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Improved Brightness-preserving Bi-histogram Equalization (BBHE) Technique Based on the Pelican Optimization Algorithm (POA) for Image Enhancement

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ABSTRACT

Image enhancement is essential in image analysis, which employs intricate procedures and techniques. Enhancing photos of plant diseases is a complex task in image processing because of low image quality and numerous image characteristics. The outcomes substantially affect the clinical diagnosis and observation of diseases. Real-world optimization problems are challenging, and many applications have been developed to manage enhancement problems. Optimization algorithms, such as the pelican optimization algorithm (POA), that have high productivity need to be utilized to solve these problems. This research introduces a new technique called brightness-preserving bi-histogram equalization (BBHE) with POA (BBHE-POA). BBHE-POA is used to enhance the visual quality of plant disease images, with the aim of improving their overall appearance. BBHE, which can preserve the original brightness to a specific extent, is applied and studied mathematically. An optimization algorithm is employed to determine the ideal configuration of BBHE by amplifying the average brightness of equalized subimages surrounding the input mean. Then, qualitative and quantitative analyses of three enhancement techniques, namely, the proposed technique, standard BBHE, and discrete wavelet transform, are performed. Several measurement metrics, such as structural similarity index, absolute mean brightness error, entropy, peak signal-to-noise ratio, and elapsed time, are applied. Experiments show that proposed technique achieves excellent performance qualitatively and quantitatively and produces good values for all data images.

Introduction

The primary preprocessing phase for various computer vision purposes is image enhancement. This phase's goal is to enhance image quality and boost the information's interpretability and perception [1]. The procedure can be extended to methods of improving medical images. The augmentation process is made increasingly difficult by acquisition errors, image fuzziness, and the variability of brightness and noise levels. The goal of applying the enhancement approach is to change the properties of medical images and provide them an improved form.

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The main factor in assessing the quality of a picture is contrast, which is produced by the luminance reflection of two nearby locations. The problem of low contrast is resolved by reinforcing the region of interest through the use of picture-enhancing techniques. Improvement methods have been developed to effectively visualize images [2].

These techniques are categorized as spatial- and transform-domain methods in accordance with how they affect processing. One of the traditional spatial-domain techniques is histogram equalization (HE), which improves the consistency of the image grey distribution.

A popular HE-based technique for small regions is adaptive histogram equalization (AHE), which effectively minimizes the loss of image features. Its drawback is noise over-amplification [3]. AHE is used to improve the contrast of an image, especially in areas that are influenced by uneven illumination or have poor contrast [4]. It applies distinct equalization functions to various picture regions depending on the local image statistics, in contrast to classic HE that uses the same equalization function to the entire image.

The AHE procedure entails partitioning the image into discrete areas or tiles, calculating the histogram of each tile, and independently equalizing each tile's histogram. AHE improves the overall contrast while maintaining the image's local contrast. Thus, it is suitable for photos with intricate textures, such as satellite or medical photos [5]. However, AHE has restrictions.

For example, in sections with homogenous images where the local histogram is narrow, it can introduce artifacts, which may cause the output image to exhibit a discernible grid-like pattern known as the halo effect. Several AHE variants, such as contrast-limited AHE (CLAHE), have been proposed to overcome this restriction; CLAHE restricts the contrast enhancement in each tile to avoid the halo effect [6].

New HE techniques that preserve the mean while improving image quality include brightness-preserving bi-histogram equalization (BBHE), dualistic subimage histogram equalization (DSIHE), and minimum mean brightness error bi-histogram equalization (MMBEBHE).

BBHE, a newly improved contrast enhancement algorithm, was proposed by [7]. It is a new extension that applies independent HE across tow sub by decomposing the input image on the basis of its mean. Using the input mean, BBHE divides the input image's histogram into two equal portions [8]. The input mean is referred to as the threshold point. Afterward, each component is equalized independently to solve the brightness preservation issue mentioned above. The histogram for a DSIHE input image is separated into two halves at the point where each section has an equal amount of image pixels. The new BBHE extension that offers maximum brightness preservation is called MMBEBHE. These methods are improved variants of traditional HE and use independent equalizations of the subimages produced by breaking down the original image [9].

Optimization is the systematic examination and selection of the most optimal solution in a given group of viable solutions for given problem [10]. An optimization problem has multiple viable solutions. Each optimization issue in modeling consists of three primary components: decision variables, constraints, and objective functions. Population-based optimization algorithms are efficient systems within the category of stochastic methods [11].

These algorithms were derived from events in the field of swarm intelligence, the innate behaviors of animals and insects, the principles of physics, the conduct of players, the regulations in different games, and the processes of evolution.

In optimization algorithms, the process of determining the best solution involves initially generating a specific number of solvable solutions randomly in consideration of the restrictions of the specific problem [12]. The random solutions are further enhanced by the various steps of the algorithm and a technique that is based on competition. The optimal solution for the optimization problem is determined after the implementation of the method.

Various optimization algorithms, such as the pelican optimization algorithm (POA), are used to obtain appropriate solutions. Image processing and its related disciplines are among the many areas where POA is used [13]. Moreover, POA's performance has been compared with that of eight famous optimization algorithms, namely, particle swarm optimization (PSO), teaching–learning-based optimization, gray wolf optimization, whale optimization algorithm, marine predator algorithm, tunicate swarm algorithm, gravitational search algorithm (GSA), and genetic algorithm (GA) [14].

The remainder of this paper is structured into sections. A review of relevant studies on image improvement by using optimization methods is provided in Section 2. Conventional BBHE is examined in Section 3, and recommended techniques are provided accordingly. In Section 4, the experimental results are compared statistically and qualitatively by using the structural similarity index measure (SSIM), absolute mean brightness error (AMBE), and entropy with elapsed time. The final section presents the conclusion.

Literature-Review

Numerous frameworks for improving images have been created. Techniques for improving the appearance of images allow for effective visual interpretation [15]. They improve the efficiency of subsequent tasks, including object identification and tracking, computer vision, image segmentation, and image processing. Researchers have focused their attention on HE-based algorithms among the different kinds of contrast enhancement techniques [15]. To enhance low-contrast images, Zuiderveld introduced CLAHE as a generalization of adaptive HE (AHE). CLAHE is one of the popular and effective methods that have been used for various image kinds. Liang et al. developed double-plateau histogram equalization (ADPE), an adaptive contrast enhancement method for infrared pictures.

Piecewise affine histogram equalization was employed by Lisani et al. [16] to improve image contrast. This method is an optimization of classical HE, where the cumulative histogram is divided into segments. Yang proposed a modified contrast-stretching method (LCS) to improve an image with uneven lighting. Intensity transformation considers lower- and upper-frequency information, with log transformation overstating high-frequency information and traditional manipulation processing low-frequency information [17]. Several algorithm optimization strategies that mimic animal behavior have been developed recently. Gorai and Ghosh viewed image enhancement as an optimization problem, which they solved with PSO. Their methodology uses an objective function that is based on edge information and entropy and global/local transformation [18]. The best-enhanced image is obtained with the fitness function, and PSO is used to optimize the transformation function's parameter. The results showed that LCS, HE, and GA do not perform as well as PSO does. To determine the ideal parameter values for the transformation function, Yaghoobi et al. recommended using the Bayesian heuristic approach (BHA) [19]. They employed entropy and edge information as the fitness function. They found that BHA outperforms LCS, HE, GA, and PSO and selected it for its simplicity, easy implementation, and robustness.

To create an efficient search methodology for picture improvement, Anupriya and Akashtayal merged many nature- inspired optimization algorithms into one optimization process [20]. Through an impartial assessment of the generated image, three hybrid algorithms, namely, GA–simulated annealing (SA), PSO–SA, and differential evolution (DE)–SA, were compared. The results demonstrated that the hybrid techniques outperform individual GA, PSO, and DE. A unique medical image enhancement technique that is based on CLAHE and POA was employed in [21] to increase the visual quality of images. Medical generation utilizing the text-to-image generative model is the first step in the procedure.

PSO has been utilized to address picture enhancement problems, which are regarded as optimization problems [22]. In [23], local and global picture information were utilized in a parameterized transformation algorithm. The results were compared with those of various image improvement methods, such as contrast stretching, HE, and GA-based image enhancement. The use of ant colony optimization (ACO), which is a novel automatic enhancement method that is based on real-coded particle ant colonies, for image processing problems was recommended by the researchers. The maximization of the number of pixels at the edges and the suggested ACO produced superior results.

Another research presented a novel criterion for evaluating the quality of enhanced images and suggested an image enhancement technique for gray-level images on the basis of CS-PSO [24]. The histogram stretching picture enhancement method adopts two swarm-based optimization techniques, namely, PSO and cat swarm optimization, for the parameter tweaking procedure. Four level contrast aberrations in a dataset were used to test various techniques. This work improved the basic PSO algorithm by presenting an effective objective method for grey-level image enhancement via the standard PSO algorithm [25].

An algorithm for decomposing dull images was proposed by [26] for discrete wavelet transform families. The four approximation coefficients obtained after decomposition were further manipulated using fuzzy logic to enhance the image, and inverse discrete wavelet transform was utilized to reform the image. Meanwhile, an enhancement technique was proposed in [27] to enhance the image quality of artwork with historical importance. A color space model with discrete wavelet transform was utilized up to two levels to obtain approximation and detail coefficient bands. On the basis of these subbands, gamma correction was applied adaptively to brighten the features of dark and dull images [27].

Methodology

Datasets

The dataset used in this study comprises images of tomato plants. The collection is composed of photos of tomato diseases that contain intriguing locations. Specifically, it shows distinct characteristics in its plants that may be identified and categorized. To evaluate the effectiveness of the proposed technique, we utilized the well-used and universally accessible PlantVillage dataset. This dataset has 1,000 samples representing 15 distinct plant species. We examined the photos of tomato plants from the PlantVillage dataset.

The primary reason for utilizing the PlantVillage dataset is the inclusion of photos exhibiting substantial variations in the proportion, color, and placement of the afflicted regions. All photographs of diseased tomato plants are kept using the red, green, and blue (RGB) color space. A total of 15 images are included. Figure 1 displays examples from the dataset that were obtained as findings.

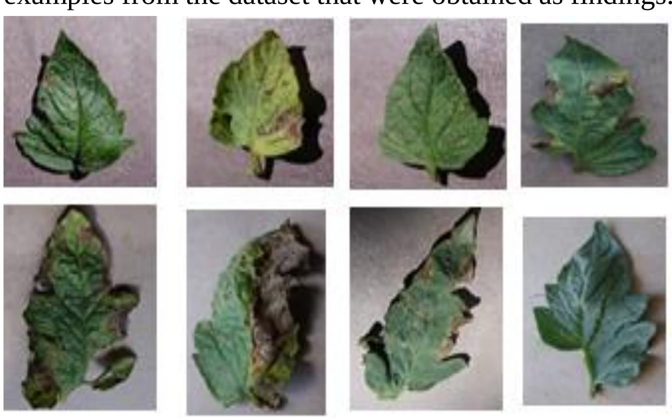

Figure 1. Samples from the tomato plant disease dataset

POA

POA is a recently developed metaheuristic optimizer that utilizes swarm intelligence as its underlying principle. This technique employs autonomous pelicans that navigate the search space to locate the most optimal prey [28]. Owing to collective intelligence, all agents share common knowledge to enhance their performance. Similar to other nature-inspired algorithms, its behavior imitates animal behavior. In this particular scenario, POA exhibits the foraging behavior observed in a collective of pelicans.

This fundamental behavior is analogous to that in PSO, where a flock of birds collectively maintains a specific proximity while looking for food. This behavior forces their prey to ascend to the surface of the water and migrate to shallow regions, allowing the pelicans' ability to catch their target. The initialization of the population members is defined using the equation [29]

$$X_{i,j} = I_j + rand\,(u_j - I_j)\;, i = 1,2\,, \ldots\ldots, N\;, j = 1,2\,, \ldots\ldots m, \ldots \quad (1)$$

The value of the jth variable, which is determined by the ith candidate solution, is denoted as xi,. N is the number of variables, *m* represents the number of issues, and *rand* is a random number in the interval [0,1]. *lj* and *uj* are the lower and upper limits of the problem variables, respectively [30]. The population matrix specifically defines the individuals that make up the pelican population in POA. The information is provided.

$$\mathrm{X} = \begin{vmatrix} X_1 \\ X_i \\ X_N \end{vmatrix} N * m = \begin{vmatrix} X_{1.1} & X_{1.j} & X_{1.m} \\ X_{i.1} & X_{i.j} & X_{i.m} \\ X_{N.1} & X_{N.j} & X_{N.m} \end{vmatrix} N * m \quad (2)$$

The population matrix, denoted as X, represents the population of pelicans. Xi refers to the ith individual pelican in the population. The objective function values are derived using the equation

$$\mathrm{F} = \begin{vmatrix} F_1 \\ F_i \\ F_N \end{vmatrix} N * 1 = \begin{vmatrix} F(X_1) \\ F(X_i) \\ F(X_N) \end{vmatrix}. \quad (3)$$

The objective function vector is denoted by F. The hunting strategy of POA consists of an initial exploration phase, during which POA identifies various locations within the research space. This phase is followed by an exploitation phase, where POA focuses on converging toward a superior solution in the identified hunting area. The candidate solution that emerges as the best after the iterations of the algorithm is considered the optimal solution for the specified issue [31]. POA also incorporates a global optimum solution, which is updated in each iteration once all pelicans have updated their respective locations.

The pelican with the highest fitness score is selected as the potential replacement for the existing global best solution. This candidate will replace the existing global optimum only if it surpasses the current global optimum. Once the iteration concludes or the termination conditions are satisfied, the final solution is determined by the last value of the global best solution. Multiple annotations pertain to POA [32].

The act of moving toward a specific object or location with a predetermined step size is a prevalent feature in numerous algorithms that draw inspiration from the foraging behavior of animals. Typically, the aim is defined, and it is generally the optimal choice. It signifies that the agent tends to approach a favorable position. This movement may be traced back to PSO, where each agent (referred to as a bird) advances toward the accumulation of the weighted global best solution and the weighted local best solution [32].

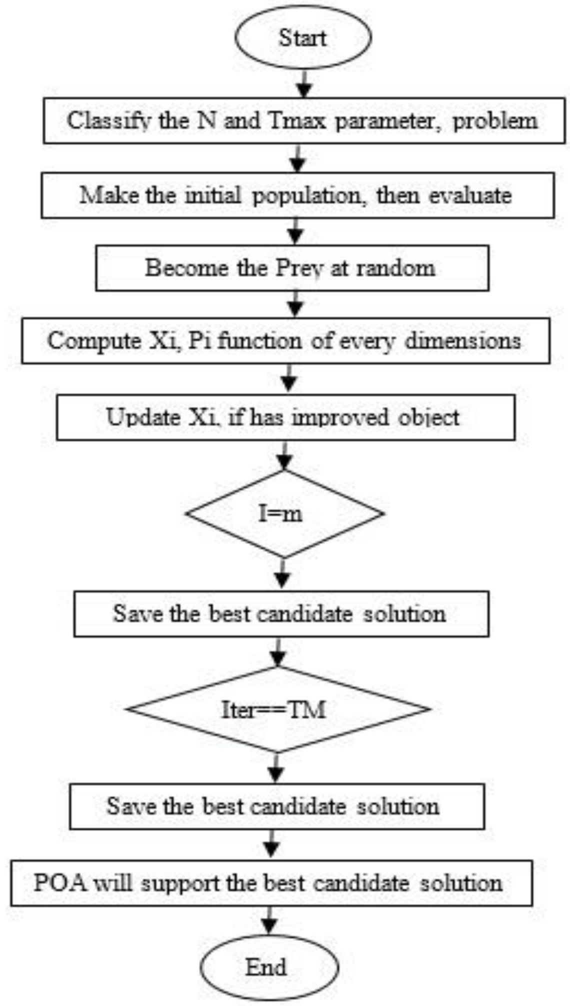

Figure 2. Flow chart of the pelican optimization algorithm

BBHE

The authors suggest a unique modification called BBHE to address the limitations of traditional HE [33]. The core principle of the BBHE algorithm involves applying independent HE to two subimages produced by dissecting the input image in accordance with its mean. The equalized subimages are then constrained to be bounded by each other around the input mean. The proposed algorithm for effectively maintaining the average brightness of a given image is demonstrated mathematically, and its performance surpasses that of standard HE. Moreover, it enhances image contrast, resulting in a natural enhancement that can be applied in consumer electronic products [34].

Let G_m represent the mean of image G and suppose that

$$G_m \in \{ G, G_1, \ldots \ldots G_L - 1\} . \quad (4)$$

On the basis of the mean, the input image is decomposed into subimages GL and GU as ~~[35]~~

$$G = G_L \, U \, G_U . \quad (5)$$

Subimage GL is composed of

$$(G, G1, \ldots . G_M), \quad (6)$$

and subimage GU is composed of

$$(Gm - 1, , Gm - 1, \ldots . GL - 1)\text{-}. \quad (7)$$

Similar to the HE example where an increasing density function is utilized as a transform function, the following transform functions that exploit the cumulative density functions are defined [36].

$$f_L(g) = G_0 + (G_M - G_0) C_L(g) \quad (8)$$

$$fU(g) = Gm + 1 + (GL - 1 - GM + 1)\, CU(g) \quad (9)$$

Depending on these transform functions, the divided subimages are equalized separately with the organization of the results, resulting in equalized subimages that represent the output of BBHE.

Proposed BBHE-POA

In the proposed BBHE-POA enhancement technique, image preprocessing, such as clipping and resizing, is first phase for the input images. Plant disease images are applied to obtain the required nature data for investigation and analysis. All 15 input images are resized to 225 × 225 pixels in RGB format. During image acquisition, BBHE-POA is denoted as contrast enhancement utilizing basic BBHE.

In this technique, an input image is divided into two parts on the basis of the mean value of the gray brightness levels. Then, histograms of the two subimages are formed. The histogram of the first subimage contains gray brightness level values from the minimum to the mean value, while the second one contains gray brightness level values from the mean to the maximum value.

These histograms are equalized separately, and the final image is the combination of the subimages. The evaluation of the clip limit (p) depends on using POA to improve the mean brightness of the equalized sub-images that are bounded by each other around the input mean. In this regard, estimation of the mean suitable value is essential to obtain a successful implementation. By regarding the enhancement issue as an optimization problem, POA enhances the effectiveness of the operation. POA is employed to explain optimization problems in various fields, and it was primarily presented for image-processing purposes. Figures 3 and 4 show the study's methodology and the pseudocode of BBHE-POA.

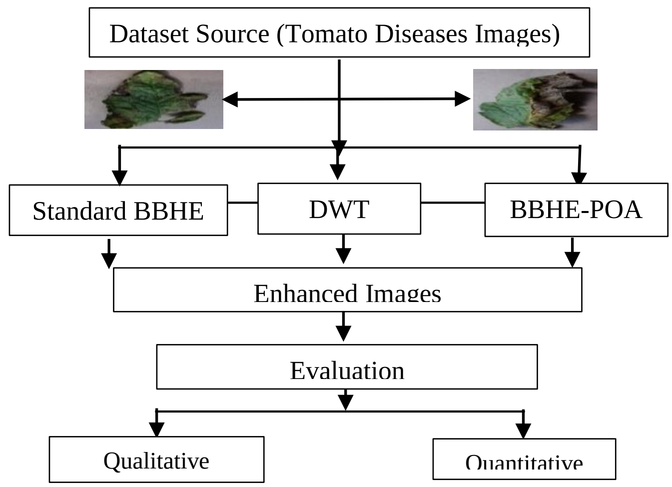

Figure 3. Flow chart of the methodology

*1- Input: initial tomato plant diseases of size 225 * 225 pixels in RGB*
//// BHEE
2- Standard BHEE enhancement technique
/ /// Pelican optimization algorithm (POA)
3- Input the mean brightness of a given image
4- Determination of the population size (M) and number of iterations
5- Initialization of pelicans' positions and calculation of the mean brightness
6- For t = 1:T
7- Generation of the prey's position at random
8- For I = 1:N
9- Exploration and exploitation
10- For j=1:m
11- New status calculation of the jth
12- End
13- End
14- Updating the ith population
15- End
16- Update and output the best solution obtained by POA
17- Estimated value of p
18- Output: enhanced images

Figure 4. Pseudocode of BBHE-POA

Results

This paper presents qualitative and quantitative results. The results of standard BBHE are compared with those of BBHE-POA for 15 input images of tomato plant diseases. The quantitative results are based on SSIM, AMBE, entropy, peak signal-to-noise ratio (PSNR), and elapsed time measures.

Qualitative results

This section presents an illustration of the results via MATLAB. Five different images are considered and shown as samples in the figure. BBHE-POA and standard BBHE provide different enhancement degrees. The proposed technique produces better images compared with standard BBHE. Figure 4 shows that the images created by the proposed technique are clearer than those created by standard BBHE.

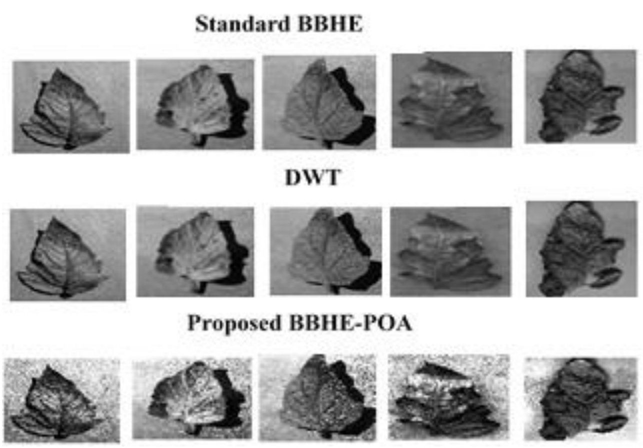

Figure 5. Samples of qualitative results of the techniques

Quantitative analysis

Table 1 presents the SSIM values obtained by standard BBHE and the proposed BBHE-POA for the dataset. A high SSIM value means that the quality of the image is excellent. In all the images, the performance of the proposed technique is better than that of the standard one, and its SSIM values are higher. Table 2 shows a comparative analysis of the dataset. It indicates that the proposed technique has a higher AMBE value for the enhanced images compared with the standard technique.

Table 3 presents the entropy values of the two techniques for 15 images in the dataset. The entropy of the proposed technique is higher than that of the standard technique. Thus, using the proposed BBHE-POA is better than using the standard technique. Meanwhile, Table 4 shows that the proposed technique has shorter elapsed time for the enhanced images compared with the standard BBHE technique.

Table 1. SSIM values of the techniques

Im. no	Standard BBHE	DWT	Proposed BBHE-POA
1	9.1503	9.1991	9.3346
2	9.1101	9.1890	9.3822
3	9.1822	9.2871	9.4213
4	9.0271	9.1987	9.3941
5	9.1352	9.1897	9.3863
6	9.2900	9.2996	9.3873
7	9.1452	9.2001	9.3810
8	9.0942	9.1987	9.3753
9	9.1732	9.2191	9.3002
10	9.0290	9.1892	9.3912
11	9.0101	9.1911	9.3546
12	9.1259	9.2121	9.3457
13	9.0981	9.1981	9.3861
14	9.1091	9.1891	9.3921
15	9.1218	9.1872	9.3785

Table 2. AMBE values of the techniques

Im. no	Standard BBHE	DWT	Proposed BBHE-POA
1	8.9823	8.8990	9.1943
2	8.9902	8.9976	9.1834
3	8.9012	8.9366	9.2849
4	8.3432	8.8764	9.2834
5	8.8821	8.9022	9.2832
6	8.9231	8.9876	9.2834
7	8.9231	8.9871	9.2833
8	8.9112	8.9761	9.2712
9	8.9822	8.9967	9.2901
10	8.8213	8.9784	9.2923
11	8.6352	8.9922	9.1230
12	8.8601	8.9621	9.2456
13	8.6342	8.9721	9.2840
14	8.2855	8.9071	9.2818
15	8.9712	8.9872	9.2861

Table 3. Entropy Values for Techniques

Image	Standard BBHE	DWT	Proposed BBHE-POA

1	**19.8645**	**20.6723**	**21.3997**
2	**19.8654**	**19.9099**	**21.9094**
3	**18.8764**	**20.7621**	**22.6312**
4	**18.9875**	**20.9765**	**23.0965**
5	**19.7643**	**20.8772**	**21.8502**
6	**18.9754**	**20.8765**	**22.0675**
7	**18.7987**	**20.8642**	**22.5210**
8	**18.5432**	**20.9764**	**22.9865**
9	**19.0874**	**20.8632**	**21.7645**
10	**19.7642**	**21.8752**	**23.8764**
11	**19.0342**	**20.8752**	**23.7534**
12	**19.8531**	**20.7412**	**22.0877**
13	**20.0085**	**21.8642**	**23.0756**
14	**19.4523**	**20.9872**	**22.2868**
15	**18.8562**	**20.6412**	**21.8650**

Table 4. PSNR values of the techniques

Im. no	Standard BBHE	DWT	Proposed BBHE-POA
1	**3.7893**	**3.9083**	**4.8990**
2	**3.7834**	**3.8903**	**4.8482**
3	**3.8003**	**4.3463**	**4.8001**
4	**3.8753**	**3.1425**	**4.8874**
5	**3.8039**	**3.9893**	**4.9014**
6	**3.8053**	**4.2345**	**4.6312**
7	**3.8963**	**4.1245**	**4.7743**
8	**3.8312**	**4.2534**	**4.6904**
9	**3.8763**	**4.1364**	**4.6302**
10	**3.8090**	**4.1543**	**4.7546**
11	**3.8954**	**4.2399**	**4.7401**
12	**3.7990**	**4.5473**	**4.8183**
13	**3.9067**	**4.2853**	**4.7945**
14	**3.8543**	**4.4839**	**4.9865**
15	**3.8965**	**4.2335**	**4.7993**

Table 5. Elapsed time values of the Techniques

Image	Standard BBHE	DWT	Proposed BBHE-POA
1	**4.067312**	**4.006474**	**2.285214**
2	**3.609812**	**3.598763**	**3.007342**
3	**3.756121**	**3.588261**	**3.021337**
4	**3.775328**	**3.687652**	**2.990741**
5	**4.721091**	**4.342019**	**3.976342**
6	**4.888421**	**4.652092**	**3.997342**
7	**3.764321**	**3.564232**	**3.010063**
8	**3.776416**	**3.576221**	**2.863501**
9	**4.765310**	**4.341982**	**3.974513**
10	**4.543091**	**4.390731**	**3.976542**
11	**4.543109**	**4.398643**	**3.905312**
12	**4.652106**	**4.498611**	**4.909873**
13	**3.754232**	**3.715403**	**3.976542**
14	**4.167483**	**4.000432**	**3.900168**
15	**3.875439**	**3.643210**	**2.086423**

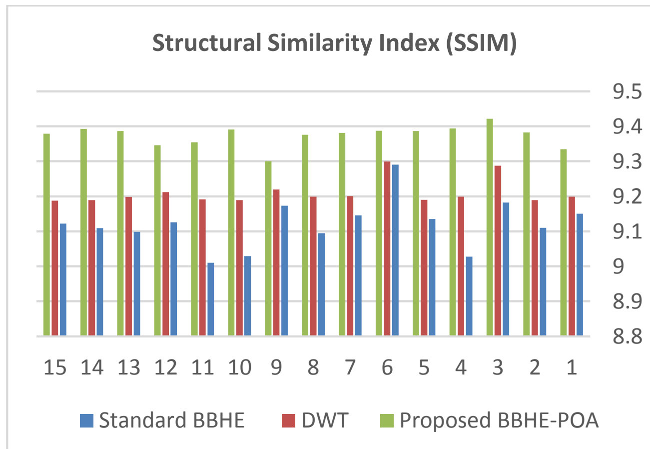

Figure 6. SSIM values of the techniques

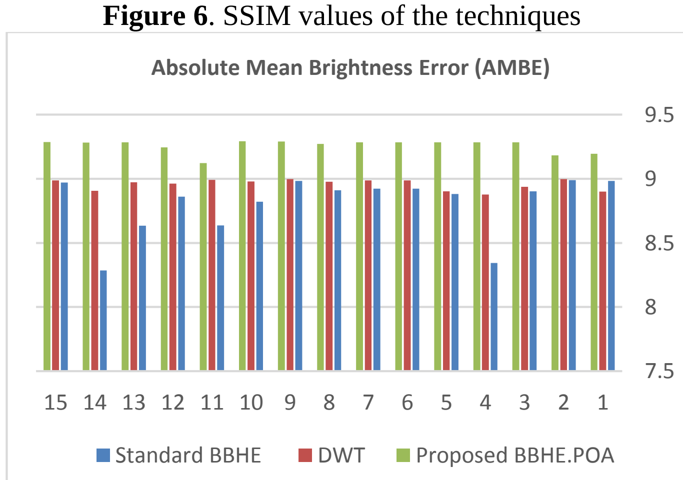

Figure 7. AMBE values of the techniques

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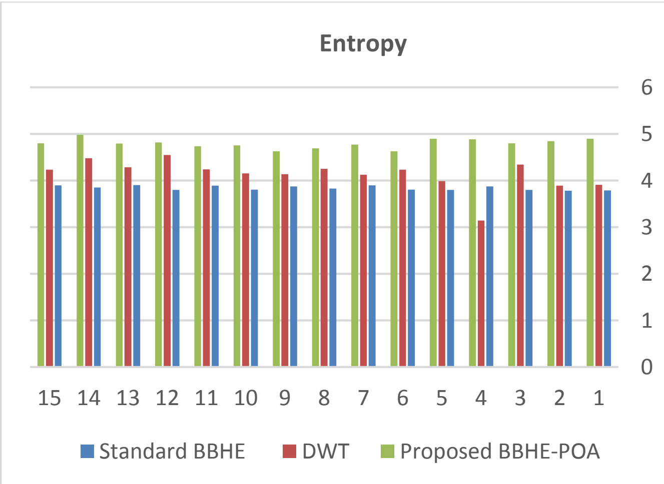

Figure 8. Entropy values of the techniques

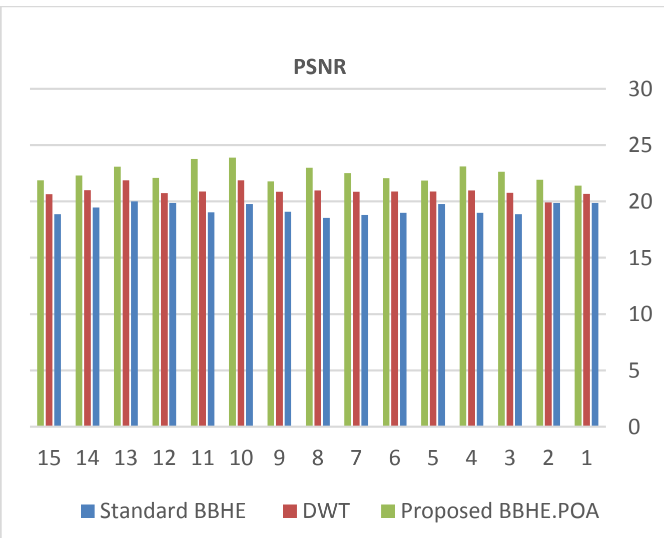

Figure 9. PSNR values of the techniques

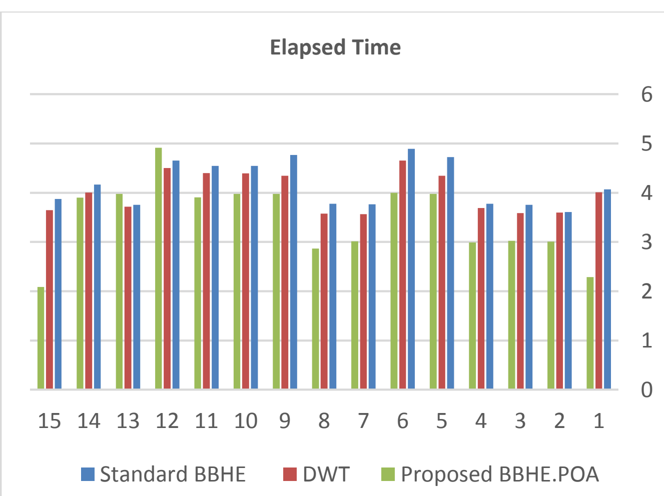

Figure 10. Elapsed time values of the Techniques

Figure 5 shows that the original images are the signal, and the corresponding enhanced fundus images are noise. The images enhanced by the proposed technique has an SSIM value of around 9.4213, which indicates better performance compared with the two other techniques. Figure 7 illustrates that the BBHE technique has a small AMBE value. BBHE-POA preserves more brightness and enhancement and has a higher AMBE value than standard BBHE, as can be seen in the same figure. Figure 7 presents an analytical representation of the abovementioned measures and indicates that the original image has specific average information.

Table 9 shows a comparative analysis of the dataset image. The proposed technique has higher PSNR for enhanced images compared with standard BBHE. Entropy decreases when BBHE and DWT are used, indicating that some information is lost. This information loss leads to false detection of features. BBHE-POA has higher entropy than the original image, which means that this technique enhances the output image. Figure 9 indicates that the proposed technique has shorter elapsed time (i.e., 2.086423 ms) for all the output images compared with the standard approach. The Materials and Methods section presents the procedures and data analysis.

Conclusion

Image preprocessing is required for improved image analysis. In color image processing, color image enhancement is a critical topic because distortion in color images influences subsequent analysis processes, such as segmentation. BBHE is a widely used method in image enhancement. It divides input images into two parts on the basis of the mean value of the gray levels. Then, histograms of the two subimages are produced. The goal of this study is to develop a standard BBHE technique for image enhancement.

This goal is achieved by verifying an appropriate optimization algorithm, namely, POA. The use of an optimization algorithm while enhancing the image is demonstrated in the present study by employing plant images. The improved mean brightness values of the equalized subimages are bounded around the input mean in the standard BBHE technique. Fifteen natural tomato disease images are used as a dataset. The images are from the PlantVillage site, a famous dataset source. Three enhancement techniques, namely, BBHE-POA, standard BBHE, and DWT, are applied. Several performance measures, such as SSIM, AMBE, entropy, PSNR, and elapsed time, are employed to compare the three techniques.

The visual qualitative and quantitative test results indicate that the proposed BBHE-POA achieves better results in all the performance measures compared with the other techniques. The improved BBHE-POA achieves better enhancement compared with the other techniques. Future research can be conducted based on this work. For example, POA can still be adjusted. This algorithm can also be merged or hybridized with other techniques.

References

[1] Linwei, F. Fan, Z. Hui, F. & Caiming, Z. (2019) Brief review of image denoising techniques. *Visual Computing for Industry, Biomedicine, and Art*, pp 1–12.

[2] Guo, L. Wan, R. Su, G.-M. Kot, A. & Wen, B. (2021). Multi-Scale Feature Guided Low-Light Image Enhancement. *International Conference on Image Processing (ICIP),* 554–558.

[3] Zhang, Z. Jiang, Y. Jiang, J. Wang, X. Luo, P. & Gu, J. 2021. STAR: A Structure-Aware Lightweight Transformer for Real-Time Image Enhancement. *International Conference. Computer Vision*, pp 4106–4115

[4] Guo, C. Li, J. Guo, C. Loy, J. Hou, S. Kwong, & Cong, R. Zero-reference deep curve estimation for low-light image enhancement. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2020.*

[5] Cai, J. Gu, S. & Zhang, L, (2018) Learning a deep single image contrast enhancer from multi-exposure images. *IEEE Transactions on Image Processing.*

[6] Rahman, Z. & Jobson, D. (2004) Glenn Woodell. Retinex processing for automatic image enhancement. *Journal of Electronic Imaging*. 13(1), 554–558.

[7] Kim, Y. (1997). Contrast enhancement using brightness preserving bi-histogram equalization. *IEEE transactions on Consumer Electronics*, 43(1), 1-8.

[8] Fari, A. (2012). Image Enhancement using Histogram Equalization & Spatial Filtering. *International Journal of Science & Research (IJSR)*, Vol.1 No.3, pp.15-20.

[9] Chu, S. Tsai ,P. & Pan, J. (2006). Cat swarm optimization, *proceedings of the 9th Pacific Rim International Conference on Artificial Intelligence*, pp. 854-858, 2006, Guilin, China.

[10] Farshi, T.R. Battle (2021) royale optimization algorithm. *Neural Computer*. (4)l, 33, pp 1139–1157.

[11] Abualigah, L.; Yousri, D.; Abd Elaziz, M.; Ewees, A.A.; Al- qaness, M.A.& Gandomi, A.H. Aquila (2021) Optimizer: A novel meta-heuristic optimization Algorithm. Computer. Ind. Eng., 157, 107250.

[12] Geetha, K.; Anitha, V.; Elhoseny, M.; Kathiresan, S.; Shamsolmoali, P. & Selim, M.M. (2021) An evolutionary lion optimization algorithmbased image compression technique for biomedical applications. *Expert System Journal*, 38, e12508.

[13] Yadav, R.K.; Mahapatra, R.P. Hybrid metaheuristic algorithm for optimal cluster head selection in wireless sensor network. *Pervasive and Mobile. Computing* (2021)., 79, 101504.

[14] Trojovský, P., & Dehghani, M. (2022). Pelican optimization algorithm: A novel nature-inspired algorithm for engineering applications. *Sensors*, 22(3), pp 2-34.

[15] Stephan, P. Stephan, P. Kannan, T. & Abraham, R. (2021). A hybrid artificial bee colony with whale optimization algorithm for improved breast cancer diagnosis. *Neural Computer*. 33, 13667–13691.

[16] Kaul, S. Kumar, Y , Ghosh, U. & Alnumay, W . Nature-inspired optimization algorithms for different computing systems: Novel perspective and systematic

review. Multimedia. Tools Application . 81, 26779–26801.

[17] Alcudia, V. Vega-Rodríguez, M. Artificial bee colony algorithm based on dominance (ABCD) for a hybrid gene selection method. *Know. Based System.* 2020, 205, 106323.

[18] Abbas, S. Jalil, Z. Javed, A. Batool, I. Khan, M. Noorwali, A. Gadekallu. T. Akbar, A. BCD-WERT: A novel approach for breast cancer detection using whale optimization based efficient features and extremely randomized tree algorithm. *PeerJ Computer Science*, 1-11

[19] R. Arun, S. Madhu . R. Nair, R. Vrinthavani and R Tatavarti. "An Alpha Rooting Based Hybrid Technique for Image Enhancement". *Online publication in IAENG*, 24th August 2011.

[20] Singh, K. & Kapoor, R.. (2014) Image enhancement using Exposure based Sub Image

Histogram Equalization, *Pattern Recognition Letters* No. 36, pp10–14. 2014

[21] Amir ,S. & Kiani, F. (2023) Sand Cat swarm optimization: A nature-inspired algorithm to solve global optimization problems." *Engineering with Computers*. pp 2627-2651.

[22] Ritu, C. & Bhadoria,S. (2011) An improved image contrast enhancement based on histogram equalization and brightness preserving weight clustering histogram equalization. International Conference for Communication Systems and Network Technologies (CSNT). *IEEE*.

[23] Ghaedi, A. Bardsiri, A. & Shahbazzadeh, M. (2023) Cat hunting optimization algorithm: a novel optimization algorithm. *Evolutionary Intelligence*, vol .16, no 2, pp 417-438.

[24] Moniruzzaman, M. Shafuzzaman, M. & Hossain, M. F. (2014). Brightness preserving Bi-histogram equalization using edge pixels information. In 2013 *international conference on electrical information and communication technology*.

[25] Haddadi, Y.., Mansouri, B., & Khodja, F. Z. I. (2024). A novel medical image enhancement algorithm based on CLAHE and pelican optimization. *Multimedia Tools and Applications*, 1-20.

[26] Kothandaraman, D., Balasundaram, A. Korra, S., Sudarshan, E. & Vijaykumar, B. (2020, December). Enhancing dull images using discrete wavelet families and fuzzy. *In IOP conference series: materials science and engineering* (Vol. 981, No. 2, p. 022020.

[27] Swarup, J., & Sreedevi, I. (2022). DWT based historical image enhancement technique using adaptive gamma correction. *Journal of Algebraic Statistics*, 13(1), 654-664.

[28] Zhou, C., Zhou, S., Xing, J., & Song, J. (2021). Tomato leaf disease identification by restructured deep residual dense network. *IEEE Access*, 9, 28822-28831.

[29] Li, M., Zhou, G., Chen, A., Li, L., & Hu, Y. (2023). Identification of tomato leaf diseases based on LMBRNet. *Engineering Applications of Artificial Intelligence*, 123, 106195. doi.org/10.1016/j.engappai.2023.106195

[30] Raj, A., Punia, P., & Kumar, P. (2024). A novel hybrid pelican-particle swarm optimization algorithm (HPPSO) for global optimization problem. *International Journal of System Assurance Engineering and Management*, 1-16.

[31] Gao, Y., Xia, X., & Guo, Y. (2023). A Thermal Error Prediction Method of High-Speed Motorized Spindle Based on Pelican Optimization Algorithm and CNN-LSTM. *Applied sciences*, 14(1), 381

[32] Jamal, S., Pasupuleti, J., Rahmat, N., & Tan, N. M. (2024). Multi-Objective Optimal Energy Management of Nanogrid Using Improved Pelican Optimization Algorithm. *IEEE Access*, 12, 41954-41966

[33] Kusuma, P., & Prasasti, A. (2022). Guided pelican algorithm. *International Journal of Intelligent Engineering and Systems*, 15(6), 179-190.

[34] Li, Y., Yuan, Z., Zheng, K., Jia, L., Guo, H., Pan, H., & Huang, L. (2022). A novel detail weighted histogram equalization method for brightness preserving image enhancement based on partial statistic and global mapping model. *Image Processing journal*, 16(12), 3325-3341

[35] Mishro, P.., Agrawal, S., Panda, R., & Abraham, A. (2021). A novel brightness preserving joint histogram equalization technique for contrast enhancement of brain MR images. *Biocybernetics and Biomedical Engineering*, 41(2), 540-553

[36] Chen, S. & Ramli, A. (2003). Minimum mean brightness error bi-histogram equalization in contrast enhancement. *IEEE transactions on Consumer Electronics*, 49(4), 1310-1319.

تحسين تقنية BBHE استنادًا إلى خوارزمية تحسين البجع (POA) لتحسين الصور

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الخلاصة:

إن تحسين الصورة له أهمية قصوى في تحليل الصور، وذلك باستخدام إجراءات وتقنيات معقدة. إن تحسين صور أمراض النبات مهمة معقدة في معالجة الصور بسبب وجود خصائص صور منخفضة الجودة والعديدة. وتؤثر النتائج بشكل كبير على التشخيص السريري ومراقبة الأمراض. غالبًا ما تكون مشاكل التحسين في العالم الحقيقي صعبة للغاية وتتعامل العديد من التطبيقات مع مشاكل التحسين. لحل المشكلات، يجب استخدام خوارزميات التحسين مثل خوارزمية تحسين البجع ((POAالتي تتمتع بإنتاجية عالية. يقدم هذا البحث تقنية جديدة تسمى معادلة الهيستوجرام للحفاظ على السطوع جنبًا إلى جنب مع خوارزمية تحسين البجع (.(BBHE – POAتستخدم لتحسين الجودة المرئية لصور أمراض النبات، بهدف تحسين مظهرها العام. يتم تطبيق خوارزمية BBHE ودراستها رياضيًا حيث يمكنها الحفاظ على السطوع الأصلي لتوسعات محددة. يتم استخدام خوارزمية التحسين للحصول على التكوين المثالي لخوارزمية BBHE عن طريق تضخيم متوسط سطوع الصور الفرعية المتساوية المحيطة بمتوسط الإدخال. في النتائج، تم تطبيق تحليل نوعي وكمي لثلاث تقنيات تعزيز وهي BBHE القياسي وتحويل الموجة المنفصلة (.(DWTعدة قياسات في التحليل الكمي على الصور المحسنة مثل (SSIMمؤشر التشابه الهيكلي)، و(AMBEخطأ متوسط السطوع المطلق) إنتروبيا، و(PSNR نسبة ضوضاء إشارة الذروة) والوقت المنقضي على التوالي. وكخلاصة، تثبت التجارب أن التقنية المقترحة تحقق أداءً متفوقًا نوعيًا وكميًا عندما أنتجت قيمًا جيدة وأفضل لجميع صور البيانات

الكلمات المفتاحية: تحسين الصورة، تقنية BBHE، خوارزمية تحسين البجع.