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Pelican Optimization based Histogram Equalization for Contrast Enhancement and Brightness Preservation

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Abstract: Image contrast is very important visual characteristics that will considerably improve the appearance of the image. In this paper image contrast is to be enhanced optimally to accurately portray all the data in the image using nature inspired meta-heuristic algorithms. Algorithms have been devised and proposed to enhance the contrast of low contrast images in this work. Poor image contrast caused by a low-quality capturing device, biased user experience, and an unsuitable environment setting during image capture is the main problem encountered during the image enhancement process. Histogram Equalization (HE), a frequently used technique for contrast enhancement, typically produces images with unwanted artifacts, an unnatural appearance, and washed-out appearances. The degree of enhancement is beyond the control of the global HE. The quality of an image is crucial for human comprehension, making image contrast enhancement (ICE) a crucial pre-processing stage in image processing and analysis. In the current study, the Pelican Optimization Algorithm, a contemporary meta-heuristic (MH) algorithm influenced by nature, is used as the foundation for the grayscale image contrast enhancement (GICE) approach (POA). The comparison of proposed method with existing contrast enhancement techniques has been done on the basis of standard image quality metrics. The proposed algorithm performance on standard test image and Kodak dataset demonstrates that total image contrast and information provided in the image are both greatly improved by the suggested POA-based image enhancement technique.

Index Terms: Conventional Histogram Equalization, Image Contrast enhancement, Local Histogram Equalization, Meta-heuristic, Pelican Optimization Algorithm

1. Introduction

Image contrast enhancement (ICE) is an essential step for various computer vision and machine learning techniques. However, the limited range of grey-level distribution of the images, as well as shortcomings including intensity in-homogeneity, low contrast, and poor image quality, arise due to inadequate lighting and improper camera settings. These problems degrade the accuracy of computer vision and image recognition processes where many images are to be used. Therefore, increasing the contrast of the images during the computer vision process has now become a demanding step. ICE process is a possible nonlinear optimization issue where purpose is to make the input image's visual contrast stronger. The histogram equalization is a frequently used approach for improving contrast, typically produces images with unwanted artifacts, unnatural and washed-out appearances. The quality of an image is crucial for human comprehension, making image contrast improvement a crucial pre-processing stage in computer vision and image recognition. In earlier days, goal of ICE was achieved globally by updating the gray levels of low-contrast images as efficiently as possible to improve the visual quality. The traditional approach of increasing visual contrast by rescaling the dynamic dimension and histogram composition of the image is known as Conventional Histogram Equalization (CHE). However, the quality of image enhancement is not guaranteed by traditional histogram equalization since it encounters noise amplification in areas of approximate uniformity and considers global contrast. AHE is a local histogram equalization that has been generalized from CHE. AHE is an adaptive approach but results in too much noise amplification in near constant regions. CLAHE avoids noise amplification problem by restricting the contrast. Before implementing histogram equalization, every histogram bin that exceeds the set contrast limit will have its pixels cropped and then allocated equitably to other bins. CLAHE rely on manual setting of parameters and parameters are figured out at the location of the greatest entropy curvature. Other important image features for parameter consideration can also be included.

1.1. Contrast Limited Adaptive Histogram Equalization

CLAHE method a local and adaptive HE approach relies on two parameters. The first parameter, tile size (TS), specifies the number of tiles used to partition the image. Consequently, the picture has been divided into several local tiles or zones. The clip limit (CL) limits noise amplification and prohibits the histogram of each tile's intensity values from going over the desired CL. Because noise is enhanced in homogenous regions, the CLAHE technique lowers noise amplification while raising the brightness of the foreground and background of the image by a similar weight. Furthermore, parameter determination necessitates a longer processing time. Because CLAHE is subjective, manually establishing the settings significantly rely on individual prior experience (TS and CL). Standard CLAHE parameter (TS & CL) values produce excessively and unnaturally improved results. Because determining the ideal values for the numerous CLAHE-style non-linear image transformation parameters can be difficult, many academics have examined various optimization approaches as an alternative method.

If p_a is average pixel count p_m and p_n represents number of pixels in the x and y dimension respectively. The actual histogram is cropped by CL for every contextual region as can be calculated from equation (1).

$$CL = p_a \times N_{CL} \tag{1}$$

N_{CL} is the normalized clip limit. The application of the clip limit on the height of the histogram can be seen in equation (2).

$$H_i = \begin{cases} CL & if N_i \geq CL \\ N_i & else \end{cases} \quad i = 1,2, \ldots \ldots (l-1) \tag{2}$$

N_i is a histogram of ith tile and H_i is the height of ith tile's histogram. Total clipped pixels p_c are:

$$p_c = (p_m \times p_n) - \sum_{i=0}^{L-1} H_i \tag{3}$$

Remaining clipped pixels or residual pixels p_r given in equation (4) are to be redistributed over the entire grey-level range.

$$p_r = {}^{p_c}\!/_{L} \tag{4}$$

Now, an updated clipped histogram is given by equation (5)

$$H_i = \begin{cases} CL & if N_i + p_r \geq CL \\ N_i + p_r & else \end{cases} \quad i = 1, 2, \ldots \ldots (l-1) \tag{5}$$

Equation (5) is repeated until all the undistributed pixels measures using equation (3) and equation (4) are redistributed. Contextual region's cumulative histogram is provided by equation (6).

$$C_i = \frac{1}{(p_m \times p_n)} \sum_{j=0}^{i} H_j \tag{6}$$

2. Literature Review

The images having a limited range of gray-level distribution, as well as shortcomings including intensity in-homogeneity, low contrast, are the consequences of inadequate lighting and improper camera settings. Image contrast enhancement (ICE) updates the grey levels of low contrast images as effectively as possible in order to enhance visual quality while also simplifying post processing procedures. Both global and local contrast enhancement can be created by using intensity transformation algorithms. Histogram equalization (HE) is the term for the conventional method of enhancing visual contrast by up-scaling the image's dynamic range [1, 2].

With adaptive histogram equalization (AHE) [3], equalization is accomplished using image statistics gleaned from the area surrounding each pixel. Compared to global procedures, these techniques offer stronger enhancing effects. The low contrast input image is divided into non-overlapping sub-images by AHE, and each sub-image is then given histogram equalization. Bilinear interpolation is used to combine the sub-images to create the final image. However, in histogram equalized photographs, irritating artefacts, a negligible decrease in brightness, and noise enhancing can be seen. The AHE technique addresses the CHE's weakness of intensity inhomogeneity effectively. AHE takes the longest to run, but on the other hand it magnifies the noise in the images that are produced. Various HE based schemes found in literature are discussed in further section.

The Region based histogram equalization (RHE) methods includes Contrast-Limited Adaptive HE (CLAHE) Zuiderveld [4], Partially Over-loaded Sub imaging HE [5], exposure based sub-image HE [6], adaptive Bi-HE (ABHE) algorithm [7] and Median and Mean Bi-HE plateau limit [8]. Wu et al. [9] suggested histogram modification based reversible data hiding with image contrast enhancement. Bhandari et al. [10] proposed fuzzy-DCT scheme which includes histogram division on the basis of density function and then using fuzzy c-means clustering to make clusters of brightness levels followed by histogram equalization. A method for modifying logarithmic histograms was developed by Bhandari [11] in 2019, while Subramani and Veluchany [12] proposed an approach based on a fuzzy inference system for HE. Multiple Layers Quick Block Overlapped HE (BOHE) approach with several stages of improvement was proposed by Tao et al. [13].

The Histogram-based division includes bi-histogram and multiple sub-histogram methods. Bi-histogram category includes include brightness preserving HE (BBHE) [14], dual sub-image HE (DSIHE) [15]. Further improvement in BBHE includes minimal mean brightness error bi-HE [16], range-Limited Bi-HE [17], non-parametric modified HE (NMHE) [18] and adaptive contrast enhancement using modified HE (ACMHE) [19]. Otsu-based thresholding and entropy-based thresholding [20] separates the image into background and foreground. BBHE method generate sub-histograms based on mean value and DSIHE do median based input image segmentation whereas MMBEBHE performs the threshold based histogram separation. But, poor enhancement in image contrast and washed out details effect is still existing. Kong and Isa [21] uses DCT for local fine-tuning of the image but results in creation of dark regions in an image. Dynamic Clipped HE, as proposed by Reddy and Reddy [22], resulting in homogeneous distribution of intensity while increasing entropy. The model presented by Khan et al. [23] equalizes low-contrast images optimally but has a significant computational complexity. The enhancement model for underwater image enhancement presented by Bai et al. [24].

Multiple sub-histogram-based image division include approaches recursive mean separate [25] and recursive sub-image HE (RMSHE) [26], dynamic histogram equalization (DHE) Wadud et al. [27], brightness preservation DHE (BPDHE) Ibrahim and Kong [28], DQHEPL Ooi and Isa [29], quadrants dynamic HE (QDHE) [30], median and mean sub-image clipped HE (MMSICHE) [31]. Entropy dynamic sub-HE (EDSHE) Parihar and Verma [32] generates unwanted artifacts with more processing time. Khandway and Bhandari [33] proposed method which suffers from washed out appearance. Majeed and Isa's [34] calculates the clip limit CL value in an iterative and adaptive manner, although this method does not always result in the optimal CL values and processing time is very lengthy. Ding et al. [35] worked for maritime image enhancement.

For the purpose of enhancing visual contrast, many NIOAs (nature-inspired optimisation algorithms) have been hybridised with HE. Among these techniques are those used by Hashemi et al. [36], Qinqing et al. [37], Agrawal and Panda [38], Mohan and Mahesh [39], Draa and Bouziz [40], and Joshi and Prakash [41], which identify the best parameter values for a variety of non-linear transformation functions. To enhance mammography pictures paper [38] used the cuckoo search algorithm (CSA), whereas Mohan and Mahesh [39] used particle swarm optimisation (PSO) in conjunction with the CLAHE. GA optimised Bi-HE for image enhancement are used by Babu and Rajamani [42]. ABC algorithm was applied to achieve parameter optimization of incomplete beta function (IBF) [43]. In another study Dhal et al. [44, 45] used hybridized model of multi-objective cuckoo search algorithm (MOCS) with otsu based bi-weighted threshold HE (OBBWTHE) and ABC algorithm with Multi-threshold HE for mammogram images histopathology images respectively. Also Dhal and Das [46] utilizes firefly algorithm with histogram equalization. Wan et al. [47] exploited PSO for infrared images. Singh et al. [48], deployed PSO with gamma-correction in case of satellite images. Method narrated by Bhandari et al. [49] used slap folks swarm optimization method for maximization of image entropy, PSNR and edge intensities. For medical images several methods are proposed such as histogram equalization using krill herd optimization HE-KHO by Khandway et al. [50], cuckoo search brightness preserving HE scheme (CS-BPHE) Bhandari and Maurya [51] and adaptive histogram equalization using genetic algoithm (GAAHE) Acharya and Kumar

[52]. Majeed and Isa [53] introduced new technique divides the image into three sub-images and then CLAHE with whale optimization algorithm (WOA) is applied on each of these sub-images.

To determine optimal parameters for CLAHE, Kuran et al. (2021) [54] uses multi-objective cuckoo search (MOCS) with entropy as first fitness function and second fitness function computes fast noise variance estimation (FNVE). Fawzi et al. (2021) [55] proposed adaptive clip limit tile size histogram equalization which assigns the optimum clip limit (CL) with minimum and maximum tile size limits. Khan et al. (2022) [56] proposed hybridization of PO (Political Optimizer) in conjunction with AβHC (adaptive β hill climbing) to get optimize parameters of transformation function incomplete beta function (IBF).

The most recent improved image contrast enhancement technique is shown in Table 1 along with its objective function and NIOA.

Table 1. Comparison of different NIOA based ICE methods

Year	Method and Author	Objective Function	Meta-heuristic Algorithm (MHA)	Drawbacks
2020	SSA-PL A.K. Bhandari, [49]	$fitness\ Funct. = 0.5\ (Entropy \times\ Edge) +\ 0.5\ PSNR$	SSA	Histogram based technique results in loss of local image details.
2021	CLAHE-MOCS U.Kuran, [54]	2-Fitness Functions (Entropy and FNVE)	MOCS	This method takes longer time for local and global search.
2021	AEIHE S.H.Majeed, [53]	$fitness\ Funct. = (E\ \times\ \text{SSI})$	WOA	Poor performance on images with multiple exposures.
2021	ACLTSHE A. Fawzi et al. [55]	$fitness\ Funct. = (E\ \times\ PSNR)$	WOA	Method do not consider structural details.
2022	HE-WOACSA A.K.Bhandari [58]	Entropy Based	WOA + CSA	Histogram Segmentation based technique results in poor performance and longer computation time.
2022	IBF-AEFA S. Mukhopadhyay et al. [57]	$fitness\ Funct. = (E\text{ntropy} \times \text{SSI}\ \times\ E\ \times\ C\ \times \text{RMSE})$	$AEFA$	Transformation function based method results in over-enhancement and local optima problem is there.
2022	Ei^2PO A. H. Khan $et\ al.$ [56]	$fitness\ Funct. = \text{Edge} \times Entropy$	$PO + A\beta HC$	Transformation based technique take longer processing time.

Mukhopadhyay et al. (2022) [57] uses artificial electric field algorithm to find the optimal values for transformation function but this method enhances only edge information. Bhandari et al. [58] combines whale optimization algorithm with crow search algorithm to determine clip limit for each sub-histograms. Rajwar et al. [64] presented list of most cited Meta-heuristic Algorithms (MHA) where PSO and GA are the leading MHAs. According to Dhal et al. [65], NIOA is heavily utilized in the ICE domain, they categorize NIOAs into various classes and explore how to apply NIOA to various image formats. This research paper came to the conclusion that the field of NIOA-based image improvement is still relatively new and developing with new ideas and applications, and that 68% of ICE algorithms are bio-inspired.

From literature review it is clear that visual quality of output enhanced images can be improved for higher image quality metrics. Also, level of enhancement needs to be controlled. The most of the enhancement approaches exhibits high execution time and user has always to worry about the choice of optimal parameters. Moreover, NIOA based HE suffers from tendency of getting stuck at local optima or false optima location. Major research gap found is inefficient HE for contrast enhancement in low contrast images due to improper tuning of control parameters.

3. Optimization Problem

The three fundamental components of an optimization problem are choice variables, constraints, and objective function. Science and technological advancements have made optimization problems more difficult and caused the emergence of new optimization problems that must be solved utilizing stochastic methods like meta-heuristic algorithms (MHA).In order to produce efficient solutions to optimization issues, MHA do random scanning of the problem-solving space. These algorithms are popular and widely used. Due to variations in the methods used to find and update their candidate solutions, MHA behave differently in remarkably similar problems. In this procedure, the problem-solving space is initialized with fixed number of randomly viable solutions. Potential solutions are then modified and enhanced depending on the algorithm instructions using a repetition-based method. The problem's best candidate solution is presented as the answer after the method has been fully implemented.

The most popular EAs, GA [68, 69], is based on a model of reproduction. The behavior of living things in nature has served as inspiration for the development of swarm-based algorithms (SAs). PSO [70, 71] is based on natural bird behavior, CSA [72] is based on cuckoos' brood parasitism behavior, and WOA [73] is based on bubble-net hunting method and the natural behaviors of humpback whales. Most recent SA based technique and its performance in ICE domain is presented in upcoming sections.

3.1 Pelican Optimization Algorithm

A number of NIOAs are devised in order to render a universal framework capable of addressing the vast majority of real-world issues. Complicated and nonlinear parts of the optimization process have been identified as optimization difficulties for image-enhancing systems. Exploration and exploitation determine the potential of various NIOAs to identify optimized solutions. To determine the candidate solution, the meta-heuristic algorithm's behavior is assessed using the fitness measure. Pelicans are members of the Pelican Optimization Algorithm (POA) [74], a new population-based optimization technique. The fundamental purpose of POA's design was to mimic the hunting strategies and behaviors of pelicans. POAs outperform eight well-known optimization approaches in terms of high exploration and exploitation potential. Each population member provides a potential answer for a search space-based solution for the variables in the optimization challenge. To begin, population individuals are arbitrarily allocated using equation (7).

$$x_{i,j} = l_j + rand.\left(u_j - l_j\right) \tag{7}$$

where $i = 1,2,3,..,N$; $j = 1,2,3,....,m$. $x_{i,j}$ is the value of jth variable defined by the ith candidate approach. N is the number of population members, m is the number of population instances and $rand$ is the arbitrarily number in the interval$[0,1]$. The terms l_j and u_j are the lower and upper bound of problem variables respectively. If X_i is ith pelican, then the population matrix of population members is as shown in equation (8).

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{NXm} = \begin{bmatrix} x_{1,1} \dots x_{1,j} \dots x_{1,m} \\ \vdots \quad \ddots \quad \vdots \quad \ddots \quad \vdots \\ x_{i,1} \dots x_{i,j} \dots x_{i,m} \\ \vdots \quad \ddots \quad \vdots \quad \ddots \quad \vdots \\ x_{N,1} \cdots x_{N,j} \cdots x_{N,m} \end{bmatrix} \tag{8}$$

The objective vector F and its values for ith candidate solution is given by equation (9).

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N\times 1} \tag{9}$$

The Phase 1 of the algorithm starts when the pelican moves towards prey and in Phase 2 pelican wings on the water surface.

Phase 1: In this phase pelican's (search agents) position is updated around the randomly selected pelican (prey) in the search space to find out target using equation (10).

$$x_{i,j}^{P_1} = \begin{cases} x_{i,j} + rand.\left(p_j - I.x_{i,j}\right), & F_p < F_i \\ x_{i,j} + rand.\left(x_{i,j} - p_j\right), else, \end{cases} \tag{10}$$

$X_{i,j}^{P_1}$ is the new status of ith pelican in jth dimension and I is the random number with value 1 or 2. p_j is the location of prey in jth dimension and F_p is its objective function value. Equation (11) is used to update agent's position.

$$X_i = \begin{cases} X_i^{P_1}, F_i^{P_1} < F_i \\ X_i \quad else \end{cases} \tag{11}$$

$X_i^{P_1}$ is the new status of ith pelican and $F_i^{P_1}$ is its objective function value based on phase 1.

Phase 2: In this phase agents hunting is performed using equation (12)

$$x_{i,j}^{P_2} = x_{i,j} + R.\left(1 - \frac{t}{T}\right).(2.rand - 1).x_{i,j} \tag{12}$$

$x_{i,j}^{P_2}$ is new status of ith pelican in the jth dimension based on phase 2. R is constant equal to 0.2. $R.\left(1 - \frac{t}{T}\right)$ is neighborhood radius of $x_{i,j}$, t is iteration counter and T is the maximum number of iterations. In exploitation phase, final position is updated only if new fitness value for the agent is better than old fitness value using equation (13).

$$X_i = \begin{cases} X_i^{P_2}, F_i^{P_2} < F_i; \\ X_i, \quad else; \end{cases} \tag{13}$$

$X_i^{P_2}$ is the new status of ith pelican and $F_i^{P_2}$ is the objective function based on phase 2.

In the current study, Pelican Optimization, a contemporary meta-heuristic algorithm influenced by nature, is used as the foundation for the grayscale image contrast enhancement. The Pelican Optimization is used to find the best settings in adaptive histogram equalization, and a fitness function is defined for computing contrast, entropy, and gradient data.

4. Proposed Pelican Optimization based Enhancement Algorithm

The proposed approach Grayscale image contrast enhancement using pelican optimized histogram equalization aim to enhance image local details by optimizing enhancement parameters of CLAHE adaptively and automatically shown in Fig. 1. In the proposed approach, Tile size (TS) takes 4 values $TS = 4, 6, 8, 10$ since, $TS < 4$ leads to under-enhancement and $TS > 10$ leads to over-enhancement. Additionally, although a modest CL value barely improves image contrast, a high CL score smoothen the histogram's pixel allocation. Normalized Clip Limit (N_{CL}) is calculated for each tile size at each iteration using equation (14).

$$N_{CL} = \frac{number\ of\ pixels\ of\ selected\ gray\ level}{Total\ number\ of\ pixels} \tag{14}$$

Now, this normalized clip limit value is used to calculate CL using equation (1). Now to find the optimum TS and CL value, the fitness function has to be defined.

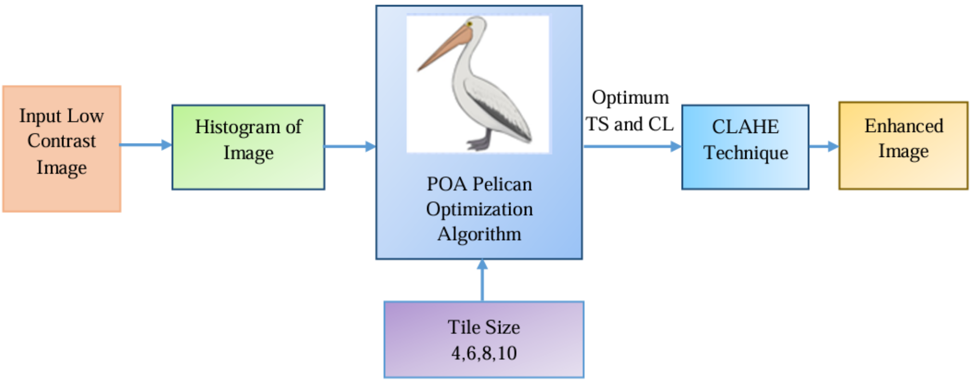


Fig. 1.Process Design of proposed technique

4.1 Optimization Fitness Measure

The quality of the candidate solutions is measured against the value of the objective function. An objective function is necessary to determine the fitness of the suggested solution. According to the problem, the function's solution should either reach maxima or minima. A tunable parameter, the fitness function($\emptyset$), represented by equation (15), varies depending on the three characteristics of the image.

$$\emptyset = Contrast\ X\ Entropy\ X\ Gradient \tag{15}$$

If N_g is the number of discrete gray levels in the quantized image, then contrast and entropy can be determined from normalized GLCM [66]. GLCM analyses intensity variation at the targeted pixel. By figuring out how frequently reference and neighbor pixels with particular amplitude and given spatial relationship appear in an image, GLCM matrix [59, 60] characterize the texture of an image. Then, from this matrix, statistical measurements are taken. The GLCM reflect the overall average degree of correlation between pairs of pixels in several areas.

Let,$p(m,n)$ is the $(m,n)th$ entry in a normalized GLCM.

Contrast is

$$Contrast\ (C) = \sum_{m=0}^{N_g-1}\sum_{n=0}^{N_g-1}|m-n|^2 p(m,n) \tag{16}$$

Entropy is given as shown in equation (17).

$$Entropy\ (E) = -\sum_{m=0}^{N_g-1}\sum_{n=0}^{N_g-1} p(m,n)\log\big(p(m,n)\big) \tag{17}$$

Canny edge detection [61, 63] is regarded as one of the most reliable and accurate techniques for detecting edges in images. This algorithm is more noise-resistant and only detects edges where there is a substantial change in intensity. Hysteresis thresholding is also used to filter out false edges; it only detects edges that are rated "strong" by a high threshold and "weak" by a low threshold. When there are several options in a local neighbourhood, canny uses non-maximum suppression to select the best pixel for edges. After obtaining Canny edge map of input image, now statistics of co-occurrence between adjacent pixels is used to calculate gradient information.

$$Gradient\ (G) = \log\left(\log(E(I_{canny}))\right)\frac{n_{edges}(I_{canny})}{M\times N} \tag{18}$$

whereI_{canny} is the Canny edge image of size $M \times N$, $E(I_{canny})$ is the sum if the intensity of pixel margins, n_{edges} is the number of pixel margins in the Canny image.

The equation (15) need to be maximized for contrast enhancement since all the three features of images are to be increased till occurrence of optimum fitness value. The fitness factor is to be maximized and the optimum value $\emptyset$ is determined by applying Pelican Optimization Algorithm [74] to the fitness function. Mathematically, it is represented as:

$$\emptyset_{opt} = \max(\emptyset) \tag{19}$$

Table 2. Average PSNR, MSSIM and VIF values based on various variables of fitness function ($\emptyset$) on Kodak dataset

Contrast	Entropy	Gradient Information	Avg. PSNR	Avg. MSSIM	Avg. VIF
C	-	-	17.81	0.773	0.43
-	E	-	19.63	0.879	0.54
-	-	G	20.01	0.892	0.60
C	E	-	20.90	0.899	0.64
-	E	G	22.13	0.902	0.69
C	-	G	23.25	0.926	0.71
C	E	G	**28.18**	**0.963**	**0.83**

On the Kodak dataset [67], an ablation study is carried out to choose the objective function's variables and to define the fitness function for optimization. On the Kodak dataset [30], an ablation study is conducted to select the objective function's parameters and to define the fitness function for optimization. From Table 2 it has been observed that high average values of PSNR, MSSIM and VIF is achieved when three important features of images as represented by C, E and G are considered together.

4.2 Detailed steps of Proposed Method

1. Take a low-contrast image as input and get its histogram.
2. Now, do image divisions as per each TS=4, 6, 8, 10, Based on the input low contrast image and TS value, the main parameters identified as input to POA are$TS, \emptyset,\ N_{CL}, CL,\ best_TS,\ best_CL,\ best_\emptyset$. CL value is computed for each TS. CLAHE is executed for each CL and TS pair.
3. To make certain POA will give optimum CL and TS values, a fitness function $\emptyset$ is introduced. POA requires a high fitness value to get optimum results.
4. The CLAHE will now use the final best values as input parameters to improve all sub-images and create final improved image.

The pseudo-code and flowchart of suggested method is presented in Fig. 2 and Fig. 3 respectively. In order to facilitate visualization in the flowchart, the fitness function $\emptyset$ has been represented by the letter F in Fig. 3.

```
Begin
Readtheinputlowcontrastimage
Compute histogram of an low contrast image
Initialize TS(k) = {4,6,8,10}, POA parameters m = 2, N = 20 and itr = 30, TS, φ, CL, best_TS
              = 0, best_CL = 0, best_φ = 0
Initialize Pelican position
While itr ≤ 30
   for itr → 1
      N search agents move randomly along the histogram according to the exploration and
                     exploitation phase equations of POA Algorithm
                                  for k = 0 to 3
                     Agent select random gray level
                     Compute CL of selected gray level
                     Apply CLAHE based on the combination of computed CL and TS(k)
                     Compute Ø
                          if Ø > best_Ø
                               best_Ø = Ø
                               best_CL = CL
                               best_TS = TS
                          end if
           end for
   end for
end while
end
Contrast enhancement by using optimum CL and TS pair
```

Fig. 2. Pseudocode of the suggested technique

5. Experimental Results and Analysis

This section, is a presentation of how well our suggested strategy, performed using the standard image and dataset. Experiment I is carried over the standard test image “Lena”. Experiment II is performed on the Kodak Image Dataset (Dataset of 25 Color Images of size (512×384) [67]. The KODAK dataset is frequently used in grayscale image contrast enhancement (GICE) and other image processing programmes and its images are transformed into the equivalent grey-scale versions, which are used as the basis for our experimentation. The performance of various image augmentation and denoising algorithms is benchmarked or validated using full reference picture quality metrics, where reference image is given for comparison.

Metrics [75, 76] to quantify the proposed enhancement algorithm's performance are peak signal-to-noise ratio (PSNR) measured in dB, mean structural similarity Index (MSSIM) and visual information fidelity criterion (VIF). PSNR is the ratio between the maximum power of the input signal and the signal noise. PSNR is commonly stated as a logarithmic quantity using the decibel scale because many signals have a very wide dynamic range. Mean Structural Similarity Index (MSSIM) is a structural degradation [76] oriented technique unlike PSNR, which uses a single pixel as a unit for comparison, the MSSIM index uses a pixel patch of $11X11$ centered on the test pixel MSSIM metric checks the structural similarity between images. VIF is human visual system inspired metric based on natural scene statistics. Higher values each of these metrics signifies better contrast enhancement technique. The value of MSSIM and VIF ranges from 0 to 1.

5.1 Parameter Selection

To achieve a fair comparison, the NIOA algorithms GA, PSO, CSA, and WOA are chosen. This is done on the basis of a prior literature review of optimization methods used for DIP applications. When handling challenging optimization issues in the field of image processing, all of these methods have demonstrated competitive performance. These NIOA being compared have their parameter settings appropriately adjusted for the challenge at hand. Population size of 20 is considered for each. Various control parameters for each of them which are used to successfully simulate the proposed work are shown in Table 3.

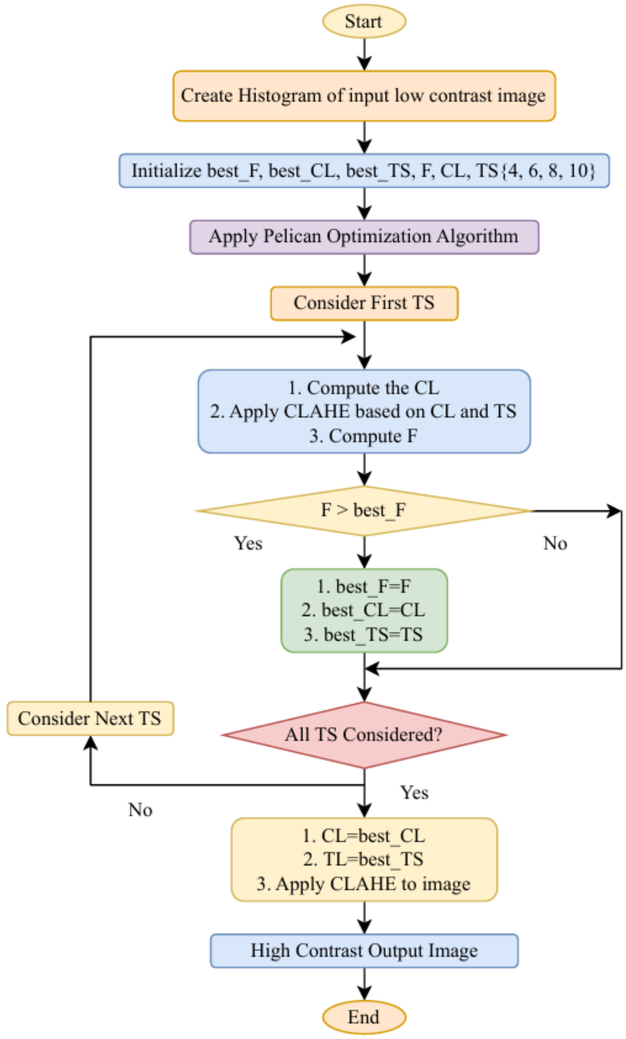


Fig. 3. Flowchart of suggested technique

Table 3. Parameter setting for the compared algorithm

Algorithm	Parameters Values
POA	$N\ (Palicans) = 20, R(Constant) = 2, itr = 20.$
WOA	$N(Humback\ Whales) = 20, I\ (random\ number) in\ [-1,1], r(andom\ vector)\ in\ [0,1],$ $Convergence\ Parameter\ (a) = 2\ to\ 0, itr = 30.$
CSA	$N\ (Nests) = 20, Mutation\ probability\ valur\ (P_a) = 0.25,$ $\beta(Scale\ factor) = 1.5, itr = 200.$
PSO	$N\ (Particles) = 20, Inertia\ weight = (0.4\ 0.9),$ $Cognitive\ and\ Social\ Constant(C_1 C_2) = (2\ 2), itr = 200.$
GA	$N\ (Individuals) = 20, Mutation\ Probability = 0.03\ ,$ $Crossover\ Probability = 0.9, itr = 300.$

5.2 Qualitative Results on Lena Image

Fig. 4 displays low-contrast Lena image and the corresponding output-enhanced image along with their respective histograms. Fig. 5 (a-e) shows convergence plots based on GA, PSO, CSA, WOA and POA for the objective function used in the problem.

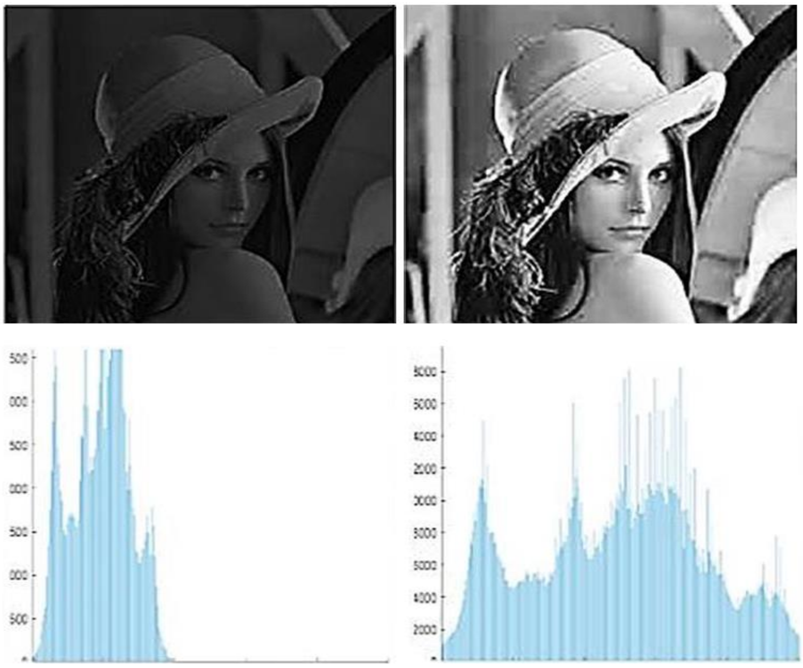
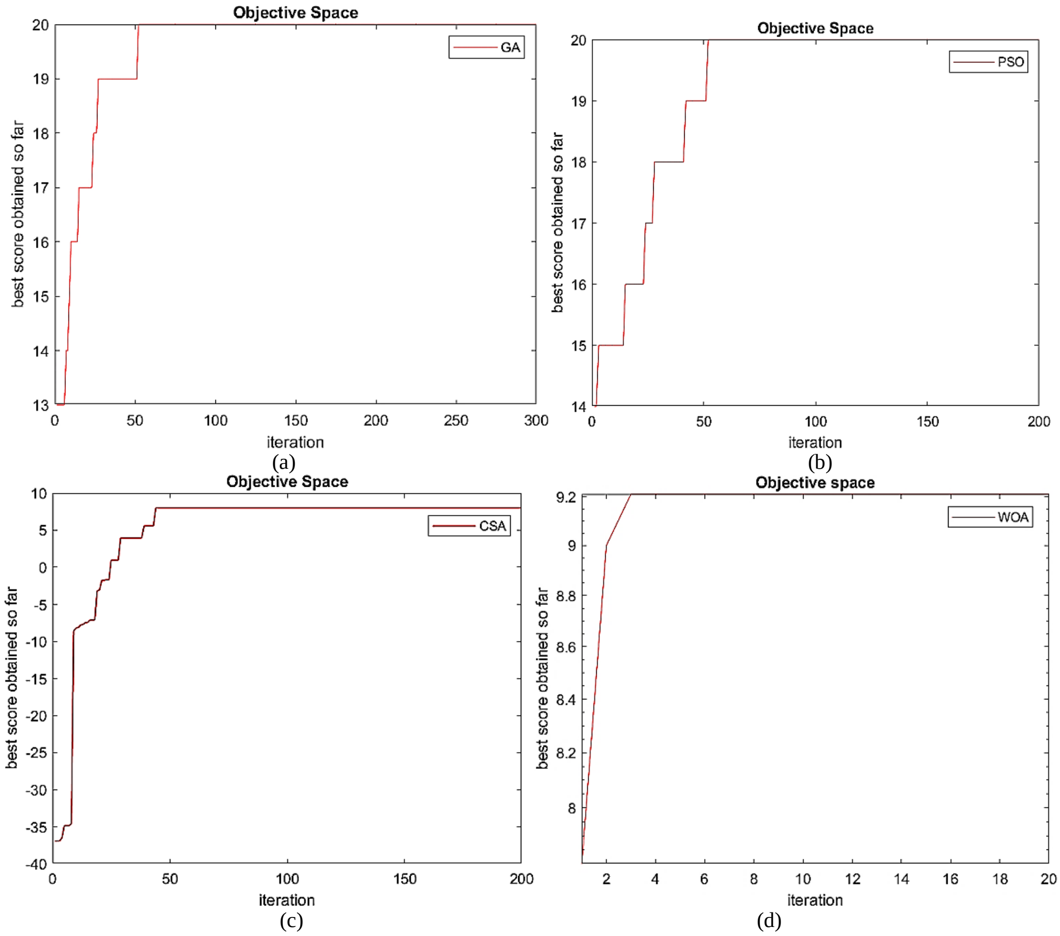
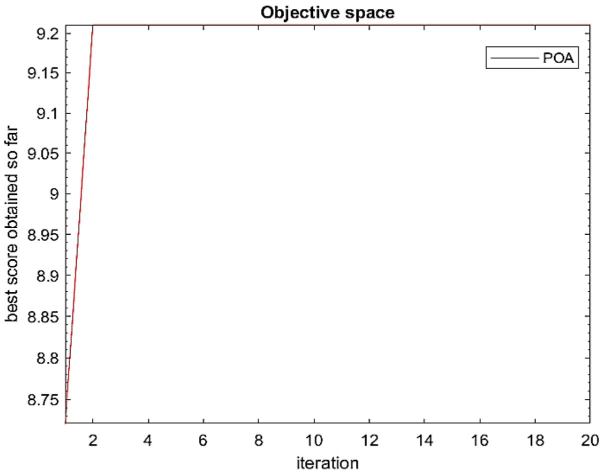


Fig. 4. Low Contrast Lena Image (1st row: left) and Enhanced Output Image (1st row: right) with their respective histograms (2nd row).

5.3 Convergence Performance of Proposed Approach

Proposed objective function is optimized with NIOA such as POA, WOA, CSA, PSO and GA. WOA and CSA are used recently [54, 55] in low contrast image enhancement domain for CLAHE parameter optimization.





(e)

Fig. 5. Convergence Plots for Lena Image using (a) GA (b) PSO (c) CSA (d) WOA (e) POA.

Performance is checked for same number of agents. Convergence performance is checked on Lena image for all these algorithms as depicted from Fig. 5 (a-e). GA and CSA converges faster in comparison to PSO at$itr = 50$. POA and WOA converges with minimum number of $itr = 2\ and\ 3$ respectively.

Fig. 6. Kodak Dataset: 25 Color images are converted to gray scale images

Fig. 7. Low contrast input grayscale images

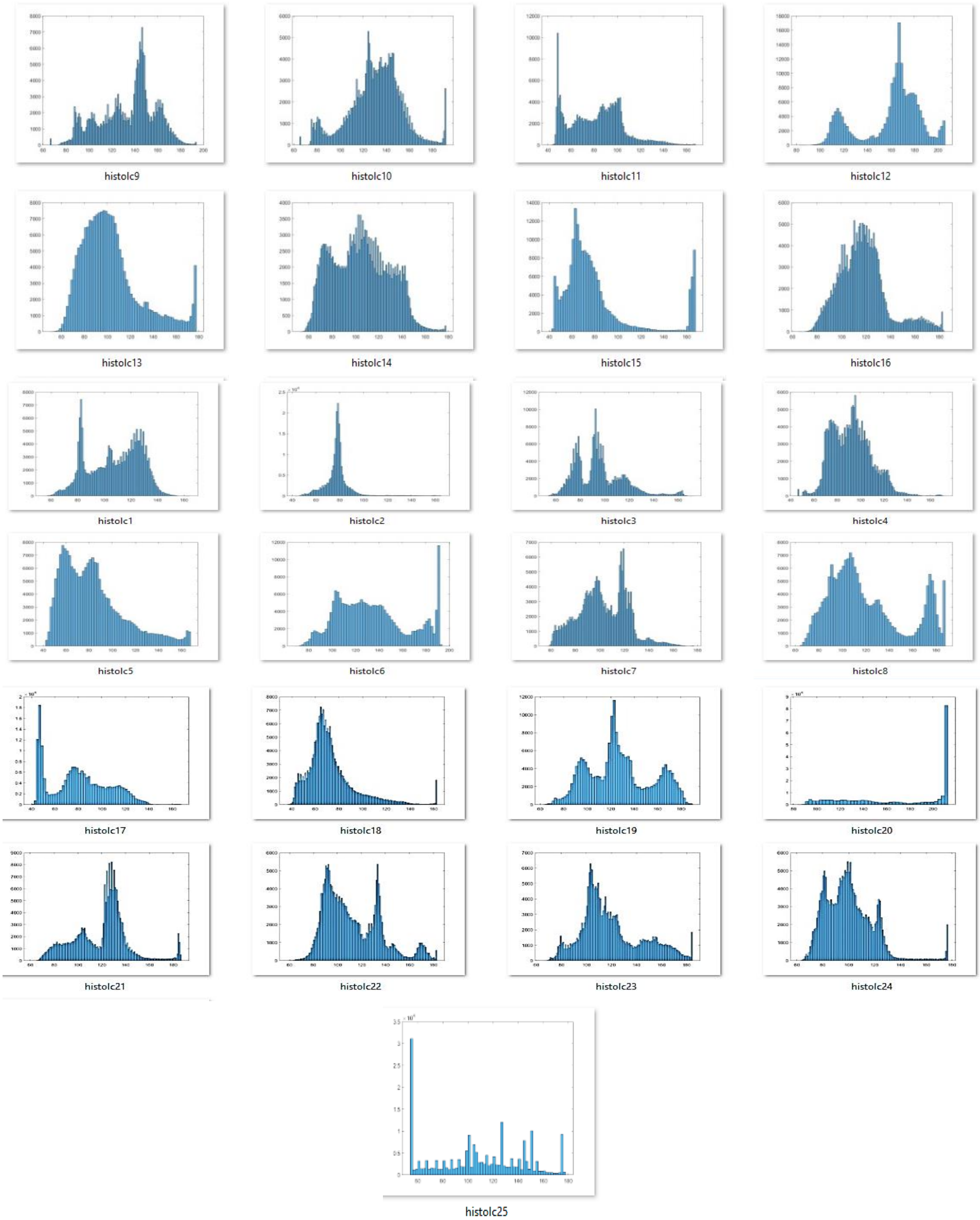


Fig. 8. Histogram of input images

Fig. 9. High Contrast output Images

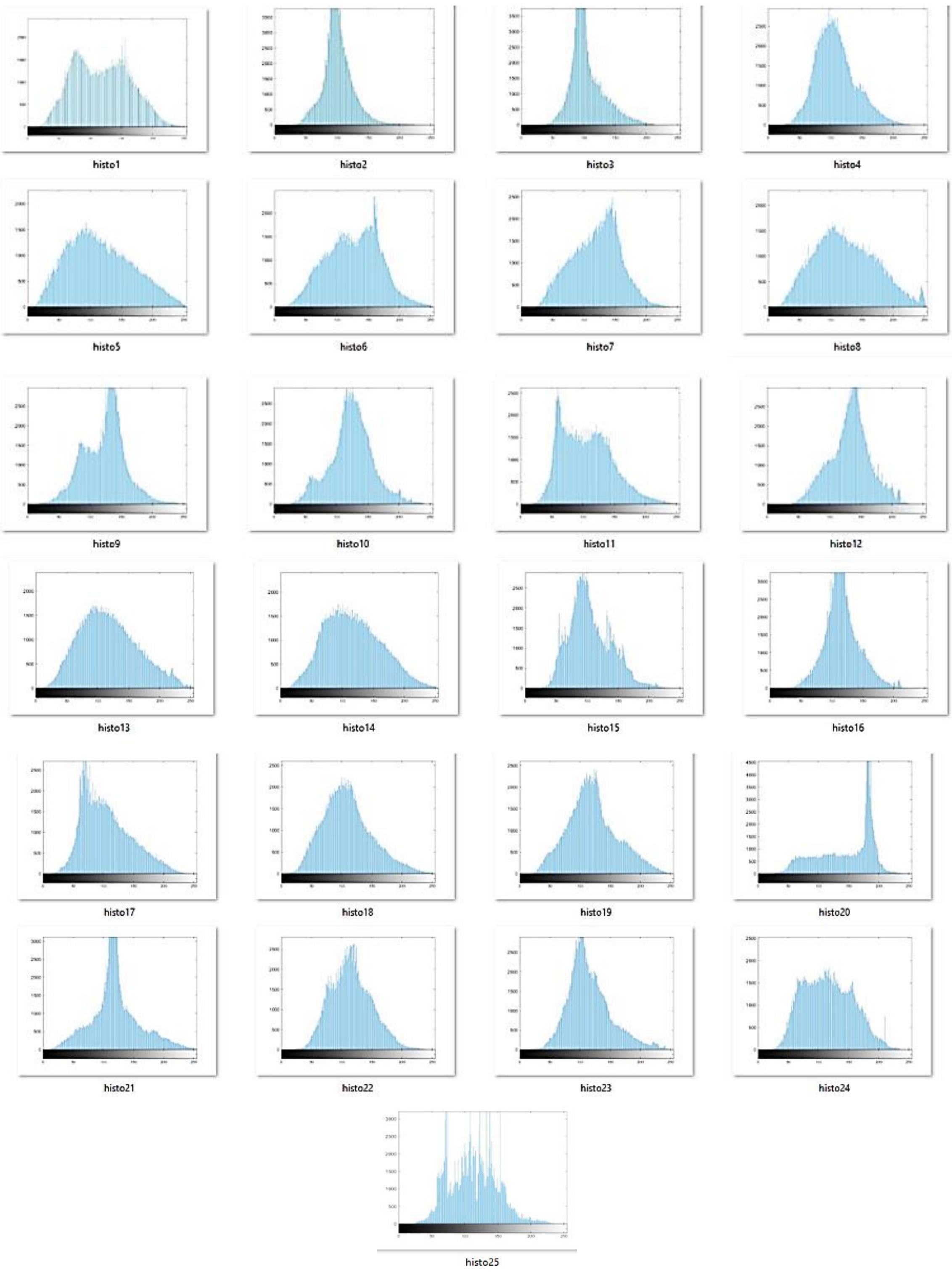


Fig. 10. Histograms of respective high contrast output images

5.4 Qualitative Results on Kodak Dataset

The suggested method's qualitative assessment is based on an examination of the visual appeal or quality of the images. Fig. 6 shows original grayscale images of the Kodak dataset abbreviated as gim1-gim25. Fig. 7 represents the original low-contrast input images named gimlc1-gimlc25 and their corresponding histograms histolc1-histolc25 in Fig. 8. The enhanced visual results hco1-hco25 on all Kodak images are depicted in Fig. 9 along with the appropriate histogram histo1-histo25 of the improved image displayed by them in Fig. 10.

It should be remembered that the histograms show how densely the pixel intensity values are distributed, $x - axis$ of histogram stands for the intensity of the grey levels and $y - axis$ show frequency. The pixel values in a well-contrast image should be evenly spaced out across the [0, 255] range. The associated histograms show that the pixel metrics of the ground truth images are distributed across the range [0, 255]. Histograms are centred at a constrained region for Lena (Fig. 4) and the low contrast image from the KODAK dataset in Fig. 8 (histolc1-histolc25). According to the histograms of the output images in Fig. 10 (histo1–histo25), the range [0, 255] contains a highly well-spread distribution of pixel values.

A total of 20 iterations for the population size of 20 are executed using the POA for each image. For the Lena image, relevant graphs have been drawn and are shown in Fig. 5 (e). It is clear from convergence graphs that the proposed method converges faster with 20 search agents.

Table 1 shows that on the Kodak dataset, an ablation study is carried out to choose the parameters of the objective function's contrast, edge and gradient. Parameters are selected to maximization of the fitness function which results in a high value of PSNR and MSSIM. With the use of Pelican optimization algorithms, Kodak dataset results are verified in terms of PSNR and MSSIM for $itr = 30\ and\ N = 20$.

5.5 Quantitative Results

PSNR and MSSIM are used to test effectiveness of the suggested augmentation technique. Higher values each of these metrics signifies better contrast enhancement technique. The evaluation of the outcomes with some of the most innovative image contrast enhancement techniques, as is evident from Table 4 and Table 5. Table 4 displays the average PSNR=26.44 dB and average MSSIM=0.986 obtained using the suggested method on Lena image.

Table 4. Comparative analysis of the proposed technique with some of the existing techniques on Lena image

Method	PSNR	MSSIM	VIF
ACM-HE [19]	19.80	0.975	0.57
NPMHE [18]	12.97	0.883	0.32
EAIE-CSA [38]	13.19	0.864	0.31
ICE-IPSO [37]	14.39	0.914	0.37
ABC-ICE [40]	16.35	0.905	0.42
EICE-ABC [41]	16.75	0.902	0.44
ICE-GA [36]	20.81	0.960	0.57
ICE-ABC [43]	23.97	0.972	0.57
ICE-LHM [11]	25.76	0.982	--
BPHS-CSA [51]	23.59	0.952	--
IBF-AEFA [57]	25.80	0.980	0.71
AEIHE [53]	26.39	0.945	--
IAECHE [34]	22.21	0.930	--
DCLHE[22]	22.44	0.985	--
BHMICE [21]	20.44	0.915	--
Proposed Method	26.44	0.986	0.82

PSNR improvement is significant except for AEIHE [53] and MSSIM values are showing little improvement in comparison to ICE-LHM [11], IBF-AEFA [57] and DCLHE [22]. Fig. 11 and Fig. 12 shows average PSNR and MSSIM plots for Lena image.

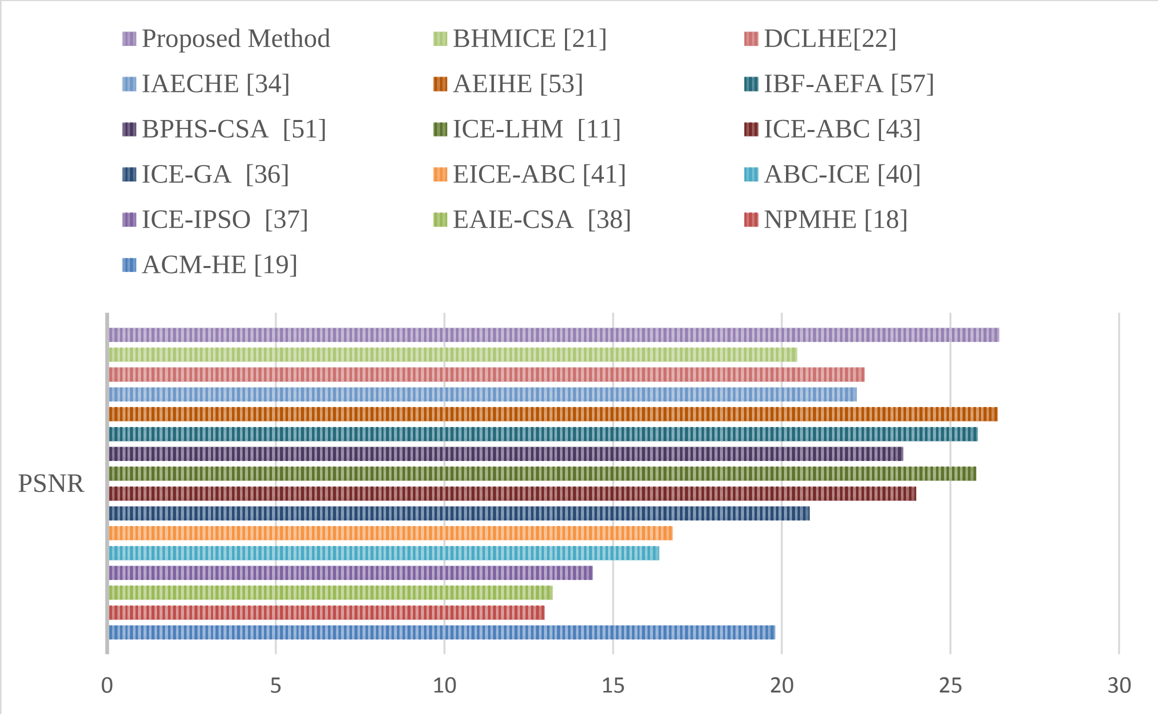


Fig. 11. Average PSNR plots for Lena image

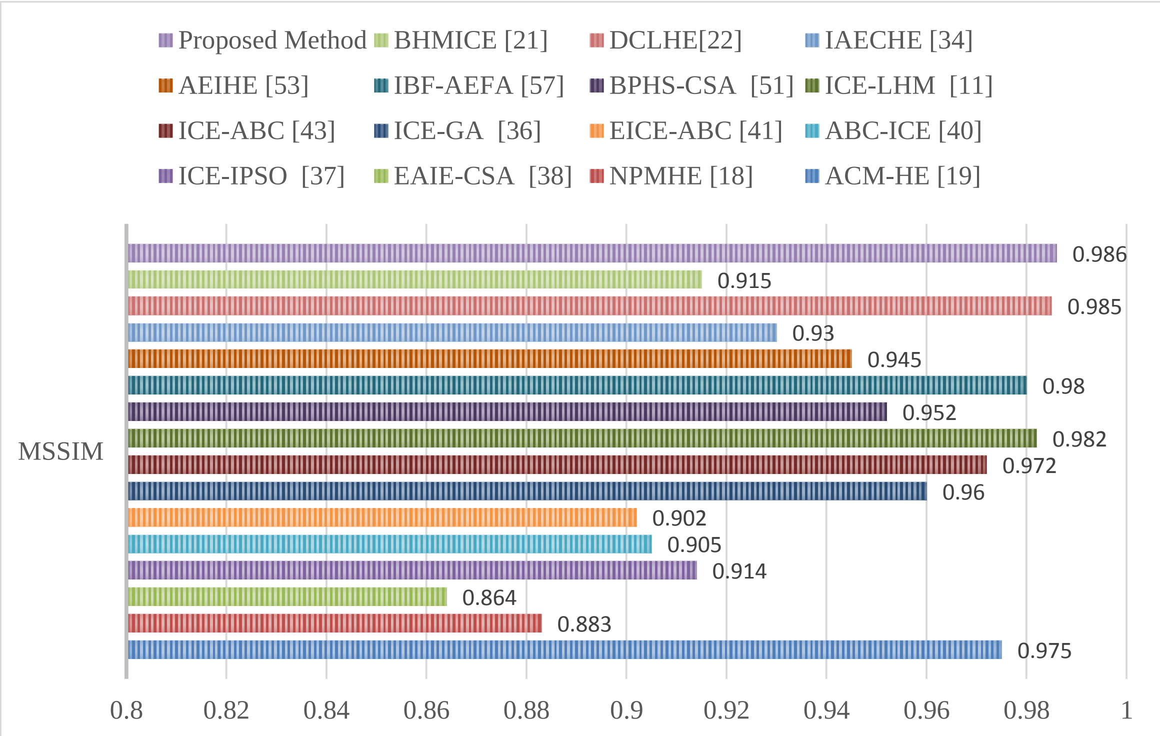


Fig. 12. Plots of average MSSIM values for Lena image

Table 5. Average values of PSNR and MSSIM for KODAK dataset after enhancement by proposed approach

High Contrast Output Image	**PSNR**	**MSSIM**	**VIF**
hco1	30.80	0.9825	0.822
hco2	26.73	0.9976	0.737
hco3	30.38	0.9834	0.838
hco4	30.21	0.9523	0.815
hco5	26.18	0.9743	0.574
hco6	27.80	0.9317	0.621
hco7	29.56	0.9783	0.657
hco8	28.66	0.9565	0.656
hco9	29.27	0.9741	0.607
hco10	29.44	0.9619	0.696
hco11	28.35	0.9942	0.599
hco12	25.76	0.9203	0.424
hco13	27.89	0.9340	0.598
hco14	30.31	0.9512	0.802
hco15	24.07	0.9389	0.579
hco16	28.42	0.9534	0.793
hco17	26.91	0.9291	0.673
hco18	27.89	0.9786	0.672
hco19	28.03	0.9699	0.823
hco20	23.33	0.9554	0.585
hco21	29.61	0.9845	0.811
hco22	28.04	0.9466	0.781
hco23	28.83	0.9818	0.763
hco24	30.68	0.9732	0.851
hco25	27.14	0.9691	0.795
Average Results	**28.18**	**0.9630**	**0.831**

Table 5 displays the average values of PSNR=28.18dB and MSSIM=0.963 obtained using the suggested method on each of the 25 images from the Kodak dataset. Table 6 displays the suggested technique's overall average efficiency that is shown to be superior to the ICE techniques already in use for Kodak dataset as depicted from there metrics values PSNR=28.18 dB, MSSIM=0.963. Fig. 13 shows that proposed approach achieves higher PSNR in comparison to existing methods whereas MSSIM performance improves little in comparison to ICEABC [43] as clear from Fig. 14.

Table 6. Comparative of the propsed approach with a few cutting-edge techniques for the KODAK dataset.

Method	**PSNR**	**MSSIM**	**VIF**
ICE-GA [36]	18.87	0.881	0.51
ICE-IPSO [37]	19.84	0.911	0.53
EAIE-CSA [38]	15.46	0.862	0.52
NMHE [18]	17.78	0.724	0.63
ABC-ICE [40]	13.56	0.852	0.60
ACMHE [19]	16.26	0.791	0.41
EICE-ABC [41]	13.79	0.861	0.69
ICEABC [43]	24.66	0.951	0.75
RDH-2D [9]	24.85	0.928	--
IBF-AEFA [57]	25.69	0.940	0.81
Proposed	28.18	0.963	0.83

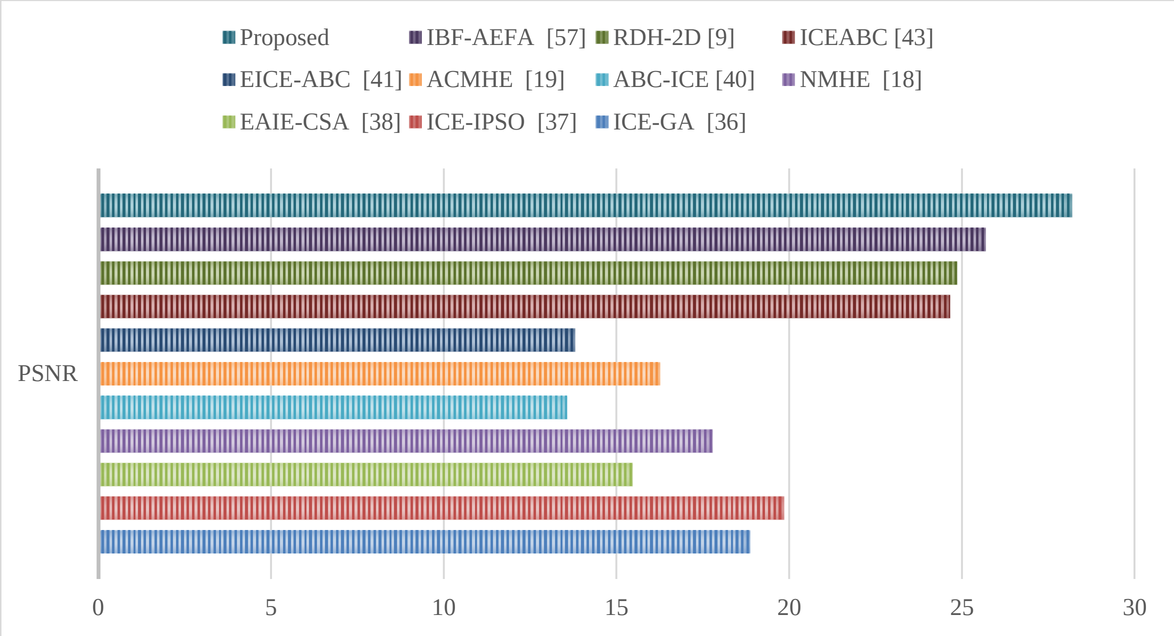


Fig. 13. Graphical representation of Average PSNR results on KODAK dataset.

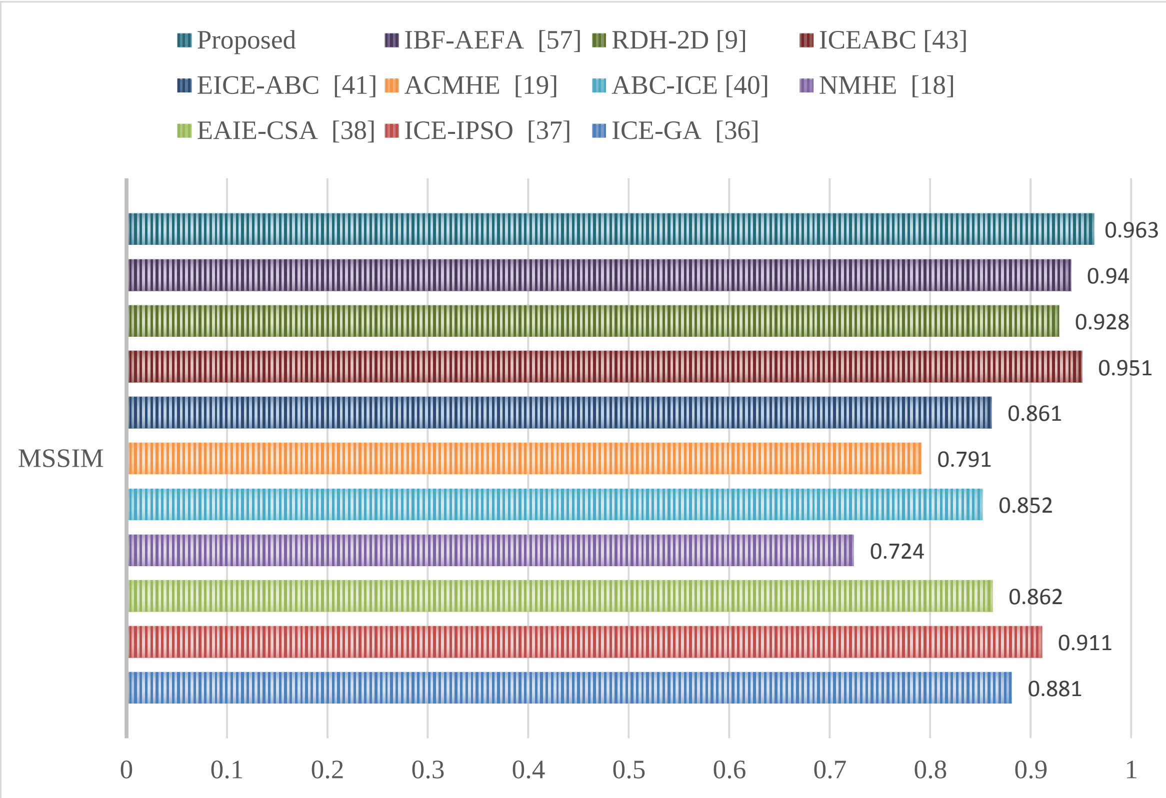


Fig. 14. Plots of average MSSIM values for KODAK dataset

Table 7. Comparison of average computation time for KODAK dataset.

Method	NIOA	Computation Time (in seconds)
CLAHE	GA	257.84
	PSO	23.11
	CSA	257.84
	WOA	23.11
	POA	22.02

In POA, the exploration-exploitation capability is more as clear from equation (12). As number of iterations grows, the ratio $\frac{t}{T}$ starts increasing resulting in the best exploitation of the neighbourhood of interested pixels. Table 7 compares proposed technique's execution time. Suggested method runs faster with computation time of 22.02s in comparison to other optimization algorithms. Hence, it is evident that proposed approach outperforms the existing methods in terms of said evaluation metrics.

The proposed algorithm's computational cost is determined by taking into account four major POA phases for each of the four tile sizes. To begin, the complexity of algorithm startup processes is $O(N)$. Second, the challenges of the computations involved in determining the fitness function by each population member over two phases is $O(2.T.N)$. Third, the computational complexity of prey creation and evaluation is $O(T) + O(T.m)$ at each iteration. Finally, the computational complexity of solutions with N population members and $m = 2$ dimensions that are updated in two phases is $O(2.T.N.m)$. Because four TS are considered at each iteration, the overall computational complexity is given as:

$$Total\ Computational\ Complexity = O(4N + 4T.(1 + m).(1 + 2N))$$

5.6 Contribution of proposed method

The quality of resultant image is degraded in typical HE-based approaches by introducing artificial look, and the enhancement rate must be regulated by suitable parameter value selection. An objective function that can automatically demonstrate how much an image may be improved without human involvement. The conventional CLAHE model requires previous knowledge of the user for manual parameter determination, which is a time-consuming approach. The proposed technique seeks to improve local details as well as information richness. A significant number of NIOA techniques are unable to clear about choosing fitness function that may direct potential outcomes of MHA to optimal solution, even though they can disclose concealed information in a deteriorated image. As a result, ablation studies are conducted to examine the image's extraordinarily rich information content, which includes edge, entropy, and contrast information. This ablation investigation aids in the discovery of crucial features for the development of a new objective function. Proposed method calculates parameter values adaptively and automatically and achieves optimum enhancement by applying POA to a new fitness function for maximization. The Pelican Optimization Algorithm is a recently created NIOA algorithm that is being applied for the first time in image processing challenges. POA demonstrated to be the best in terms of search space exploration and exploitation, as it does not get trapped at local maxima and employs a less number of configurable parameters. Optimization is achieved with less iteration, which was proven to be less time demanding.

6. Conclusion

In this research work Using CLAHE parameter optimization, this work aims to amplify low-contrast images adaptively and automatically. For the first time, as far as we are aware, POA recently designed MHA is applied in the GICE sphere. Histogram clip size limit is calculated by relying on picture features for the fitness function, clipping is automatically regulated following the image's characteristics. Based on quality measures like PSNR and MSSIM, a comparative study on the benchmark image dataset demonstrates that the suggested technique outperforms the current methods. This work covers non-real-time application areas and focuses to produce image that appear pleasing to human eyes with enhanced structure followed by low sensitivity to noise. Main aim is to improve the low-contrast images by of optimization of CLAHE parameters by proper formulation of fitness function. Histogram clip limit by making fitness function based on image attributes, clipping is modified dynamically in keeping with image features. POA and WOA based optimization converges at a faster rate in comparison to CSA based optimization and Comparative analysis illustrates that suggested method performs better than other methods using quality metrics like PSNR, MSSIM, etc.

References

[1] R. C. Gonzalez and R. E. Woods, Digital Image Processing, 4th ed. Upper Saddle River, NJ: Pearson, 2017.
[2] W. K. Pratt, Introduction to Digital Image Processing. London, England: CRC Press, 2013.
[3] J. B. Zimmerman, S. M. Pizer, E. V. Staab, J. R. Perry, W. McCartney, and B. C. Brenton, "An evaluation of the effectiveness of adaptive histogram equalization for contrast enhancement," IEEE Trans. Med. Imaging, vol. 7, no. 4, pp. 304–312, 1988.
[4] K. Zuiderveld, "Contrast limited adaptive histogram equalization," in Graphics Gems, Elsevier, 1994, pp. 474–485.
[5] J.-Y. Kim, L.-S. Kim, and S.-H. Hwang, "An advanced contrast enhancement using partially overlapped sub-block histogram equalization," IEEE Trans. Circuits Syst. Video Technol., vol. 11, no. 4, pp. 475–484, 2001.
[6] K. Singh and R. Kapoor, "Image enhancement using Exposure based Sub Image Histogram Equalization," Pattern Recognit. Lett., vol. 36, pp. 10–14, 2014.
[7] J. R. Tang and N. A. Mat Isa, "Intensity exposure-based bi-histogram equalization for image enhancement," TURK. J. OF ELECTR. ENG. COMPUT. SCI., vol. 24, pp. 3564–3585, 2016.
[8] S. F. Tan and N. A. M. Isa, "Exposure based multi-histogram equalization contrast enhancement for non-uniform illumination images," IEEE Access, vol. 7, pp. 70842–70861, 2019.

[9] Wu, Hao-Tian, Weiqi Mai, ShuyiMeng, Yiu-Ming Cheung, and Shaohua Tang, "Reversible data hiding with image contrast enhancement based on two-dimensional histogram modification," IEEE Access, vol. 7, pp. 83332-83342, 2019.
[10] A. K. Bhandari, S. Shahnawazuddin, and A. K. Meena, “A novel fuzzy clustering-based histogram model for image contrast enhancement,” IEEE Trans. Fuzzy Syst., vol. 28, no. 9, pp. 2009–2021, 2020.
[11] A. K. Bhandari, “A logarithmic law based histogram modification scheme for naturalness image contrast enhancement,” J. Ambient Intell. Humaniz. Comput., vol. 11, no. 4, pp. 1605–1627, 2020.
[12] B. Subramani and M. Veluchamy, “Fuzzy contextual inference system for medical image enhancement,” Measurement (Lond.), vol. 148, no. 106967, p. 106967, 2019.
[13] P. Tao, Y. Pei, M. Celenk, Q. Fu, and A. Wu, “Adaptive image enhancement method using contrast limitation based on multiple layers BOHE,” J. Ambient Intell. Humaniz. Comput., vol. 11, no. 11, pp. 5031–5043, 2020.
[14] Y.T. Kim, "Contrast enhancement using brightness preserving bi-histogram equalization." IEEE transactions on Consumer Electronics, vol. 43, no. 1, pp. 1-8, 1997.
[15]Y. Wang, Q. Chen, and B. Zhang, “Image enhancement based on equal area dualistic sub-image histogram equalization method,” IEEE Trans. Consum. Electron., vol. 45, no. 1, pp. 68–75, 1999.
[16] S. D. Chen and A. R. Ramli, ‘‘Minimum mean brightness error bihistogram equalization in contrast enhancement,’’ IEEE Trans. Consum. Electronics, vol. 49, no. 4, pp. 1310–1319, Nov. 2003.
[17] C. Zuo, Q. Chen, and X. Sui, “Range Limited Bi-Histogram Equalization for image contrast enhancement,” Optik (Stuttg.), vol. 124, no. 5, pp. 425–431, 2013.
[18] S. Poddar, S. Tewary, D. Sharma, V. Karar, A. Ghosh, and S. K. Pal, "Non‐parametric modified histogram equalisation for contrast enhancement," IET Image Processing, vol. 7, no. 7, pp. 641-652, 2013.
[19] K. Santhi and R. S. D. WahidaBanu, “Adaptive contrast enhancement using modified histogram equalization,” Optik (Stuttg.), vol. 126, no. 19, pp. 1809–1814, 2015.
[20] K. G. Dhal and S. Das, “Combination of histogram segmentation and modification to preserve the original brightness of the images,” Pattern Recognit. Image Anal., vol. 27, no. 2, pp. 200–212, 2017.
[21] T. L. Kong and N. A. M. Isa, “Bi-histogram modification method for non-uniform illumination and low-contrast images,” Multimed. Tools Appl., vol. 77, no. 7, pp. 8955–8978, 2018.
[22] E. Reddy and R. Reddy, “Dynamic clipped histogram equalization technique for enhancing low contrast images,” Proc. Nat. Acad. Sci. India Sect. A, vol. 89, no. 4, pp. 673–698, 2019.
[23] M. F. Khan, D. Goyal, M. M. Nofal, E. Khan, R. Al-Hmouz, and E. Herrera-Viedma, ‘‘Fuzzy-based histogram partitioning for bihistogramequalisation of low contrast images,’’ IEEE Access, vol. 8, pp. 11595–11614, 2020.
[24] L. Bai, W. Zhang, X. Pan, and C. Zhao, “Underwater image enhancement based on global and local equalization of histogram and dual-image multi-scale fusion,” IEEE Access, vol. 8, pp. 128973–128990, 2020.
[25] S. D. Chen and A. R. Ramli, “‘Contrast enhancement using recursive mean separate histogram equalization for scalable brightness preservation,” Trans. Consum. Electron, vol. 49, no. 4, pp. 1301–1309, 2003.
[26] K. S. Sim, C. P. Tso, and Y. Y. Tan, “Recursive sub-image histogram equalization applied to gray scale images,” Pattern Recognit. Lett., vol. 28, no. 10, pp. 1209–1221, 2007.
[27] M. Abdullah-Al-Wadud, M. Kabir, M. AkberDewan, and O. Chae, “A dynamic histogram equalization for image contrast enhancement,” IEEE Trans. Consum. Electron., vol. 53, no. 2, pp. 593–600, 2007.
[28] H. Ibrahim and N. Pik Kong, “Brightness preserving dynamic histogram equalization for image contrast enhancement,” IEEE Trans. Consum. Electron., vol. 53, no. 4, pp. 1752–1758, 2007.
[29] C. Ooi and N. Mat Isa, “Adaptive contrast enhancement methods with brightness preserving,” IEEE Trans. Consum. Electron., vol. 56, no. 4, pp. 2543–2551, 2010.
[30] C. Ooi and N. Mat Isa, “Quadrants dynamic histogram equalization for contrast enhancement,” IEEE Trans. Consum. Electron., vol. 56, no. 4, pp. 2552–2559, 2010.
[31] K. Singh and R. Kapoor, “Image enhancement via median-mean based sub-image-clipped histogram equalization,” Optik (Stuttg.), vol. 125, no. 17, pp. 4646–4651, 2014.
[32] A. S. Parihar and O. P. Verma, “Contrast enhancement using entropy‐based dynamic sub‐histogram equalisation,” IET Image Process., vol. 10, no. 11, pp. 799–808, 2016.
[33] P. Kandhway and A. K. Bhandari, “An optimal adaptive thresholding based sub-histogram equalization for brightness preserving image contrast enhancement,” Multidimens. Syst. Signal Process., vol. 30, no. 4, pp. 1859–1894, 2019.
[34] S. H. Majeed and N. A. M. Isa, “Iterated adaptive entropy-clip limit histogram equalization for poor contrast images,” IEEE Access, vol. 8, pp. 144218–144245, 2020.
[35] C. Ding, X. Pan, X. Gao, L. Ning, and Z. Wu, “Three adaptive sub-histograms equalization algorithm for maritime image enhancement,” IEEE Access, vol. 8, pp. 147983–147994, 2020.
[36]S. Hashemi, S. Kiani, N. Noroozi, and M. E. Moghaddam, “An image contrast enhancement method based on genetic algorithm,” Pattern Recognit. Lett., vol. 31, no. 13, pp. 1816–1824, 2010.
[37] G. Qinqing, C. Dexin, Z. Guangping, and H. Ketai, “Image enhancement technique based on improved PSO algorithm,” in 2011 6th IEEE Conference on Industrial Electronics and Applications, pp. 234-238, 2011.
[38] S. Agrawal and R. Panda, “An efficient algorithm for gray level image enhancement using cuckoo search,” in Swarm, Evolutionary, and Memetic Computing, Berlin, Heidelberg: Springer Berlin Heidelberg, 2012, pp. 82–89.
[39] S. Mohan and T. R. Mahesh, “Particle Swarm Optimization based Contrast Limited enhancement for mammogram images,” in 2013 7th International Conference on Intelligent Systems and Control (ISCO), pp. 384-388, 2013.
[40] A. Draa and A. Bouaziz, “An artificial bee colony algorithm for image contrast enhancement,” Swarm Evol. Comput., vol. 16, pp. 69–84, 2014.
[41] P. Joshi and S. Prakash, “An efficient technique for image contrast enhancement using artificial bee colony,” in IEEE International Conference on Identity, Security and Behavior Analysis (ISBA 2015), pp. 1-6, 2015.
[42] P. Babu and V. Rajamani, “Contrast enhancement using real coded genetic algorithm based modified histogram equalization for gray scale images,” Int. J. Imaging Syst. Technol., vol. 25, no. 1, pp. 24–32, 2015.

[43] J. Chen, W. Yu, J. Tian, L. Chen, and Z. Zhou, "Image contrast enhancement using an artificial bee colony algorithm," Swarm Evol. Comput., vol. 38, pp. 287–294, 2018.
[44] K. G. Dhal, M. Sen, and S. Das, "Cuckoo search-based modified bi-histogram equalisation method to enhance the cancerous tissues in mammography images," Int. J. Med. Eng. Inform., vol. 10, no. 2, p. 164, 2018.
[45]K. G. Dhal, M. Sen, S. Ray, and S. Das, "Multi-thresholded histogram equalization based on parameterless artificial bee colony," in Incorporating Nature-Inspired Paradigms in Computational Applications," IGI Global, pp. 108–126, 2018.
[46] K. G. Dhal and S. Das, "Colour retinal images enhancement using modified histogram equalisation methods and firefly algorithm," Int. J. Biomed. Eng. Technol., vol. 28, no. 2, p. 160, 2018.
[47] M. Wan, G. Gu, W. Qian, K. Ren, Q. Chen, and X. Maldague, "Particle swarm optimization-based local entropy weighted histogram equalization for infrared image enhancement," Infrared Phys. Technol., vol. 91, pp. 164–181, 2018.
[48] S. Dhabal and D. K. Saha, "Image enhancement using differential evolution based whale optimization algorithm," in Advances in Intelligent Systems and Computing, Singapore: Springer Singapore, 2020, pp. 619–628.
[49] A. K. Bhandari, P. Kandhway, and S. Maurya, ''Salp swarm algorithm based optimally weighted histogram framework for image enhancement,'' IEEE Trans. Instrum. Meas., vol. 69, no. 9, pp. 6807–6815, Sep. 2020.
[50] P. Kandhway, A. K. Bhandari, and A. Singh, "A novel reformed histogram equalization based medical image contrast enhancement using krill herd optimization," Biomed. Signal Process. Control, vol. 56, no. 101677, p. 101677, 2020.
[51] A. K. Bhandari and S. Maurya, "Cuckoo search algorithm-based brightness preserving histogram scheme for low-contrast image enhancement," Soft Comput., vol. 24, no. 3, pp. 1619–1645, 2020.
[52] U. K. Acharya and S. Kumar, "Genetic algorithm based adaptive histogram equalization (GAAHE) technique for medical image enhancement," Optik (Stuttg.), vol. 230, no. 166273, p. 166273, 2021.
[53] S. H. Majeed and N. A. M. Isa, "Adaptive entropy index histogram equalization for poor contrast images," IEEE Access, vol. 9, pp. 6402–6437, 2021.
[54] U. Kuran and E. C. Kuran, "Parameter selection for CLAHE using multi-objective cuckoo search algorithm for image contrast enhancement," Intelligent Systems with Applications, vol. 12, no. 200051, 2021.
[55] A. Fawzi, A. Achuthan, and B. Belaton, "Adaptive clip limit tile size histogram equalization for non-homogenized intensity images," IEEE Access, vol. 9, pp. 164466–164492, 2021.
[56] A. H. Khan, S. Ahmed, S. K. Bera, S. Mirjalili, D. Oliva, and R. Sarkar, "Enhancing the contrast of the grey-scale image based on meta-heuristic optimization algorithm," Soft Comput., vol. 26, no. 13, pp. 6293–6315, 2022.
[57] S. Mukhopadhyay, S. Hossain, S. Malakar, E. Cuevas, and R. Sarkar, "Image contrast improvement through a metaheuristic scheme," Soft Comput., 2022.
[58] A. K. Bhandari, N. Singh, and A. Singh, "Swarm-based optimally selected histogram computation system for image enhancement," Neural Comput. Appl., vol. 34, no. 9, pp. 7053–7067, 2022.
[59] E. Faisal, A. Nugroho, R. S. Basuki, and S. Suharnawi, "GLCM based locally feature extraction on natural image," JAIS (J. Appl. Intell. Syst.), vol. 7, no. 2, pp. 128–134, 2022.
[60] C. Liu, A. Xu, C. Hu, F. Zhang, F. Yan, and S. Cai, "A new texture feature based on GLCM and its application on edge-detection," IOP Conf. Ser. Mater. Sci. Eng., vol. 780, no. 3, p. 032042, 2020.
[61] J. Canny, "A computational approach to edge detection," IEEE Trans. Pattern Anal. Mach. Intell., vol. PAMI-8, no. 6, pp. 679–698, 1986.
[62] Y. Yuan, "Noise-aware canny algorithm for edge detection," in 2022 IEEE 4th International Conference on Civil Aviation Safety and Information Technology (ICCASIT), 2022.
[63] L. Ding and A. Goshtasby, "On the Canny edge detector," Pattern Recognit., vol. 34, no. 3, pp. 721–725, 2001.
[64] K. Rajwar, K. Deep, and S. Das, "An exhaustive review of the metaheuristic algorithms for search and optimization: taxonomy, applications, and open challenges," Artif. Intell. Rev., pp. 1–71, 2023.
[65] K. G. Dhal, S. Ray, A. Das, and S. Das, "A survey on nature-inspired optimization algorithms and their application in image enhancement domain," Arch. Comput. Methods Eng., vol. 26, no. 5, pp. 1607–1638, 2019.
[66] R. M. Haralick, K. Shanmugam, and I. Dinstein, "Textural Features for Image Classification," IEEE Trans. Syst. Man Cybern. , vol. SMC-3, no. 6, pp. 610–621, 1973.
[67] Franzen R, "Kodak lossless true color image suite 4(2)," 1999. http://r0k. us/graphics/Kodak/.
[68] S. Kumari and P. Lehana, "Image content enhancement of natural images using genetic algorithm," Phys. Sci. Int. J., vol. 4, no. 9, pp. 1244–1259, 2014.
[69] J. Carson, Ed., Genetic algorithms: Advances in research & applications. Hauppauge, NY: Nova Science, 2017.
[70] V. Santhi and B. K. Tripathy, "Image enhancement techniques using Particle Swarm Optimization technique," in Human-Computer Interaction, IGI Global, 2015, pp. 860–878.
[71] R. Poli, J. Kennedy, and T. Blackwell, "Particle swarm optimization: An overview," Swarm Intell., vol. 1, no. 1, pp. 33–57, 2007.
[72] X.-S. Yang and S. Deb, "Cuckoo Search via Levy flights," arXiv [math.OC], 2010.
[73] S. Mirjalili and A. Lewis, "The whale optimization algorithm," Adv. Eng. Softw., vol. 95, pp. 51–67, 2016.
[74] P. Trojovský and M. Dehghani, "Pelican Optimization Algorithm: A novel nature-inspired algorithm for engineering applications," Sensors (Basel), vol. 22, no. 3, p. 855, 2022.
[75] Z. Wang and A. C. Bovik, "Mean squared error: Love it or leave it? A new look at Signal Fidelity Measures," IEEE Signal Process. Mag., vol. 26, no. 1, pp. 98–117, 2009.
[76] Wang, Z., Bovik, A. C., Sheikh, H. R., and Simoncelli, E. P., "Image quality assessment: from error visibility to structural similarity." IEEE transactions on image processing, 13(4), 600-612, 2004.

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