are computationally simpler and intuitive, making them suitable for real-time applications. Spatial domain methods are broadly classified into global enhancement and local enhancement techniques. The universally applied technique is Histogram Equalization (HE). This technique tries to distribute pixel values such that the resulting image has a uniform histogram with uniformity, thus increasing the contrast. The transfer function is the cumulative distribution function of the histogram. This technique is successful but results in over-enhancement and a washout effect if the image does not cover the full range of intensity values. Local enhancement overcomes the limitations by processing small regions in the image. There are various histogram equalization-based techniques like Bi-Histogram Equalization (BHE), Adaptive Histogram Equalization (AHE), Dualistic Sub-Image Histogram Equalization (DSIHE), and Exposure-based Sub-Image Histogram Equalization (ESIHE). These methods can be used as a robust framework for image enhancement, especially for applications that require detailed information to be preserved. The paper is organized as follows: Chapter 1 presents image enhancement methods, Chapter 2 reviews the literature, Chapter 3 discusses optimization methods, Chapter 4 covers histogram equalization techniques, Chapter 5 describes the proposed method, Chapter 6 presents the results and analysis, and the final chapter provides the conclusions and references.

2 Literature Review

Image enhancement is required when the camera is unable to produce high-quality photographs in low-light, low-exposure, and underwater situations. There are different low-light image enhancement methods..With current image processing techniques in low-light and underwater situations, more comfortable vision and reduced noise in images are not possible. Histogram Equalization (HE) (Chen et al., 2012) is a popular algorithm for image enhancement using a contrast enhancement technique, which is simple and easy to use. Bi-histogram equalization (BHE) (Jana et al., 2022) is a new model of histogram equalization. This model divides a histogram into two parts, referred to as sub-histograms. In the case of low-brightness and dim images, the Brightness Preserving Bi-Histogram Equalization (BBHE) (Tan et al., 2012; Kim, 1997; Yao et al., 2016) works well. The Brightness Preserving Bi-Histogram Equalization is another technique of histogram equalization, where the histogram is divided according to the average brightness level, followed by histogram equalization. This technique impacts the average brightness level of the image. The paper by Ye et al (2023) presents a dual histogram equalization technique based on adaptive image correction, which improves the contrast of the image by resolving the common problems of brightness variation and over-enhancement of the image. This new technique is an improvement over the conventional histogram equalization technique. The paper by Yuan and Dai (2024) presents an innovative technique of adaptive histogram equalization, which focuses on the consistency of visual perception, resolving the common problems of the conventional histogram equalization technique. The technique is in line with a number of image enhancement techniques for images with low contrast and low light, where there is a focus on improving the quality and details in images. The exposure-based contrast enhancement technique, where the entropy curve is used, has a number of potential applications in different fields where images are used, especially where there is a need for image enhancement in images with low contrast. Low exposure and submerged conditions were too difficult for the earlier enhancement methods like CLAHE and BBHE.CLAHE (Sonali et al., 2019) divides the image into small areas called tiles and applies the histogram equalization method to improve the features of the image, especially in situations of low light. The CLAHE (Reza, 2004) method improves the features of the image and limits the enhancement of noise, providing better visibility of the features of the image. The CLAHE method limits the enhancement of noise and improves the features of the image, especially in situations of low light. An image processing technique called Dualistic Sub-Image Histogram Equalization (DSIHE) (Wang et al., 1999), which divides the histogram of the image into two partitions and applies the histogram equalization technique to improve the features of the image. 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 develops 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 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. An experimental-based review of low-light image enhancement methods (Wang et al., 2020) is performed to improve the contrast. 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 to generate better images with more contrast through bilinear interpolation. To improve low-exposure photographs, Singh and Kapoor presented the exposure-based sub-image histogram equalization (ESIHE) (Singh et al., 2015) technique, which divides images based on their image exposure threshold. Pictures taken at low exposure have a narrow dynamic range, giving them 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 in low-exposure image enhancement remain a relatively unexplored field. An image quality measure for assessment of histogram equalization-based contrast enhancement explains how image quality is improved and is measured, and a statistical evaluation of the image quality analyzer (Chen, 2014) is performed to assess histogram equalization-based contrast enhancement methods. 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. 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, Author Kuldeep Singh published a paper proposing the method ' Exposure based Sub Image Histogram Equalization (ESIHE)' Pattern Recognition Letters, 2014 (Singh and Kapoor, 2014), it is one of the good methods for image enhancement, as per the above-mentioned paper, ESIHE methods gives better results with grayscale image low low contrast, the author presented superiority of this method by experimenting on various images. In this method, the author used a histogram having a few limitations as(i) The histogram only captures the frequency of intensity values and completely ignores the spatial arrangement of pixels, it results in two very different images in terms of structure or texture can have the same histogram, (ii) The histogram cannot detect or describe the shapes, edges, or object boundaries in an image,(iii)In color images, histograms often work on each color channel separately, this can make it difficult to get a clear understanding of the overall color relationships in the image,(iv) Histograms fail to capture the texture of an image, which is crucial in many applications such as medical imaging or pattern recognition, (v) Histograms do not consider how pixel values relate to their neighboring pixels. When shooting in low light, an image may suffer from low exposure due to the camera's imperfect aperture and shutter speed settings. The blackness of each element of an image depends on its exposure (Yadav et al., 2024; Srinivas et al., 2020) .The enhancement of the contrast of an image by changing its pixel value range is referred to as a contrast enhancement technique. The paper titled 'Low light image enhancement algorithm based on improved multi-objective grey wolf optimization (Hui et al., 2023) with detail feature enhancement' is authored by Yanming Hui, Jue Wang, Bo Li, and Ying Shi. The paper, published in the Journal of King Saud University Computer and Information Sciences, addresses a significant improvement in image enhancement of images, especially in low-light images with low light.An improved multi-objective grey wolf optimization algorithm is proposed to improve the features of the image, especially in situations of low light. Comparative analysis of image enhancement algorithms (Bane et al., 2022) is implemented under satellite imagery, medical scans, underwater images, and their parameter analysis. A review of document image enhancement based on the document degradation problem (Zhou et al., 2023), in which six tasks of document degradation are reviewed.

3 Overview of Optimization Algorithm

3.1. Grasshopper Optimization Algorithm (GOA)

It is based on the swarm behavior of grasshoppers in nature. GOA (Dinh, 2021) has been used to determine optimal exposure thresholds and image histogram parameters to maximize contrast while maintaining image brightness.

3.2. Grey Wolf Optimizer (GWO)

It mimics the leadership structure and strategy of the grey wolf's natural hunting behavior, such as alpha, beta, delta, and omega wolves. GWO (Diab et al., 2023; Mondal et al., 2020) is employed to optimize the selection of threshold levels as well as the partition of sub-images to attain the highest entropy or structure similarity to effectively enhance contrast locally and globally.

3.3. Whale Optimization Algorithm (WOA)

WOA (Ye et al., 2020; Han et al., 2024) is a simulation of the bubble-net mechanism in humpback whales, where exploration and exploitation are carried out in a spiral and encircling pattern, respectively. It is used for optimizing the exposure threshold and contrast parameters, achieving a well-balanced enhancement without over-enhancing the noise.

3.4. Hybrid Grey Wolf–Particle Swarm Optimization (HGWPSO)

HGWPSO (Rentapalli and Khairuzzaman, 2026) combines the global search of GWO with the fast convergence of PSO for better optimization of the thresholds. HGWPSO also ensures fast convergence to the optimal parameters as well as better contrast enhancement of low-contrast images.

3.5. Firefly Algorithm (FA)

FA (Ye et al., 2015; Narla et al., 2024) is analogous to flashing fireflies, wherein fireflies with higher intensities attract other fireflies, simulating global and local searches. FA is used for determining the optimal histogram partition and threshold values, resulting in better visual quality and brightness.

3.6. Harmony Search Optimization (HSO):

HSO (Srikanth and Bikshalu, 2021; Alkareem et al., 2012; Ding et al., 2023) is a nature-inspired optimization technique that is based on the improvisation process of musicians trying to reach a harmonious state, where solution vectors are used as musical harmonies. HSO can be used for optimization of parameters such as histogram thresholds or contrast levels for improved image quality in terms of brightness preservation, contrast, and overall quality.

In the Harmony Search Algorithm, the possible solutions (or elements in the solution space) are termed a "harmony", which is an n-dimensional real vector; random values are assigned to the initial population and loaded into harmony memory (HM). In the next step, a new candidate(next generation or iteration) harmony is produced by considering the elements in HM, either by adjusting the pitch or by random selection for updating the elements in HM, as a final step the elements in harmony memory by comparing the worst HM vector and the newly computed candidate harmony, this whole process is repeated number of times to satisfy termination condition. Different segmentation algorithms can be devised by coupling HSA and Otsu's algorithm.

3.6.1 Problem Statement and the parameters of the Algorithm

The problem statement and variables of the algorithm can be briefly stated as: minimization or maximization of $f(x), x = (x(1), x(2), \dots \dots . . x(n)) \in R^n$, in HSA maximization of inter-class variance is object function given in Eq.(1). The is a set of design variables.

$$J(TH) = \max\left(\sigma^{2^c}(th_i)\right), 0 \le th_i \le L - 1 \quad (1)$$

Where$x(k) \in [X_l(k), X_u(k)]$ for the range

Where k=1,2,……n

$f(x)$ is a cost function or objective function that depends on a set of variables x, and n indicates the length of the variable set. The upper and lower limits of the design variables and the Harmony Search optimization algorithm parameters are (i) size of harmony memory(HM), (ii) harmony-memory consideration rate (HMCR), (iii) pitch adjusting rate(PAR), (iv) distance bandwidth (BW), and the number of iterations or improvisations(NI).

3.6.2 Initialization of Harmony Memory

In this step, it is essential to configure the initial HM component (HMSVectors). Let

$xi = \{xi(1), xi(2), \dots xi(n)\}$ epitomize a randomly computed HM Vector: $xi(k) = X_l(k) + \left(X_u(k) - X_l(k)\right) * rand(0,1) \;\; for \;\; k = 1, 2, \dots . \mathrm{n}$,

$and \;\; i = 1, 2, \dots \;\; \dots, HMS, that \;\; is \;\; length \;\; of HM$. Hence, the lower and upper limits of the possible search space are indicated by $X_l(k)$ and $X_u(k)$ respectively. Then, in the Harmony Memory (HM) matrix, each component is a harmony vector; there are HMS such vectors present.

$$HM = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{HMS} \end{bmatrix} \quad (2)$$

3.6.3 Updating of New Harmonic Vector and Harmony Memory

From the HM matrix, a new x_{new}, a new harmony vector is generated using three operations: (i)memory consideration, (ii)random reinitialization, and (iii)pitch adjustment. In the first phase[1], the initial decision value $x_{new}(1)$ is selected arbitrarily from harmony given as $\{x_1(1), \; x_2(1) \; .. \;\; .. x_{HMS}(1)\}$. For selecting $x_{new}(1)$ a random number $r1$ with range [0, 1], if this random number is below HMCR, the $x_{new}(1)$ is generated by memory consideration; else $x_{new}(1)$ is taken through from the search range $[X_l(k), X_u(k)]$. In a similar way $x_{new}(2), \; x_{new}(3), \; \dots\dots, x_{new}(n)$ are selected accordingly; the two operations (i) memory consideration and (ii) random reinitialization will be concluded as follows:

$$x_{new}(k) = \begin{cases} x_i(k) \in \{x_1(k) \dots \dots \dots \dots . x_{HMS}(k)\} \\ X_l(k) + \left(X_u(k) - X_l(k)\right) * rand(0,1) \\ with \;\; probability \;\; of \;\; 1 - HMCR \end{cases} \quad (3)$$

Each newly generated x_{new}value inspected for where it is required pitch adjustment or not, for this purpose, the pitch adjustment rate (PAR) is devised, which is the composition of frequency and bandwidth factor(BF), these two factors are adjusted to get new x_{new} value from local search around the selected solutions of the harmony memory. The pitch-adjusted new solution $x_{new}(k)$ can be calculated by $x_{new}(k)$+/-rand(0,1)•BW with probability PAR; this pitch adjustment is very similar to the mutation process in any evolutionary bio-inspired algorithms. The range of pitch adjustment is limited by $[X_l(k), X_u(k)]$.

At the final stage, x_{new}, a new harmony vector is generated; the HM is evaluated or updated by new completion for fitness among x_{new} and the worst harmony vector x_w in HM, consequently x_w is replaced by x_{new} and becomes part of the harmony memory. For maximizing the objective function (inter-class variance), HSA will be used in this paper (Han et al., 2024).

The harmony, or a solution, uses k different elements; these variables are threshold values th_k, further used for multilevel segmentation; the population of the algorithm is represented by

$$\mathrm{HM} = [\ x_1\ , x_2\ \quad \ldots., x_{1HMS}]^T,$$
$$x_i = [\ th_1\ , th_2 \ldots\ldots.., th_k] \tag{4}$$

From the above equation, T denotes the transpose of a matrix; the maximum size of HM is indicated by HMS; each element in the harmony memory is represented by xi, where the range of i is [0, k]. In this paper, an 8-bit image with intensity ranging from 0 to 255 is considered. The parameters, HM value is taken as 50, HMCR is 0.5, PAR is 0.2, BW is 0.1, and NI is taken as 3500. The number of regions is considered to be 2 to 5.

4 Histogram Equalization-based Image Enhancement Method

The traditional histogram equalization algorithm improves the contrast of an image by redistributing the pixel values of the image. The process of the traditional histogram equalization algorithm consists of calculating the probability density function (PDF) and cumulative distribution function (CDF) of the histogram and generating a pixel mapping table using these values, according to the formula of histogram equalization. Then, using the normalized CDF, the intensity values of the pixels in each block are mapped to the new parts created, creating an image with a more uniform histogram, thus enhancing the image's contrast. For the histogram of the [first, last] interval, the corresponding calculation formulas of PDF and CDF are(as calculated in Eq.(6) and Eq. (7):

$$PDF(k) = \frac{\mathrm{n_k}}{N} \tag{5}$$

$$CDF(k) = \sum_{q=first}^{k} PDF(q) \tag{6}$$

where k is the gray level in an image, n_k is the number of pixels of the k gray level in the image histogram, and N is the total number of pixels of an image in the interval. Thus, the transformation formula for histogram equalization is:

$$\mathrm{F\ (k)\ =\ first\ +\ CDF\ (k)\ \times\ (last\ -\ first)} \tag{7}$$

In the traditional histogram equalization conversion formula, the last is 255, and the first is 0, where the last represents the final value, the first value corresponds to the starting value of the mapping interval, and the difference between them depicts the mapping interval length.

Brightness Preserving Bi-Histogram Equalization (BBHE) is a modification of conventional HE to improve the image quality while maintaining the mean brightness of the original image. In this, the image histogram is divided into two sub-histograms based on the mean intensity value. Let I be an input grayscale image with intensity levels r∈{0,1,…, L−1}, where L denotes the number of gray levels of an image. The mean intensity μof an image is computed as

$$\mu = \sum_{r=0}^{L-1} r.p(r) \tag{8}$$

where p(r) represents the probability density function (PDF)(as in Eq(3)), of intensity level r. Based on this mean value, the histogram of an image is divided into two sub-histograms. The lower sub-histogram H_L contains intensities r ≤ μ, and the upper sub-histogram H_U contains intensities r > μ(as calculated in Eq(4). Each sub-histogram is independently equalized to avoid excessive brightness distortion. The cumulative distribution functions (CDFs).

4.1 Exposure-Based Sub-Image Histogram Equalization (ESIHE)

An image with low contrast does not occupy the entire dynamic range. Images with histogram bins located towards the lower part or the darker gray levels have low intensity exposure, and images with histogram bins located towards the higher part or the brighter part have high intensity exposure. Images are said to be under-exposed and over-exposed depending on the intensity of exposure. The algorithm used in this paper, ESIHE, has three steps:

4.1.1 Exposure threshold calculation

The measure of the intensity of exposure of the image is called the exposure threshold. This Exposure threshold divides the image into under-exposed sub-images and over-exposed sub-images. The normalized exposure value range is from 0 to 1. This means that the image has a majority of the over-exposed region if the value of exposure for a particular image is greater than 0.5 and tends towards 1, and if the value tends towards 0, it means the image has a majority of the under-exposed region. In any of these cases, the image has poor contrast, which needs to be enhanced. The image intensity exposure value can be calculated as

$$Exposure = \frac{1}{L}\frac{\sum_{k=1}^{L} h(k)k}{\sum_{k=1}^{L} h(k)} \quad (9)$$

where h(k) is the histogram of an image, and L is the total number of gray levels. Another parameter X_a (as calculated in Eq. (6) related to exposure, is defined, which gives the value of the gray level boundary dividing the image into under-exposed and over-exposed sub-images.

$$X_a = (1 - exposure) \quad (10)$$

This parameter gives a value of greater or less than L/2 (gray level) for exposure value lesser or greater than 0.5, respectively, for an image with a dynamic range 0 to L.

4.1.2 Histogram clipping

Histogram clipping is used to avoid over-enhancement, resulting in the natural appearance of the image. For the first case, i.e., limiting the rate of enhancement, the first derivative of the histogram or the histogram itself is limited. The histogram bins having a value greater than the clipping threshold are limited to the threshold (Fig. 1). The average number of gray levels is called the clipping threshold. The formula for the clipping threshold T_c is given by

$$T_c = \frac{1}{L}\sum_{k=1}^{L} h(k) \quad (11)$$

$$H_c(k) = T_c \quad for\ h(k) \geq T_c \quad (12)$$

where h(k) and H_c(k)(as calculated in Eq(8)) are the original and clipped histogram respectively.

4.1.3 Histogram Subdivision and Equalization

The original histogram is divided according to the threshold value X_a as calculated above. The Histogram Subdivision process divides the original image into two sub-images, denoted by I_L and I_U, ranging from 0 to X_a, and from X_{a+1} to L - 1, respectively, which can be referred to as under- and over-exposed sub-images, respectively (Figure 1). P_L(k) and P_U(k) denote PDFs for these two sub-images as defined above.

$$P_L(k) = \frac{h_c(k)}{N_L} \quad for\ 0 \leq k \leq X_a \quad (13)$$

$$P_U(k) = {h_c(k)}/{N_U} \quad for\ X_a + 1 \leq k \leq L - 1 \quad (14)$$

where N_L and N_U are the total number of pixels in sub-images I_L and I_U, respectively. C_L(k)and C_U(k)(as calculated in Eq(16 & 17)) are related CDFs of individual sub-images, and CDFs can be defined as

$$C_L(k) = \sum_{k=0}^{X_a} P_L(k) \quad (15)$$

$$C_U(k) = \sum_{k=X_{a+1}}^{L-1} P_U(k) \quad (16)$$

ESIHE then equalizes all four sub-histograms individually. The transfer functions for histogram equalization based on C_L(k) and C_U(k) can be defined as

$$F_L = X_a \times C_L \quad (17)$$

$$F_U = (X_a + 1) + (L - X_a + 1)C_U \quad (18)$$

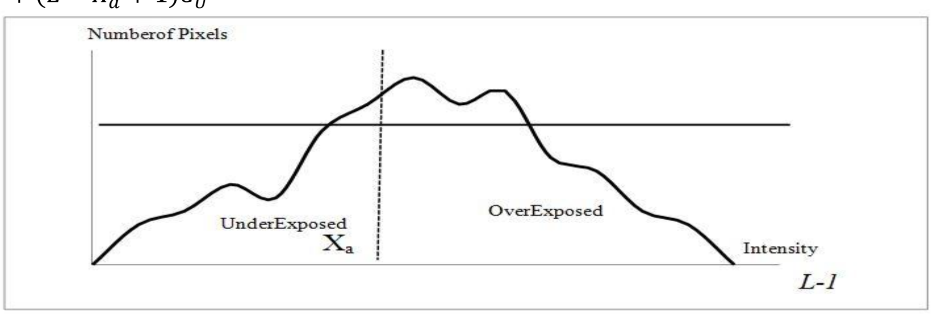

Figure 1: Process of Histogram Subdivision and Clipping

5. Proposed Method

Exposure-based Sub-Image Histogram Equalization (ESIHE) can be further enhanced by integrating nature-inspired optimization algorithms to achieve better contrast improvement while preserving brightness and structural details Techniques like Grey Wolf Optimization (GWO), Grasshopper Optimization Algorithm (GOA), Whale Optimization Algorithm (WOA), Firefly Algorithm, and Hybrid GWO-PSO (HGWPSO) are utilized for optimizing the histogram partition thresholds and exposure controls, resulting in the prevention of over-enhancement and artifact creation Of all the above algorithms, the performance of the ESIHE based on the Harmony Search Optimization (HSO) is found to be better than the other algorithms, owing to the effectiveness and efficiency of the said method in achieving a better balance between exploration and exploitation, convergence, and the ability to generate naturally enhanced images with better entropy and quality.

The performance of the HSO-based framework is found to be better in brightness preservation and contrast enhancement than other optimization algorithms. The HSO-based Exposure Sub-Image Histogram Equalization method combines the fundamental elements of the Harmony Search Optimization algorithm with conventional ESIHE to create an intelligent and adaptive image enhancement technique. In conventional ESIHE, histogram equalization and exposure adjustment are carried out by fixed or heuristic values, resulting in a change of brightness or loss of naturalness. With HSO, critical values such as exposure threshold, histogram segmentation value, and redistribution values are optimized using an objective function such as entropy maximization, contrast improvement index, or structural similarity. This is analogous to the musical improvisation process, wherein each harmony is analogous to a solution, and continuous refinement leads to an optimal trade-off between exploration and exploitation. In HSO-ESIHE, this process allows for the selection of histogram boundaries and exposure values that optimize the maintenance of mean brightness while maximizing local and global contrast. This leads to an enhanced image with higher entropy, better visibility of image details, reduced over-saturation, and minimal noise magnification compared to other optimization-assisted variants of ESIHE. In addition, HSO has the advantage of a fast convergence rate, a reduced number of control parameters, and efficiency in computation, making it well-suited for real-time or large-scale image processing tasks. The adaptive ability of HSO guarantees its performance on a wide range of low-contrast image datasets, making the HSO-ESIHE model a reliable and robust proposed enhancement model with better perceptual and quantitative quality in comparison to GWO, GOA, WOA, Firefly, and HGWPSO algorithms.

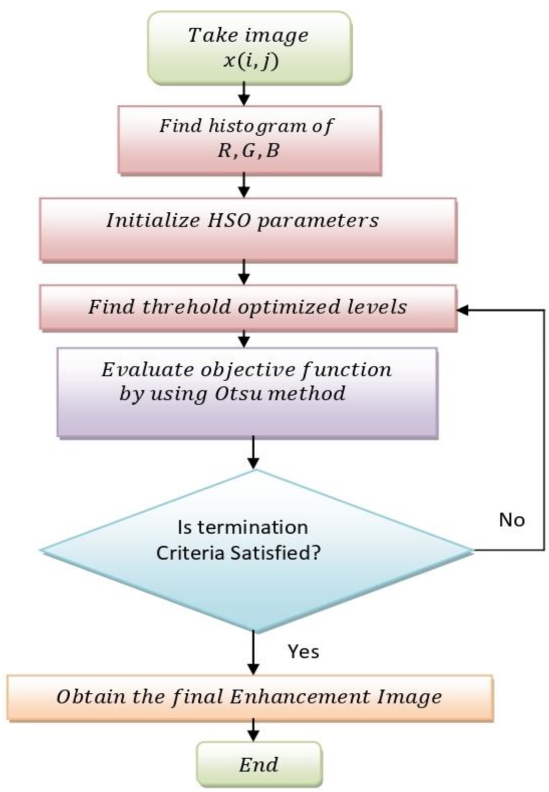

Figure 2: The first row consists of the input images, and all the rows consist of enhanced images using different methods.

6 Results and Discussion

In Fig. 3 and Fig. 4**,** a set of 15 input images is presented in the first row. Histogram Equalization (HE) is applied to these images, and the corresponding enhanced outputs are displayed in the second row. The results obtained using Brightness Preserving Bi-Histogram Equalization (BBHE**)** are shown in the third row. The fourth row illustrates the enhanced images produced by Dual Sub-Image Histogram Equalization (DSIHE**)**. The fifth row shows the results of Exposure-based Sub-Image Histogram Equalization (ESIHE)**.**

The subsequent rows display the results of ESIHE integrated with various optimization techniques**,** including Gray Wolf Optimization (GWO)**,** Grasshopper Optimization Algorithm (GOA)**,** Whale Optimization Algorithm (WOA)**,** Hybrid Grey Wolf–Particle Swarm Optimization (HGWPSO), Firefly Algorithm (FA), and Harmony Search Optimization (HSO). Among all the applied techniques, HSO demonstrates superior image quality enhancement, which can be clearly observed from the comparative visual results in the figure. As we can see in Fig. 5, four input images A, B, C, and D have been chosen in the first row. The input histograms of the four images A, B, C, and D are shown in the 2nd row, and we can see that these RGB lines are mostly concentrated in a narrow region of low intensity, which implies poor contrast and darker color. In the 3rd row, the histogram of the output image using ESIHE-HSO shows the distribution of pixel intensities over the entire range from 0 to 255, which implies high contrast and brightness. The smoother and broader distribution of the RGB channels implies higher brightness and lower intensity clustering.

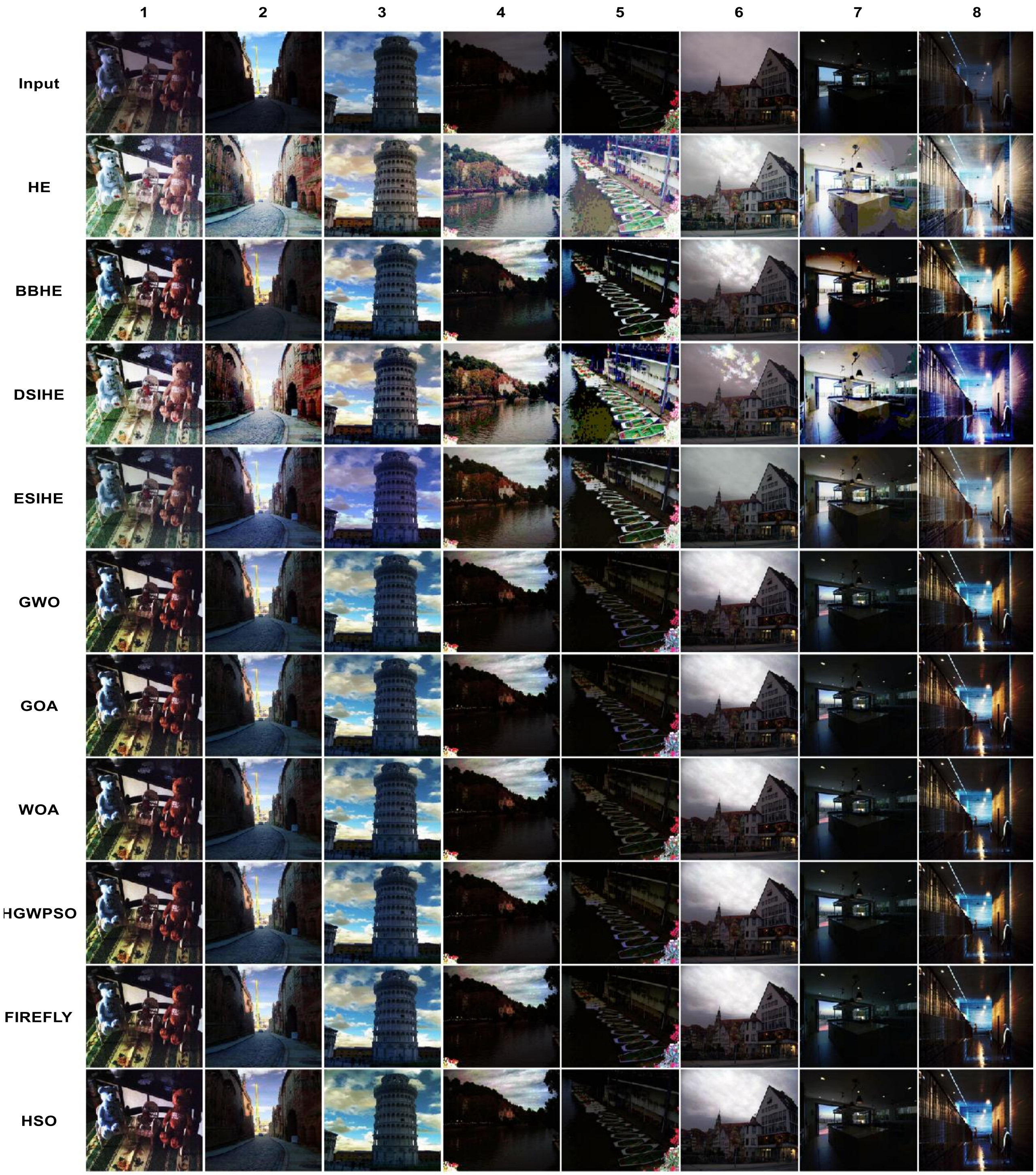

Figure 3: The first row consists of the input images, and all the rows consist of enhanced images using different methods.

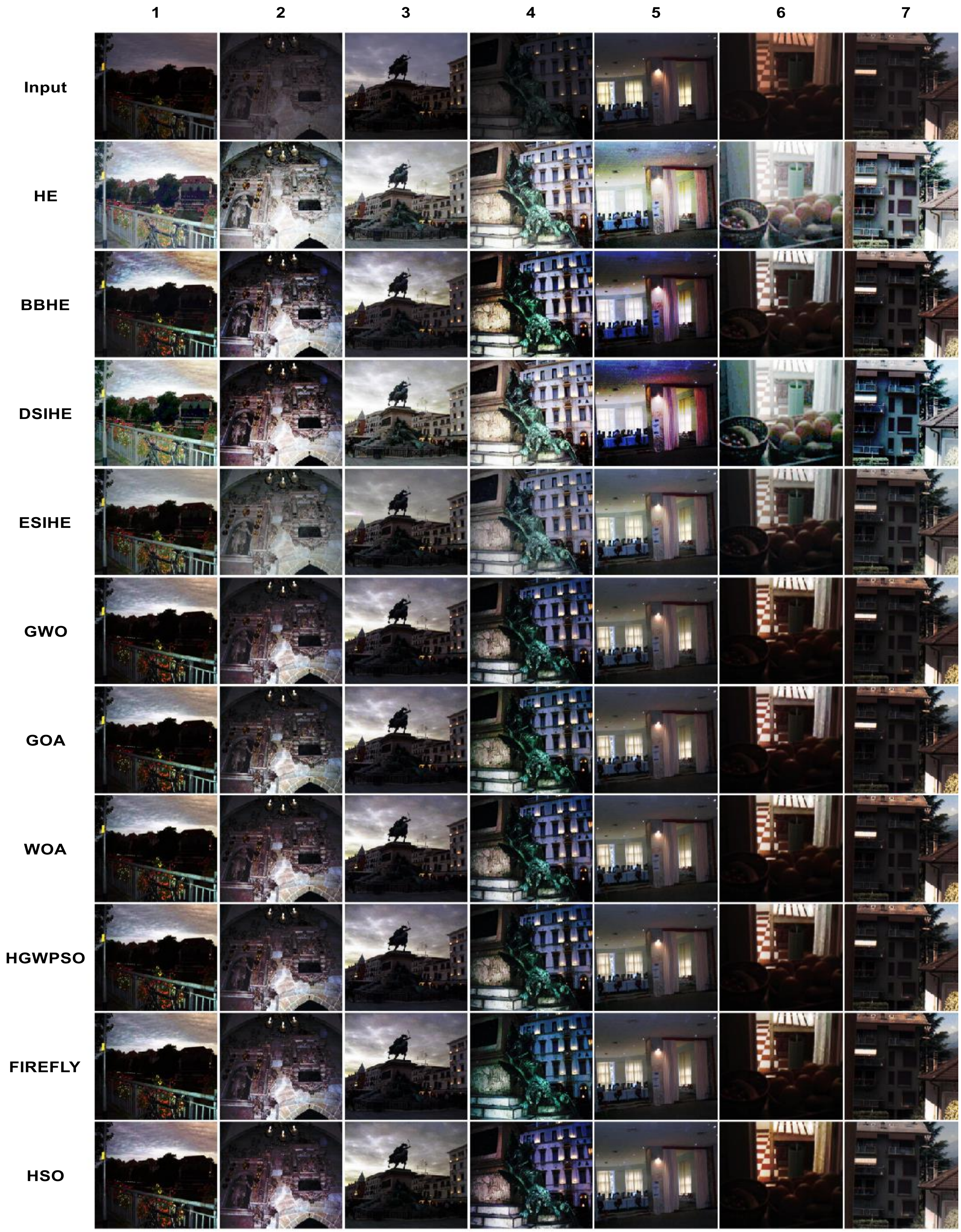

Figure 4: The first row consists of the input images, and all the rows consist of enhanced images using different methods

In Table 1, the PSNR comparison table indicates the performance of different histogram equalization and optimization-based enhancement techniques on multiple test images. The images have the lowest average PSNR value of 8.58 dB, which indicates poor image quality. The conventional enhancement techniques, such as HE, BBHE, and DSIHE, show moderate improvement in the average PSNR value of 15.28 dB, 10.64 dB, and 16.50 dB, respectively. However, among the conventional techniques, ESIHE has better performance in terms of the average PSNR value of 19.04 dB. If optimization techniques are incorporated with ESIHE, it can further increase the PSNR. GWO (18.94 dB), GOA (19.22 dB), WOA (19.08 dB), HGWPSO (19.10 dB), and Firefly (19.10 dB) have all shown good enhancement in the image. However, the proposed ESIHE-HSO algorithm has the highest PSNR of 19.44 dB on average, showing that the image reconstruction is better, noise is controlled more effectively, and contrast enhancement is more prominent than all the other techniques. Therefore, it can be concluded that optimization techniques have outperformed the conventional techniques, with HSO showing the best result in image enhancement.

Table 1: Comparison of the PSNR of Images 1 to 15

Input images	HE	BBHE	DSIHE	ESIHE	ESIHE_ GWO	ESIHE_ GOA	ESIHE_ WOA	ESIHE_ HGWPSO	ESHIE_ Firefly	Proposed ESIHE_HSO
1	8.5490	14.4114	9.5243	16.4976	17.6263	17.5635	17.5953	17.7232	17.6560	17.6485
2	8.2086	21.1752	9.5380	16.6645	20.7618	20.8375	20.8660	20.7123	20.7618	21.3946
3	15.525	18.6881	16.1835	14.9500	20.4474	20.3176	20.4498	20.4790	20.4701	20.6738
4	6.3789	13.2789	7.9928	12.8458	13.9091	13.9091	13.8913	13.9173	13.8975	13.9153
5	5.1644	13.7423	7.5475	22.4932	25.5025	25.5403	28.3617	25.4697	25.5025	29.6161
6	12.906	17.7348	19.8561	11.3127	15.5841	15.5970	15.6144	15.5813	15.5799	15.5801
7	7.9982	13.2192	8.8716	14.3016	15.0427	15.0084	14.9823	15.0812	15.0671	15.1342
8	8.1826	11.4930	11.1882	24.5569	14.9697	14.7343	14.9229	15.0613	14.8395	14.9266
9	11.280	16.4043	11.5714	14.2998	19.3342	19.3442	19.3394	19.3165	19.2809	19.3213
10	6.6854	9.6653	6.9317	13.3300	13.6529	13.1328	13.4256	13.8069	14.0632	13.6518
11	9.4983	18.0770	13.5603	23.2081	24.9806	25.1331	25.0363	24.9064	25.2095	24.5703
12	5.5176	15.5552	7.0531	10.3239	25.5322	25.6294	25.6816	25.4765	25.7227	25.3747
13	7.0118	11.5912	9.6949	16.0186	16.9477	16.3817	16.9477	17.0918	17.1077	17.0166
14	7.3248	15.9441	8.6946	17.1906	18.7611	18.4384	18.7084	18.8878	18.8877	19.8490
15	8.6099	18.3354	11.5253	19.5548	22.6831	22.6339	22.5186	22.7139	22.5974	23.0219
Avg	**8.5894**	**15.2877**	**10.6489**	**16.5032**	**19.0490**	**18.9467**	**19.2228**	**19.0817**	**19.1096**	**19.4463**

Table 2: Comparison of the SSIM of Images 1 to 15

Input images	HE	BBHE	DSIHE	ESIHE	ESIHE_ GWO	ESIHE_ GOA	ESIHE_ WOA	ESIHE_ HGWPSO	ESIHE_ Firefly	Proposed ESIHE_HSO
1	0.3732	0.751	0.4236	0.7418	0.8613	0.8593	0.8602	0.863	0.8604	0.8725
2	0.2408	0.7902	0.3289	0.4872	0.6666	0.668	0.6707	0.6648	0.6666	0.812
3	0.7631	0.8795	0.829	0.7986	0.6868	0.6769	0.6839	0.69	0.6871	0.895
4	0.1649	0.5823	0.2482	0.3056	0.7944	0.7944	0.7965	0.7899	0.7952	0.7987
5	0.0567	0.4592	0.2169	0.2434	0.74	0.7414	0.7648	0.7377	0.74	0.7806
6	0.6436	0.8331	0.76	0.6769	0.8336	0.8278	0.8427	0.8353	0.8402	0.8741
7	0.3068	0.5766	0.3582	0.6001	0.8147	0.8107	0.8114	0.8186	0.8139	0.8944
8	0.4435	0.6056	0.59	0.6343	0.7661	0.7542	0.7624	0.77	0.7596	0.7597
9	0.5369	0.739	0.5542	0.6863	0.794	0.7947	0.7905	0.7971	0.7968	0.8203
10	0.2152	0.4965	0.2503	0.3314	0.6155	0.5742	0.6016	0.6227	0.5902	0.6615
11	0.4863	0.798	0.65	0.7503	0.9366	0.9408	0.9366	0.9369	0.9424	0.9712
12	0.0902	0.6977	0.2771	0.264	0.6605	0.6635	0.6718	0.6583	0.6593	0.665
13	0.255	0.6607	0.5101	0.4619	0.8535	0.8148	0.8535	0.8579	0.8533	0.8918
14	0.3364	0.8364	0.4417	0.7483	0.7906	0.7766	0.7901	0.7933	0.793	0.792
15	0.4205	0.8358	0.5687	0.8311	0.8939	0.8929	0.8912	0.894	0.8923	0.9295
Avg	**0.3555**	**0.7028**	**0.4671**	**0.5707**	**0.7805**	**0.7727**	**0.7819**	**0.782**	**0.7794**	**0.8234**

Table 3: Comparison of MSE of Images 1 to 15

Input images	HE	BBHE	DSIHE	ESIHE	ESIHE_GWO	ESIHE_GOA	ESIHE_WOA	ESIHE_HGWPSO	ESIHE_Firefly	Proposed ESIHE_HSO
1	9110.185	2354.703	7255.19	0.022	0.017	0.018	0.017	0.017	0.017	0.017
2	9839.041	496.086	7232.35	0.022	0.008	0.008	0.008	0.008	0.008	0.007
3	2336.511	879.570	1565.77	0.006	0.009	0.009	0.009	0.009	0.009	0.009
4	14990.44	3056.285	10322.9	0.074	0.041	0.041	0.041	0.041	0.041	0.041
5	19823.95	2746.968	11437.44	0.037	0.003	0.003	0.001	0.003	0.003	0.001
6	3361.078	1095.469	672.154	0.004	0.028	0.028	0.027	0.028	0.028	0.028
7	10326.22	3098.578	8431.736	0.037	0.031	0.032	0.032	0.031	0.031	0.031
8	9894.627	4610.865	4946.058	0.046	0.032	0.034	0.032	0.031	0.033	0.032
9	4866.330	1488.154	4528.380	0.005	0.012	0.012	0.012	0.012	0.012	0.012
10	13951.70	7023.407	13179.80	0.093	0.043	0.049	0.045	0.042	0.039	0.043
11	7318.465	1012.471	2864.523	0.025	0.003	0.003	0.003	0.003	0.003	0.003
12	18255.41	1809.508	12816.67	0.032	0.003	0.003	0.003	0.003	0.003	0.003
13	12941.26	4507.764	6975.673	0.052	0.020	0.023	0.020	0.020	0.019	0.020
14	12226.86	1654.495	8782.515	0.019	0.013	0.014	0.013	0.013	0.013	0.010
15	8983.663	953.977	4576.705	0.011	0.005	0.005	0.006	0.005	0.005	0.005
Avg	**10548.38**	**2452.55**	**7039.193**	**0.032**	**0.018**	**0.019**	**0.018**	**0.018**	**0.018**	**0.017**

Table 4: Comparison of the NIQE of Images 1 to 15

Input images	HE	BBHE	DSIHE	ESIHE	ESIHE_GWO	ESIHE_GOA	ESIHE_WOA	ESIHE_HGWPSO	ESIHE_Firefly	Proposed ESIHE_HSO
1	4.9738	4.6459	4.9562	4.2715	4.1379	4.1316	4.1339	4.1201	4.1318	4.1171
2	4.8292	4.2860	4.9808	4.0188	3.9163	3.8977	3.8774	3.9130	3.9163	3.8781
3	3.3496	3.3271	3.4246	3.2385	3.2972	3.2929	3.3009	3.2811	3.2698	3.2751
4	3.6179	3.6028	3.9222	3.1196	3.0320	3.0320	3.0025	3.0606	3.0093	3.0316
5	4.5860	4.2558	4.6741	3.5606	3.5796	3.5811	3.4563	3.5909	3.5796	3.3912
6	2.8522	2.9724	3.1215	2.8524	2.9302	2.9549	2.9642	2.9359	2.9260	2.9286
7	3.3900	2.9843	3.2395	2.7204	2.7913	2.7912	2.7898	2.7834	2.7933	2.7814
8	3.6271	3.5726	3.6839	3.4032	3.1113	3.1703	3.1123	3.1075	3.1380	3.1233
9	3.3847	3.2934	3.3856	3.2044	3.1030	3.1062	3.1033	3.1153	3.1174	3.0934
10	3.2719	3.7781	3.4506	2.9968	3.3326	3.3476	3.3659	3.3217	3.2541	3.3438
11	3.5757	3.6767	3.9353	3.3912	3.4793	3.4807	3.4686	3.4765	3.4923	3.4590
12	5.0501	4.5307	5.0256	4.2921	4.1248	4.1201	4.1055	4.1119	4.1383	4.0872
13	2.2981	2.4055	2.5451	2.0545	1.9766	1.9759	1.9766	1.9635	1.9564	1.9489
14	4.6895	4.6053	4.6734	4.3501	4.2971	4.3553	4.2825	4.3037	4.3104	4.3972
15	3.2945	3.1319	3.4619	2.9565	3.1510	3.1541	3.1564	3.1562	3.1557	2.9358
Avg	**3.7860**	**3.6712**	**3.8987**	**3.3620**	**3.3507**	**3.3594**	**3.3397**	**3.3494**	**3.3459**	**3.3195**

As shown in Table 2, the SSIM (Structural Similarity Index Measure) values represent the level of improvement in terms of structure and perception using various techniques for enhancing different test images. The input images have the lowest average SSIM value of 0.355. Hence, their structural similarity is poor. HE and BBHE techniques have moderate improvement in terms of SSIM values of 0.702 and 0.467, respectively. However, DSIHE and ESIHE techniques have SSIM values of 0.570 and 0.606, respectively. When optimization algorithms are employed in ESIHE, a substantial improvement in the value of SSIM is observed.

Table 5: Comparison of the VIF of Images 1 to 15

Input images	HE	BBHE	DSIHE	ESIHE	ESIHE_ GWO	ESIHE_ GOA	ESIHE_ WOA	ESIHE_ HGWPSO	ESIHE_ Firefly	Proposed ESIHE_HSO
1	0.7918	0.8105	0.7906	0.8975	0.9004	0.9015	0.9010	0.8999	0.9011	1.2362
2	1.2264	0.8541	0.8147	1.2120	1.2466	1.2419	1.2394	1.2507	1.2466	1.4192
3	0.9283	0.9223	0.8800	1.0491	1.0585	1.0604	1.0589	1.0581	1.0583	1.0406
4	1.6155	1.0236	1.0258	1.4024	1.4062	1.4062	1.3932	1.4170	1.4030	2.3156
5	1.0349	0.8975	0.9587	1.1145	1.0277	1.0255	1.0924	1.0308	1.0277	1.8020
6	1.1436	1.1246	0.9858	1.2574	1.2570	1.2499	1.2508	1.2584	1.2594	1.1537
7	0.9475	0.9587	0.8597	1.1467	1.1461	1.1462	1.1456	1.1475	1.1466	1.4219
8	1.2983	0.9537	0.9734	1.1686	1.1610	1.1852	1.1660	1.1521	1.1754	1.5818
9	1.0356	0.8795	1.2479	1.1790	1.1821	1.1809	1.1815	1.1836	1.1867	1.1489
10	1.5853	0.8605	1.5612	1.2519	1.2575	1.3317	1.2862	1.2403	1.2139	1.9587
11	1.0335	0.8433	0.8407	1.0416	1.0363	1.0351	1.0360	1.0368	1.0346	1.2129
12	1.8118	1.0789	0.9875	1.1378	1.1230	1.1204	1.1190	1.1255	1.1145	1.7360
13	1.3769	0.8965	0.9737	0.9426	0.9517	1.0023	0.9517	0.9458	0.9515	1.6644
14	1.7622	1.0942	1.4685	1.0700	1.1182	1.1405	1.1195	1.1089	1.1082	1.5462
15	1.0777	1.0144	0.9433	1.1833	1.0339	1.0343	1.0333	1.0336	1.0340	1.2497
Avg	**1.2446**	**0.9475**	**1.0208**	**1.1369**	**1.1271**	**1.1375**	**1.1316**	**1.1259**	**1.1241**	**1.4992**

Table 6: Comparison of the Entropy of Images 1 to 15

Input images	HE	BBHE	DSIHE	ESIHE	ESIHE_ WO	ESIHE_ GOA	ESIHE_ WOA	ESIHE_ HGWPSO	ESIHE_ Firefly	Proposed ESIHE_HSO
1	6.5252	6.5098	6.5184	6.5998	6.6093	6.6096	6.6095	6.6101	6.6091	6.6099
2	5.8421	5.9101	5.8635	6.0418	6.0585	6.0611	6.0582	6.0616	6.0585	6.0564
3	7.1909	7.1709	7.1933	7.2851	7.2800	7.2813	7.2838	7.2803	7.2797	7.2846
4	5.0618	4.8799	5.0794	5.1332	5.1251	5.1251	5.1264	5.1234	5.1262	5.1250
5	4.2144	4.0352	4.2622	4.3326	4.3624	4.3626	4.3594	4.3618	4.3624	4.3597
6	6.7540	6.7167	6.6621	6.7955	6.8145	6.8170	6.8156	6.8116	6.8130	6.8143
7	5.9813	5.8826	6.0027	6.0706	6.0652	6.0652	6.0650	6.0652	6.0653	6.0621
8	6.3280	6.3007	6.2978	6.3701	6.3638	6.3638	6.3638	6.3637	6.3635	6.3642
9	6.6674	6.6152	6.6650	6.7769	6.7863	6.7836	6.7870	6.7856	6.7870	6.7860
10	5.8524	5.8233	5.8450	5.8985	5.8701	5.8708	5.8699	5.8690	5.8692	5.8691
11	6.3888	6.4325	6.3960	6.5762	6.6081	6.6092	6.6090	6.6077	6.6078	6.6085
12	4.5275	4.4492	4.5598	4.6760	4.6773	4.6770	4.6764	4.6769	4.6776	4.6780
13	6.0743	6.0398	6.0521	6.1490	6.1225	6.1229	6.1225	6.1231	6.1231	6.120
14	5.4365	5.4630	5.4826	5.5934	5.6126	5.6121	5.6123	5.6110	5.6126	5.6170
15	6.0909	6.1985	6.1805	6.2770	6.2860	6.2860	6.2898	6.2867	6.2880	6.2807
Avg	**5.9290**	**5.8952**	**5.9374**	**6.0384**	**6.0428**	**6.0431**	**6.0432**	**6.0425**	**6.0429**	**6.0444**

The algorithms employed are GWO (0.780), GOA (0.772), WOA (0.781), HGWPSO (0.781), and Firefly (0.779), and all exhibit excellent structural similarity, indicating better preservation of details and a more natural look. The ESIHE-HSO technique has the highest value of average SSIM, i.e., 0.783, thereby proving that it is the best among all in providing a balance between contrast enhancement and structural preservation. The above analysis on the SSIM value proves that the optimization algorithms employed in ESIHE are better than traditional methods, and HSO is the best among all in providing better enhancement results.

As shown in Table 3, the MSE values show the level of distortion between the original and enhanced images, and traditional HE techniques exhibit extremely high average MSE values (10548.38). This shows a high level of distortion in the enhanced images. Although both BBHE (2452.55) and DSIHE (7039.19) exhibit lower MSE values compared to HE techniques, their values are still high and represent a low level of preservation of original image details. However, a significant improvement is seen in ESIHE, where a drastic reduction in MSE values is observed. The average MSE value is reduced to 0.032. When optimization techniques are combined with ESIHE, a reduction in MSE values is seen. Techniques such as GWO (0.0179), GOA (0.0186), WOA (0.0180), HGWPSO (0.01765), and Firefly (0.01762) exhibit a low level of error. Out of all the techniques, the proposed ESIHE-HSO technique has the lowest average value of MSE, which is 0.01744, thereby validating the fact that the proposed technique has the least distortion while enhancing the contrast of the images. The MSE analysis clearly validates the fact that optimization-based ESIHE techniques significantly outperform traditional histogram equalization techniques, with HSO being the most accurate technique for enhancing images.

As can be seen in Table 4, the NIQE metric evaluates the perceptual quality of enhanced images without a reference image. The smaller the NIQE value, the better the quality and visual results. On the other hand, a higher NIQE value indicates distortion or over-enhancement of the image. From all the average results, it can be concluded that the quality of the input images has an NIQE value of 3.78. Among existing methods, DSIHE has the highest NIQE value of 3.89, indicating worse visual quality and naturalness. In addition, HE and BBHE have NIQE values of 3.78 and 3.67, respectively, indicating a slight enhancement. Moreover, after using ESIHE alone, the NIQE value is reduced to 3.36, indicating better brightness and contrast enhancement. As the optimization techniques are employed in combination with ESIHE, the NIQE values reduce by a small margin but remain at a consistently low level. GWO(3,35), GOA(3.36), WOA(3.33), HGWPSO(3.34), and firefly exhibit comparable levels of perceptual quality, with minimal differences among them. The proposed ESIHE-HSO technique has the lowest average value of 3.31 in the NIQE table, thus producing the most natural image. From the above table, it is evident that the optimization-based ESIHE techniques outperform the conventional histogram equalization techniques, among which the HSO technique has the lowest value of 3.33 in the NIQE table, thus producing the least distorted image among all the techniques.

In Table 5, the VIF (Visual Information Fidelity) metric evaluates how much visual information from the original image is preserved after enhancement. Higher VIF values indicate better visual information retention and improved perceptual quality. As can be seen in the average results, the input images have a VIF value of 1.24. However, traditional methods have varying results. BBHE and DSIHE have VIF values of 0.94 and 1.02, respectively. Both values are less than 1 and are close to each other. This shows that both methods slightly reduce or only marginally enhance the input image. HE has a VIF value of 1.24. This shows that HE is close to the input image. However, ESIHE is seen to have a VIF value of 1.136. This shows a clear improvement in the preservation of visual information. When optimization techniques are applied to ESIHE, all methods have VIF values close to 1. For instance, GWO, GOA, WOA, HGWPSO, and Firefly have VIF values of 1.127, 1.137, 1.131, 1.125, and 1.124, respectively. All values are close to 1. This shows that all optimization techniques applied to ESIHE are balanced and have good information fidelity. However, the VIF value for HSO is 1.49. The VIF values for all methods show that when optimization techniques are applied to ESIHE, all methods have good perceptual quality and no loss of information.

Table 6, the entropy values increase when the texture is richer and contrast is enhanced. According to the average values in Table 6, the entropy values for the input images are 5.93. It can be seen that traditional HE techniques, such as BBHE (5.90) and HE (5.93), produce a moderate level of entropy values for image details.
However, DSIHE (5.94) and ESIHE (6.04) produce higher entropy values compared to traditional HE techniques. When optimization techniques are applied to ESIHE, all entropy values are high. In particular, the entropy values based on ESIHE methods show a notable improvement in PSNR values compared to all other methods. This shows the success of optimization techniques in fine-tuning parameters using metaheuristics. Among all optimization-based methods, ESIHE-HSO shows a high PSNR value of 19.45 dB compared to other optimization-based methods like GWO, GOA, WOA, HGWPSO, and Firefly. This shows that PSNR values are improved for all images using the proposed HSO strategy. SSIM calculates structural fidelity and is thus meaningful for perception. HE and DSIHE have poor average SSIM values of 0.35 and 0.47, respectively. This confirms that heavy histogram equalization degrades structural content. BBHE improves SSIM but still experiences luminance distortion. The optimization-based techniques exhibit much higher SSIM values, indicating improved structural content preservation. The proposed ESIHE-HSO obtains the highest average SSIM of 0.783, indicating good luminance, contrast, and structural content preservation. MSE is used for pixel-wise distortion, where lower values of MSE are always desirable. As expected, the results obtained by HE show extremely high values of MSE, which confirms the excessive intensity deviation caused by this method. The results obtained by BBHE and DSIHE show lower values of MSE, but they are still not satisfactory. All optimization-based methods significantly reduce the MSE, among which ESIHE-HSO has the lowest average value of MSE,i.e.,0.01744. This is strongly correlated with the high PSNR values, which confirms that the proposed method has introduced minimal error during the reconstruction. Better image quality is obtained if the NIQE value is low. The HE and DSIHE schemes have higher NIQE values because of the unnatural contrast stretching and noise enhancement artifacts

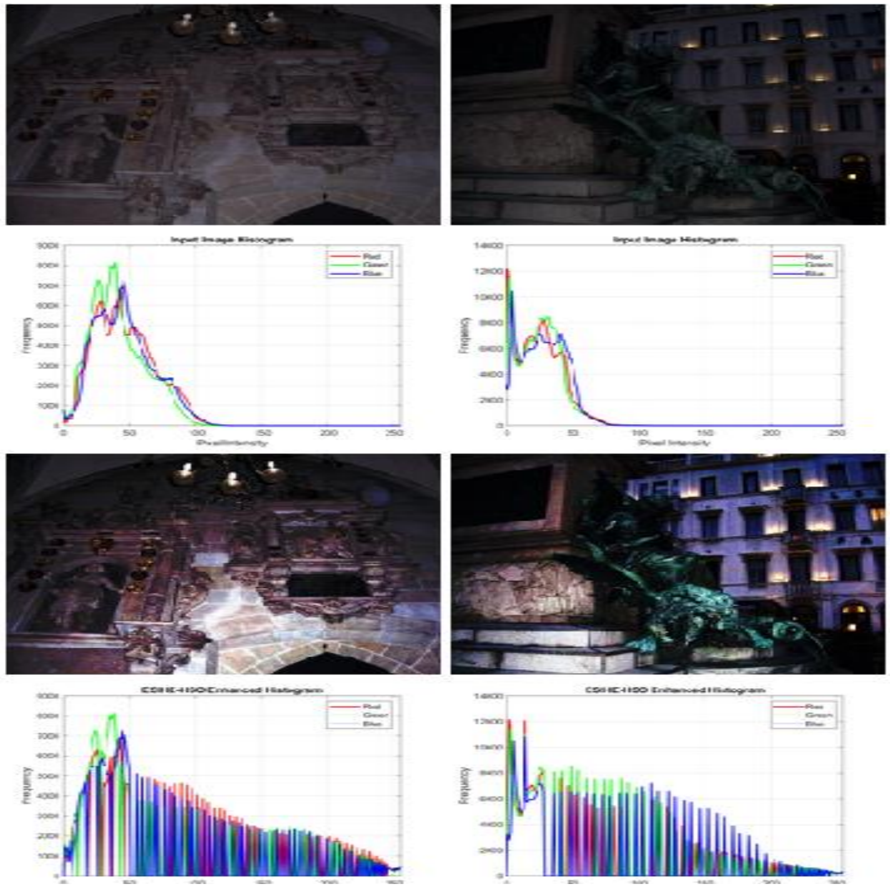

Figure. 5: The first row consists of input images, the second row is histogram of the input images, the third row is enhanced images, and forth row shows the histogram of the enhanced images

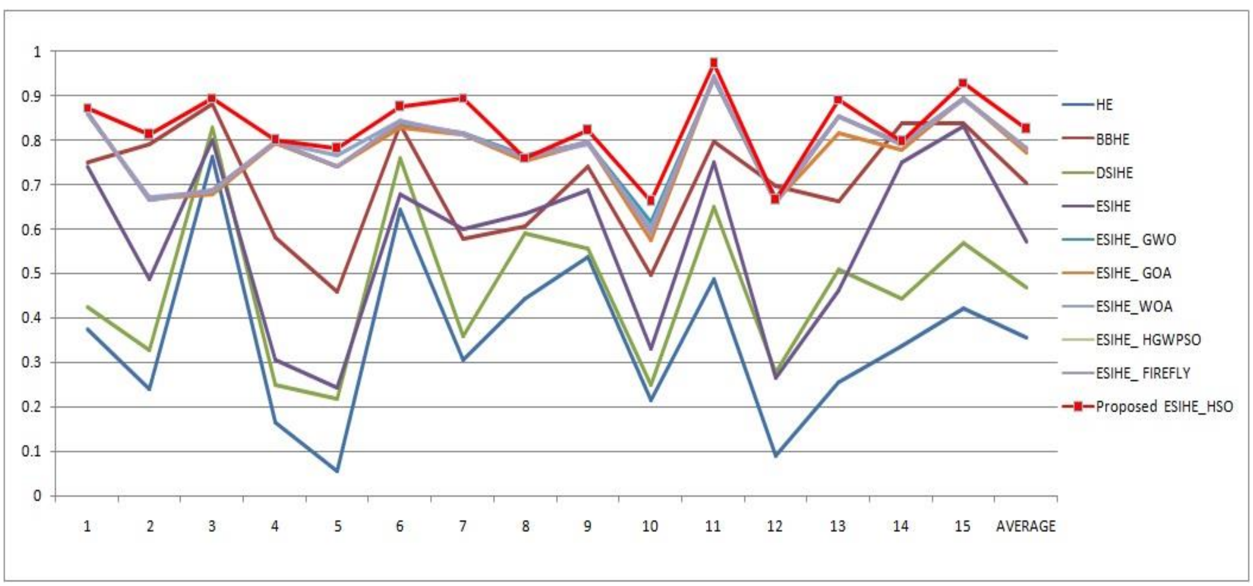

Figure. 6: Comparison of PSNR values of different image enhancement methods with the proposed method for images 1 to 15

The proposed ESIHE-HSO has the lowest average NIQE value of 3.319, which is better than all the comparative schemes. This proves that the HSO-based optimization of ESIHE preserves the naturalness of the images by closely following natural scene statistics. VIF measures the amount of visual information that is maintained after image enhancement. HE and CLAHE have low VIF values owing to information loss. Although BBHE and DSIHE have moderate enhancement, they do not maintain visual information details. The optimization-based methods have better VIF values. ESIHE-HSO has competitive VIF performance with an average VIF of 1.499**.** Entropy is employed for measuring the richness level of the image's information content. HE and BBHE exhibit..t lower entropy because of the saturation in the histogram. The ESIHE–HSO, on the other hand, attains a high and constant level of average entropy, i.e., 6.04, similar to its optimized counterparts, while providing better perceptual quality. It can be observed that overall, the results have clearly demonstrated that the ESIHE-HSO framework proposed in this study is robust, perceptually better, and quantitatively optimal.

7. Conclusion

In this research paper, a novel optimized framework for low-contrast image enhancement has been introduced, employing Exposure-based Sub-Image Histogram Equalization (ESIHE) and incorporating the use of optimization algorithms. The proposed framework has been shown to effectively eliminate the problems of over-enhancement, brightness distortion, and unnatural appearance, which are associated with the conventional ESIHE technique. Experiments conducted on images, employing objective quality metrics, indicate that the optimized ESIHE methods consistently outperform the conventional ESIHE technique in terms of contrast enhancement, structural preservation, and overall perceptual quality. Among the optimized ESIHE methods, ESIHE–HSO is found to perform better than the other image enhancement techniques.

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Data availability statements

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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Conflict of Interest

The authors declare that they have no potential conflict of interest.

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