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An enhancement of the novel cuckoo search algorithm applied in contrast enhancement of gray scale images

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Abstract

Image enhancement is a critical aspect of image processing, aimed at improving image quality for various applications. In this dynamic field, enhancing contrast in grayscale images is particularly significant across diverse domains such as autonomous driving, medical imaging, and pattern recognition. The Cuckoo Search Algorithm (CSA) has emerged as a promising optimization technique for image enhancement tasks due to its simplicity and efficacy. However, existing enhancements of CSA, notably the Novel Enhanced Cuckoo Search Algorithm, suffer from lengthy execution times, potential oversaturation in output, and challenges in convergence. This study proposes modifications to address these issues, focusing on reducing execution time, preserving image details, and improving convergence. Specifically, the modifications involve vectorization of the algorithm's existing code, fine-tuning of enhancement parameters, and replacing Levy flights with the Cauchy operator for better solution exploration. Experimental results demonstrate that the proposed modifications significantly enhance the algorithm's performance, leading to faster execution times, balanced enhancement, and improved overall performance based on the following five metrics: Fitness Value, Peak Signal-To-Noise Ratio (PSNR), Edge Detection, Entropy, and Feature Similarity Index (FSIM). The findings suggest that the Proposed Enhancement of the Novel Cuckoo Search Algorithm that employs Cauchy Operator yields superior results compared to Levy flights, making it a viable enhancement for image optimization tasks.

Keywords: Cuckoo Search Algorithm; Cauchy Operator; Grayscale Image Enhancement; Image Optimization

1. Introduction

Image enhancement is considered to be one of the most important approaches in the field of image processing. Its purpose is to improve the quality of images for specific applications. The basic principle of image enhancement is to modify the information contribution of an image so that it is more suitable for a specific application (Qi, et al., 2021). In the dynamic landscape of image processing, the enhancement of contrast in grayscale images stands as a significant pursuit. These days, the need to have enhanced images are highly required in several disciplines, such as autonomous driving, computer vision, pattern recognition, face recognition, remote sensing, medical image analysis, animal and plant disease detection, geographical information systems (GIS), smart transportation, and autonomous navigation. Furthermore, recent developments in engineering and computer sciences have heightened the need for digital image processing (Woldamanuel, 2023).

The Cuckoo Search Algorithm (CSA) is one of the more recent meta-heuristic optimization algorithms developed in 2009 by Xin-She Yang and Suash Deb based on the brood parasitism of some cuckoo species, along with Levy flights random walks (Joshi, et al., 2017). CSA was found to be a promising and interesting algorithm that has the capacity to be widely

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used by researchers across different fields. Its advantages over other optimization algorithms include its simplicity, fewer parameters compared with other algorithms, and ease of hybridization with other optimization algorithms (Shehab, et al., 2017).

In 2019, Kamoona and Patra developed an Enhanced Cuckoo Search Algorithm for contrast enhancement applied in gray scale images. While it was found effective, the algorithm was discovered to have multiple issues. Kamoona and Patra stated that the enhanced algorithm, albeit superior to existing ones, was achieved at a higher cost of execution time and higher computational complexity. The authors also suggested finding a more optimum search range for the Local/Global Enhancement parameters.

This thesis will focus on modifying the previously developed enhanced cuckoo search algorithm for contrast enhancement of gray scale images, mainly to improve the algorithm's execution time. Amidst the intricacies of this algorithm also lies a distinctive focus on improving the visual quality of grayscale images in addition to the reduction of the algorithm's space complexity and enhancement of its search parameters.

2. Material and methods

Three main ways are proposed to remediate pre-existing problems identified in the Novel Enhanced Cuckoo Search Algorithm:

2.1 Vectorization of existing MATLAB Code

The existing MATLAB code of the Novel Enhanced Cuckoo Search Algorithm can be further improved to enhance readability, efficiency, and maintainability. Variable initialization can be optimized by moving it outside the loop where appropriate. Reducing unnecessary repetitive assignments leading to a more efficient code. Additionally, vectorized code tends to be shorter, reducing the likelihood of programming errors compared to its loop-based counterparts. Vectorized code also runs faster than code containing loops due to MATLAB's optimized execution of matrix operations. The study has modified the Novel Enhanced Cuckoo Search Algorithm MATLAB Code to further improve its performance and overall execution time. Specific improvements on the code include:

2.1.1 Vectorized random initialization of nests

Instead of using nested loops to initialize the nests, the researchers vectorized operations to generate random values for all nests simultaneously. This reduces loop overhead and improves efficiency.

```
% Random initialization of nests (vectorized)
nest_cauchy = rand(pop, 4) .* (Ub_cauchy - Lb_cauchy) + Lb_cauchy;
```

2.1.2 Vectorized operations

Throughout the code, wherever possible, vectorized operations are used instead of explicit loops. Vectorized operations were done using built-in MATLAB functions that are optimized for efficiency.

```
% Random initialization of nests (vectorized)
nest_cauchy = rand(pop, 4) .* (Ub_cauchy - Lb_cauchy) + Lb_cauchy;

% Generate new solutions (vectorized)
new_nest_cauchy = get_cuckoos(nest_cauchy, bestnest_cauchy, Lb_cauchy, Ub_cauchy);
```

2.1.3 Memory preallocation

Matrices for storing results such as fitness values, best nests, and convergence plots are preallocated with the correct size before the main loop. This avoids dynamic memory allocation during runtime, which can be computationally expensive.

```
% Preallocate matrices for performance
fitconveg_cauchy = zeros(L, Max_iter);
Bestfmax_cauchy = zeros(L, 1);
Tot_time_cauchy = zeros(L, 1);
bestN_cauchy = zeros(L, 4);
```

Nu_it_cauchy = zeros(L, 1);

2.2 Fine-tuning of Parameters

Yue and Zhang (2020) set the Local/Global Enhancement optimal parameter range to the following to achieve faster computation:

a ∈ [0, 1.5]
b ∈ [G m /2, G m]
c ∈ [0, 1]
k ∈ [0.5, 1.5]

2.3 Cauchy Operator in replacement for Levy Flights

Guo et al. (2017) compared the Cuckoo search algorithm based on three random walks and found that Cauchy step excels in lowdimensional benchmark functions deeming it the fastest when compared to the Gauss and Levy methods. The four (a,b,c and k) parameters of the Local/Global enhancement are relatively low-dimensional suiting the use of the cauchy operator.

2.4 Proposed Cuckoo Search Algorithm (CSA) with Cauchy Operator Framework

The proposed enhancement discussed are summarized in Figure 1

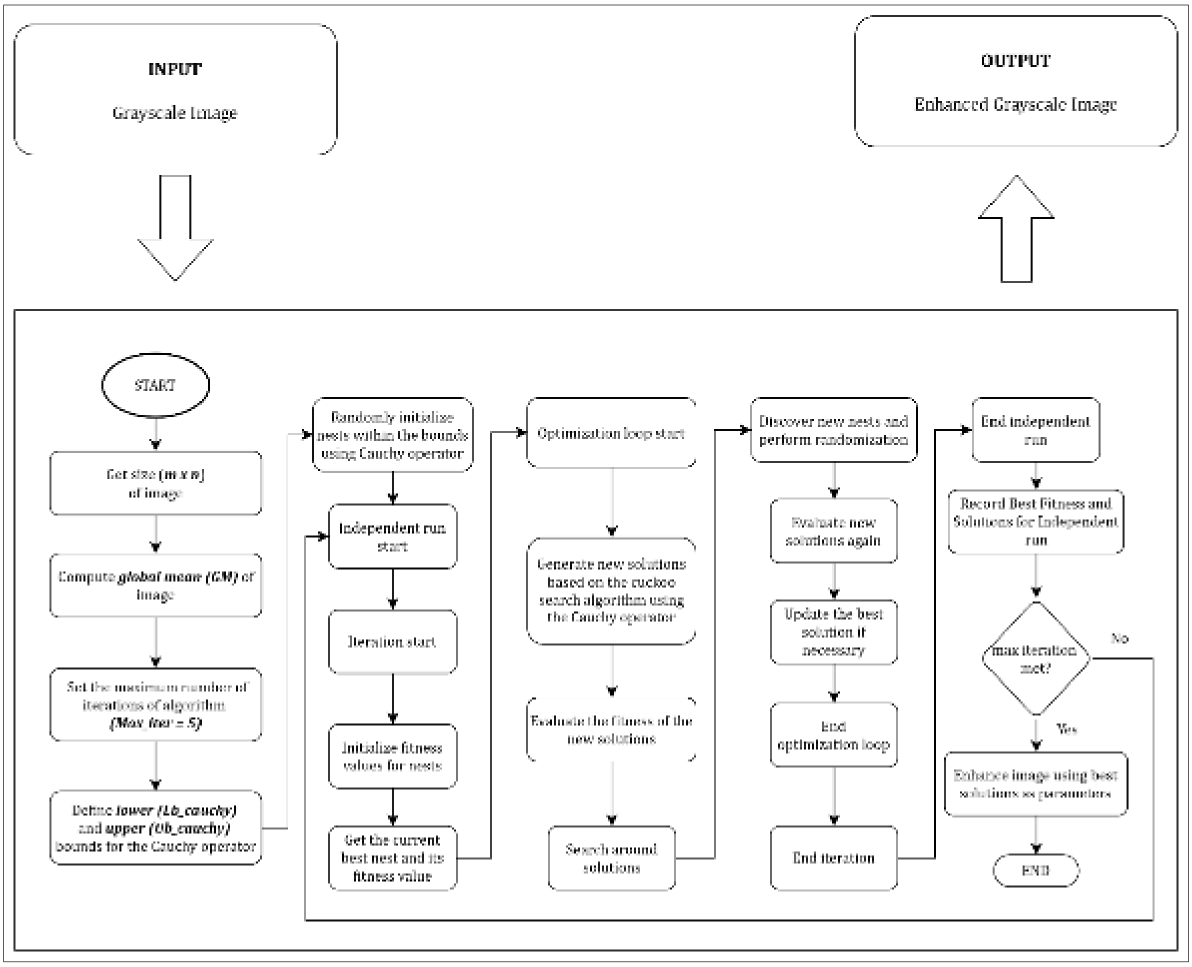

Figure 1 Proposed *CSA with Cauchy Operator*

2.5 Performance Evaluation

To measure the quality of enhanced images using the proposed ECS and to compare it with other algorithms, the following five performance measures will be used in testing to be able to make the modified algorithm have a true comparison to the previous algorithm:

2.5.1 Fitness Value

The fitness value of an individual is the value of the fitness function for that individual. Because the toolbox software finds the minimum of the fitness function, the best fitness value for a population is the smallest fitness value for any individual in the population. (MathWorks)

2.5.2 Peak Signal to Noise Ratio (PSNR)

Peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. (Journal of Network and Computer Applications, 2021)

2.5.3 Number of Detected Edges (n_edge)

Edge detection is an image processing technique for finding the boundaries of objects within images. It works by detecting discontinuities in brightness. Edge detection is used for image segmentation and data extraction in areas such as image processing, computer vision, and machine vision.

2.5.4 Entropy

Entropy is a measure of chaos in a system. Because it is much more dynamic than other more rigid metrics like accuracy or even mean squared error, using flavors of entropy to optimize algorithms from decision trees to deep neural networks has shown to increase speed and performance. (Ye, 2020)

2.5.5 Feature Similarity Index (FSIM)

Feature Similarity Index Method maps the features and measures the similarities between two images.

3. Results and discussion

The researchers picked ten images from a pool of 200 test images that represented a wide range of visual characteristics and complexities commonly encountered in image processing tasks. This focused selection allowed for a thorough evaluation of the algorithm's performance under various conditions, including different lighting conditions and object orientations. By analysing these interpretations, the researchers gained valuable insights into the algorithm's ability effectively in the context of grayscale image enhancement. MATLAB simulations for enhancing images were run using a Desktop with AMD Ryzen 5 5600x CPU and 16 gb of RAM.

3.1 Reducing Execution Time

Table 1 shows the comparison in execution time of resulting images, such as "butterfly," "baby," and "bridge," between ECS with Levy Flights and ECS with Cauchy; with the latter demonstrating significantly lower execution times, indicating improved algorithmic efficiency.

Table 1 Execution Time Comparison

IMAGE NAME	**Image Enhancement Execution Time (Secs)**	
	Existing Algorithm (ECS w/ Levy Flights)	Proposed Algorithm (ECS w/ Cauchy Operator)
Butterfly	15.89	7.68
Baby	55.33	28.05
Bridge	37.83	18.87
Bridge2	96.31	50.77
Building	37.83	18.87

Balcony	100.89	51.98
Cat	12.61	6.19
Eagle	100.89	51.98
Fruit	12.66	6.47
Watch	46.63	24.33
Average	51.69	26.52

When comparing the execution time of Enhanced Cuckoo Search (ECS) with Cauchy operator to ECS with Levy flights, Figure 2 shows that the ECSCO is 47.74% better than ECSLF suggesting that ECS with the Cauchy operator executes faster than its predecessor.

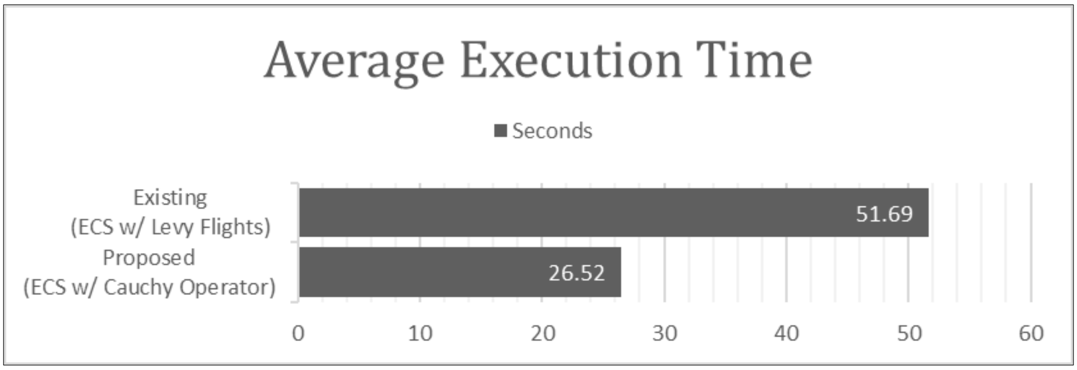

Figure 2 Average Execution Time Comparison

3.2 Balanced Enhancement

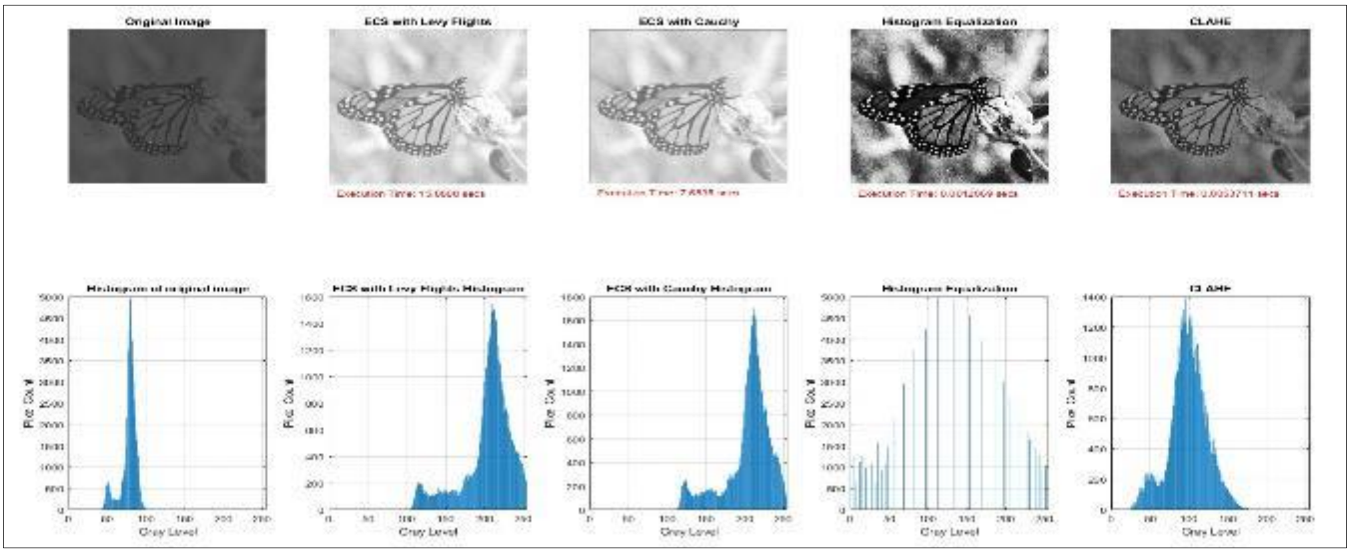

Figure 3 Resulting image and histogram comparison of butterfly

In the context of image processing, a histogram provides valuable insights into the distribution of pixel intensities within the image. A good histogram serves as a visual representation of an image's quality, revealing insights into its exposure, contrast, and overall tonal distribution. A well-distributed histogram showcases a balanced spread of pixel intensities across the entire range, from pure black to pure white, ensuring that the image captures a diverse array of tones and details. In addition to this, a centered peak within the intensity range indicates a balanced brightness level, neither overly bright nor excessively dark. The absence of clipping (where the histogram curve touches or extends beyond the boundaries of the intensity range) ensures that detail is preserved in both highlights and shadows, enhancing the image's overall clarity and detail. Furthermore, a histogram devoid of significant gaps or spikes suggests uniformity in tonal distribution, minimizing areas of missing or highly concentrated pixel values. The following figures represent the histogram comparison of the original and enhanced images using the previous and proposed modified algorithm.

In Figure 3, the histogram comparison reveals distinct differences between images processed with the Cauchy operator and those with Levy Flights. The Cauchy-enhanced image showcases a significantly compressed Gray Level and slightly fewer pixels compared to its counterpart. Furthermore, images processed with the Cauchy operator exhibit notable differences in brightness compared to those HE and CLAHE. ECS with Cauchy produces brighter results, while also presenting much smoother details compared to HE and outshining CLAHE in terms of brightness.

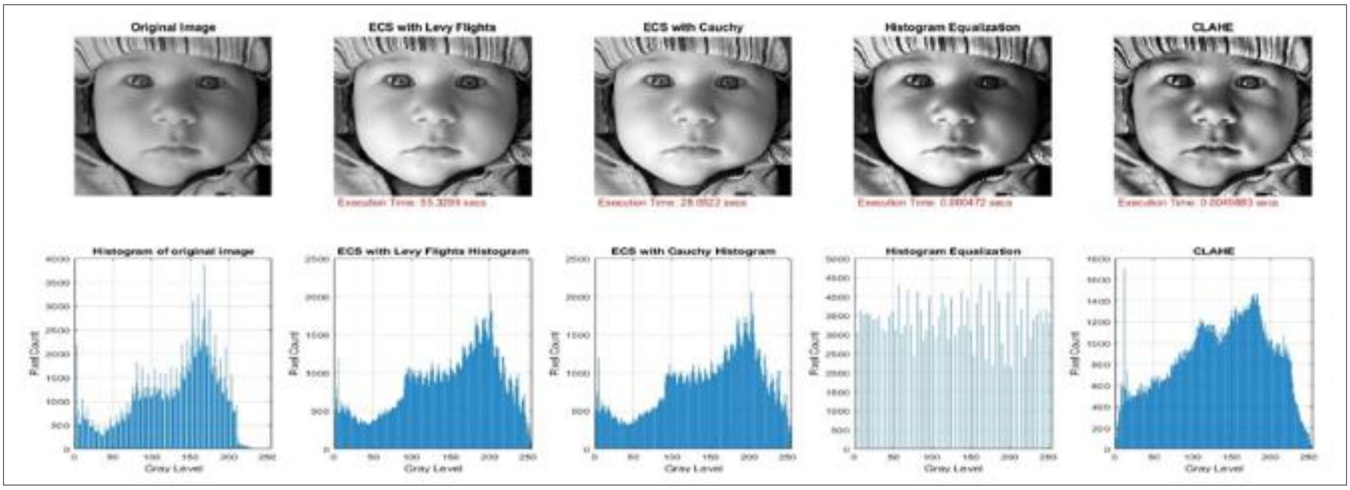

Figure 4 Resulting image and histogram comparison of baby

The Cauchy-enhanced image in Figure 4 displays a significantly compressed Gray Level compared to the Levy Flights-enhanced one, resulting in improved image quality, and faster processing. Additionally, it's darker than images enhanced with Histogram Equalization (HE) and Contrast Limited Adaptive Histogram Equalization (CLAHE), which have less compressed Gray Levels. Nonetheless, the Cauchy-enhanced image retains brighter details, showcasing superior enhancement.

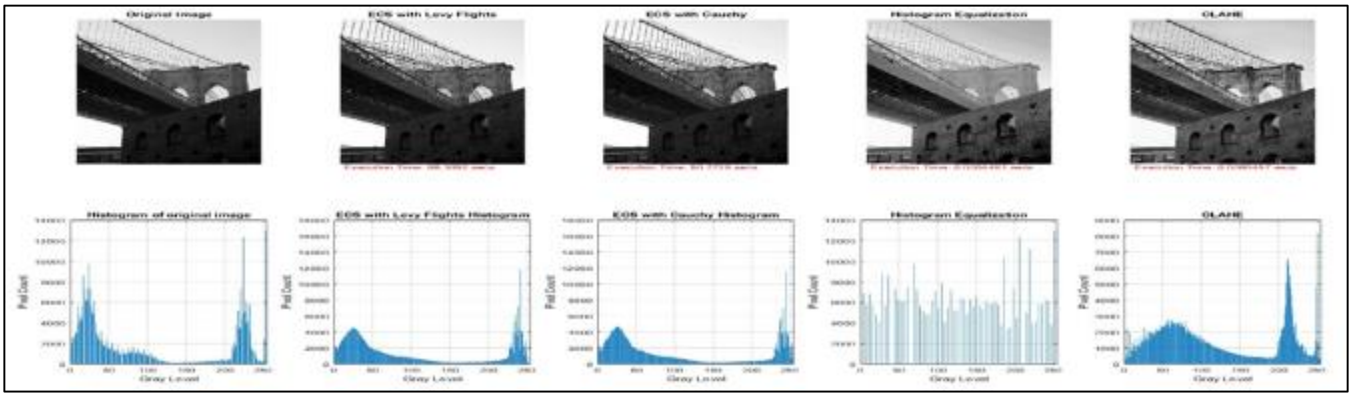

Figure 5 Resulting image and histogram comparison of bridge

Figure 5 illustrates subtle differences between histograms. The Cauchy operator significantly compresses the Gray Level and reduces pixel count compared to Levy Flights. Histogram Equalization yields less compression than Cauchy, resulting in darker shades, while CLAHE produces brighter images due to minimal pixel count despite compression.

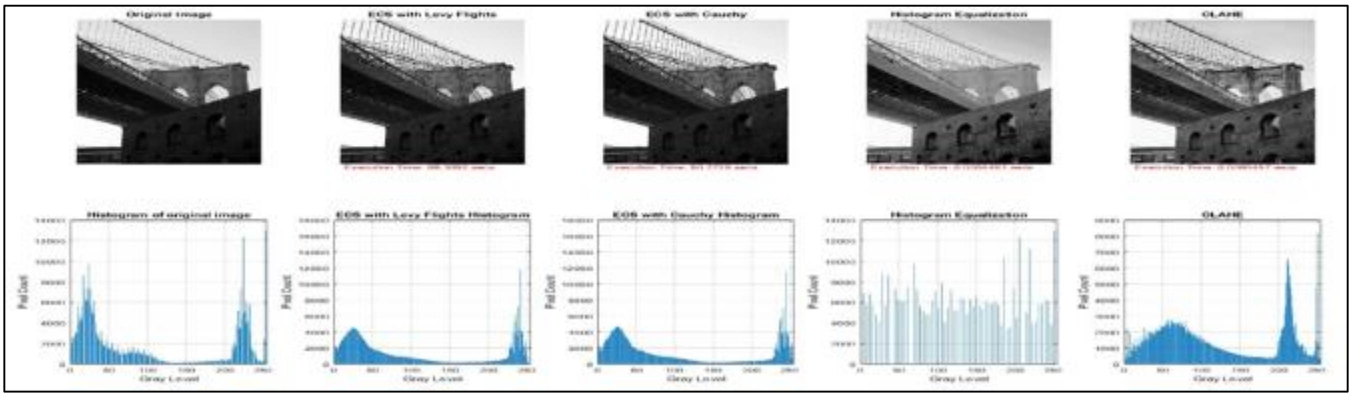

Figure 6 Resulting image and histogram comparison of bridge2

In figure 6, the histogram comparison reveals subtle differences between images processed with the Cauchy operator and those with Levy Flights. The Cauchy-enhanced image exhibits a slightly lower pixel count and more pronounced compression. However, when contrasted with images processed using Contrast Limited Adaptive Histogram Equalization (CLAHE), Enhanced Contrast Stretching (ECS) with Cauchy shows a slight underperformance. CLAHE generates images with a more compressed gray level and higher pixel count than ECS with Cauchy. Nevertheless, the distinction lies in the visual output, where ECS with Cauchy presents more refined and smoother details, highlighting its strengths despite the quantitative differences in pixel count and compression level.

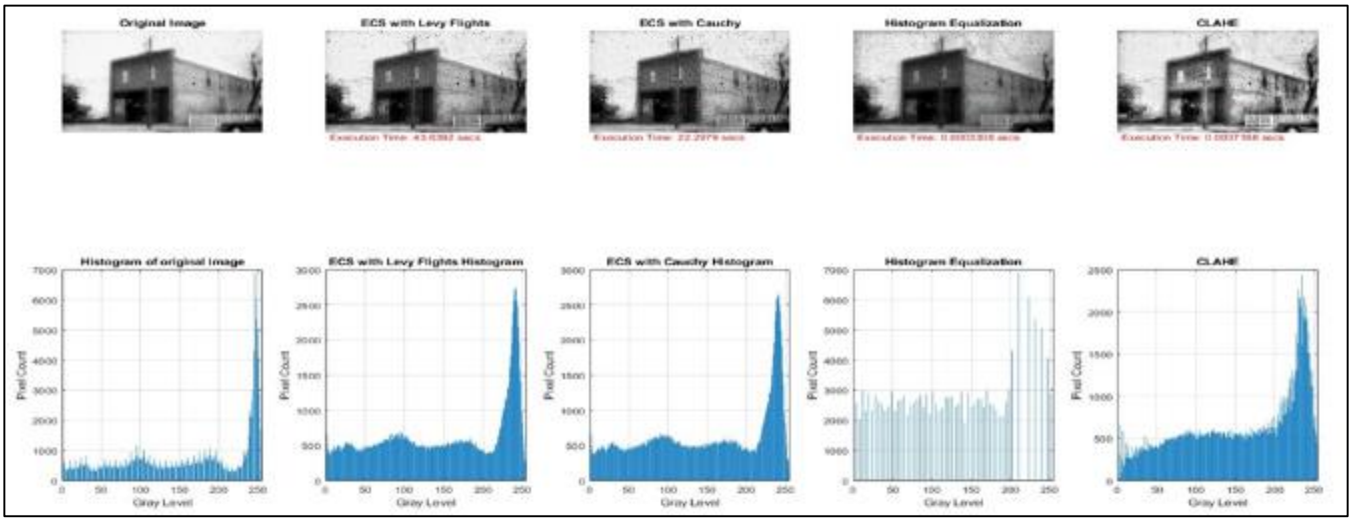

Figure 7 Resulting image and histogram comparison of building

Figure 7 reveals distinct advantages of utilizing the Cauchy operator over Levy Flights. Images enhanced with Cauchy exhibit more compressed Gray Levels and lower pixel counts. Furthermore, compared to Histogram Equalization (HE) and Contrast Limited Adaptive Histogram Equalization (CLAHE), Enhanced Contrast Stretching (ECS) with Cauchy results in a darker shade due to its more compressed Gray Level, yet maintains a brighter image than CLAHE despite its minimal pixel count.

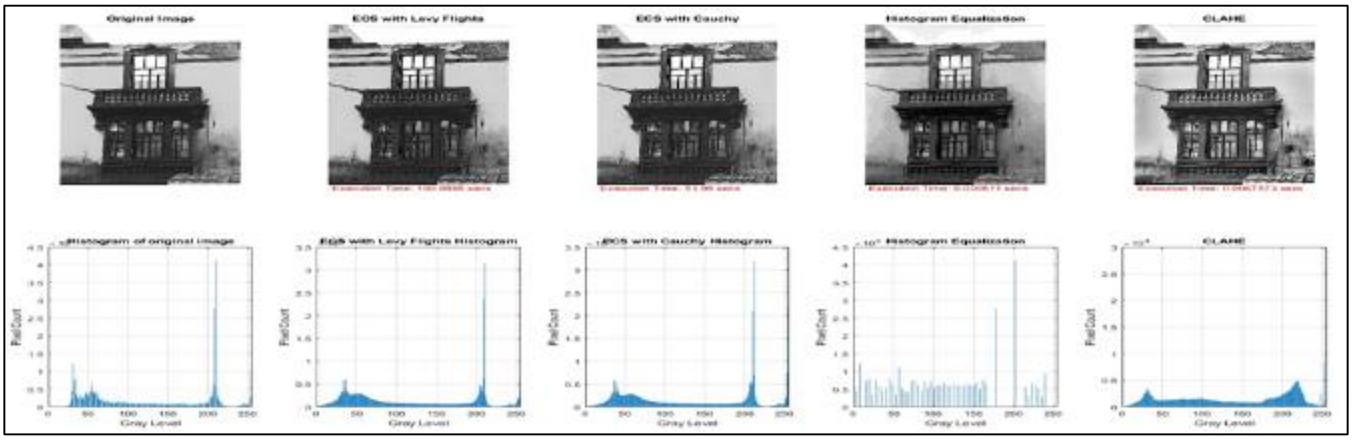

Figure 8 Resulting image and histogram comparison of balcony

The analysis in figure 8 indicates that employing the Cauchy operator results in more compressed Gray Levels compared to Levy Flights. Additionally, images processed using Enhanced Contrast Stretching (ECS) and the Cauchy operator appear darker due to the increased compression of their Gray Levels in contrast to those processed with Histogram Equalization (HE). Similarly, while ECS with Cauchy produces brighter images compared to Contrast Limited Adaptive Histogram Equalization (CLAHE), the latter's minimal pixel count contributes to its brighter appearance.

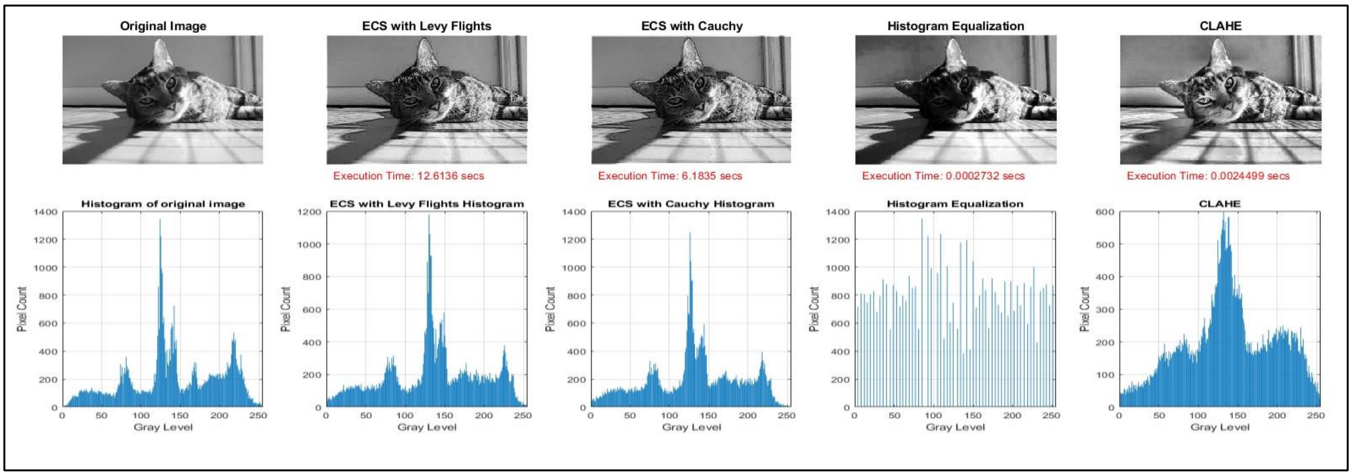

Figure 9 Resulting image and histogram comparison of cat

The histogram comparisons of Figure 9 reveal nuanced distinctions, particularly with the Cauchy operator significantly compressing gray levels and reducing pixel count compared to Levy. Additionally, Histogram Equalization produces less compression than ECS with Cauchy, resulting in darker shades. Similarly, CLAHE, while compressed, yields brighter images with minimal pixel count, enhancing brightness.

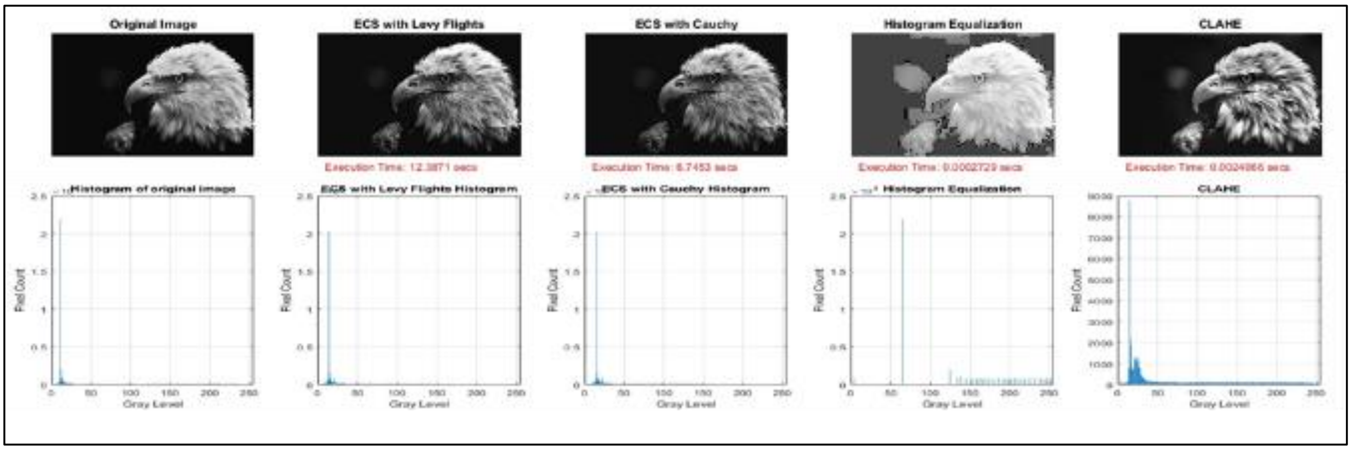

Figure 10 Resulting image and histogram comparison of eagle

In Figure 10, comparing histograms indicates subtle variations, notably with the Cauchy operator compressing gray levels more than Levy Flights, thereby improving transmission efficiency, quality, and processing speed. Histogram Equalization exhibits less compression compared to ECS with Cauchy, resulting in a grayish tone. Conversely, CLAHE, although compressing gray levels, produces images with less smoothness than ECS with Cauchy, emphasizing details.

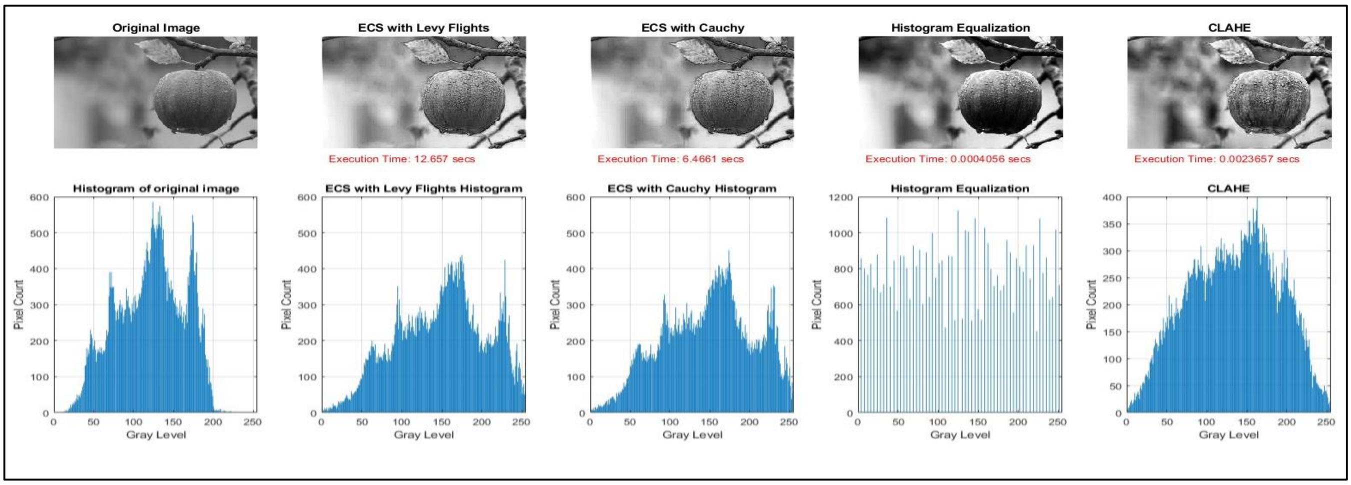

Figure 11 Resulting image and histogram comparison of fruit

Turning to Figure 11, the histogram analysis highlights nuanced differences, particularly with the Cauchy operator compressing gray levels significantly more than Levy Flights, enhancing transmission efficiency, quality, and processing speed. Additionally, Histogram Equalization yields less compression than ECS with Cauchy, resulting in darker shades. Similarly, CLAHE, despite compression, generates brighter images with reduced pixel counts, enhancing overall brightness.

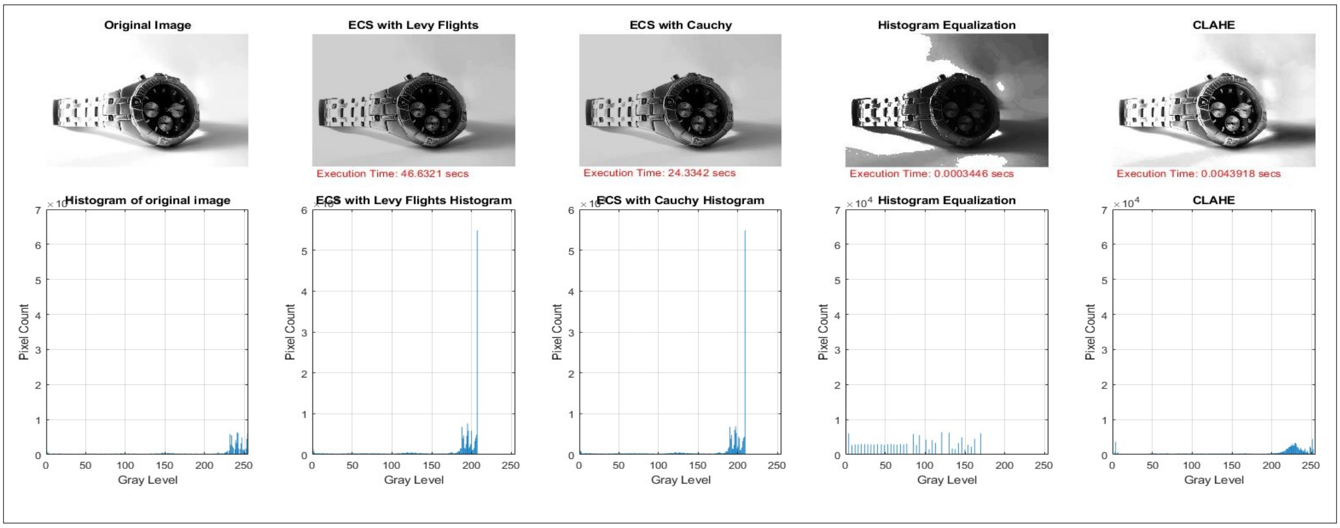

Figure 12 Resulting image and histogram comparison of watch

Finally, Figure 12 illustrates subtle distinctions, notably with the Cauchy operator compressing gray levels more than Levy Flights, thereby improving transmission efficiency, quality, and processing speed. Furthermore, Histogram Equalization exhibits less compression compared to ECS with Cauchy, resulting in darker shades. Likewise, CLAHE, though compressing gray levels, leads to brighter images with minimal pixel counts, enhancing brightness.

The application of the Cauchy operator in image enhancement, particularly in Enhanced Contrast Stretching (ECS), consistently demonstrates superior performance over other algorithms. Images utilizing Cauchy exhibit notably compressed Gray Levels and lower pixel counts compared to those employing methods like Levy Flights, Histogram Equalization (HE), and Contrast Limited Adaptive Histogram Equalization (CLAHE). This compression results in significantly improved transmission efficiency, enhanced image quality, and faster processing speeds. While some slight weaknesses may include a potential sacrifice in brightness compared to CLAHE, Cauchy's ability to deliver smoother details and overall superior image quality makes it the preferred choice for achieving optimal image enhancement outcomes.

3.3 Improving Overall Performance

The substitution of the Levy flight strategy with the Cauchy Operator presents an opportunity for enhancing the exploration capabilities of the Cuckoo Search algorithm. By adopting a more reliable and controlled exploration method, the researchers anticipate significant improvements in the algorithm's overall performance. To assess this, performance metrics including fitness value, PSNR, number of detected edges, entropy, and FSIM were evaluated to assess the algorithm's performance and convergence properties. Table 2 shows the preceding performance metrics for the 10 enhanced images.

Table 2 Five Performance Metrics for 10 Enhanced Images

Image Name		**Five Performance Metrics**				
		Fitness Value	PSNR	No. of Detected Edges	Entropy	FSIM
Butterfly	ECSCO	98.8635	6.0948	3361	6.5941	0.8352
	ECSLF	102.9048	6.2785	3282	6.6781	0.8156
Baby	ECSCO	291.8490	20.0540	9430	7.8534	0.9532
	ECSLF	291.9534	20.4923	9475	7.8451	0.9362
Bridge	ECSCO	194.8204	24.9065	5610	7.5985	0.8903
	ECSLF	195.0514	25.0474	5551	7.5937	0.8946

Bridge2	ECSCO	175.5855	23.0992	18517	7.2303	0.8919
	ECSLF	181.0464	23.3717	18682	7.2066	0.8969
Building	ECSCO	287.4830	22.2044	7974	7.7834	0.8375
	ECSLF	299.7817	22.4319	7918	7.7807	0.8484
Balcony	ECSCO	117.4597	25.3872	17100	7.0580	0.9339
	ECSLF	133.1156	23.1305	17348	7.0292	0.9097
Cat	ECSCO	246.0082	20.8404	2582	7.6040	0.8560
	ECSLF	260.0573	21.5108	2490	7.6367	0.8539
Eagle	ECSCO	23.6131	21.4754	2243	5.4323	0.8749
	ECSLF	25.4760	21.5199	2234	5.4314	0.8738
Fruit	ECSCO	236.2031	17.8645	2076	7.7365	0.8858
	ECSLF	236.2031	17.4195	2049	7.7449	0.8854
Watch	ECSCO	25.9421	15.3853	7451	5.5898	0.9310
	ECSLF	27.3080	15.0482	7600	5.5503	0.9305

3.4 Fitness Value

The fitness value indicates how well the algorithm has optimized the solution. A lower fitness value typically implies a better solution. Across all instances, the Cauchy operator consistently yields lower fitness values compared to Levy Flights. This suggests that the solutions generated by the Cauchy operator are closer to the optimal or desired values. Average fitness value is shown in Figure 13.

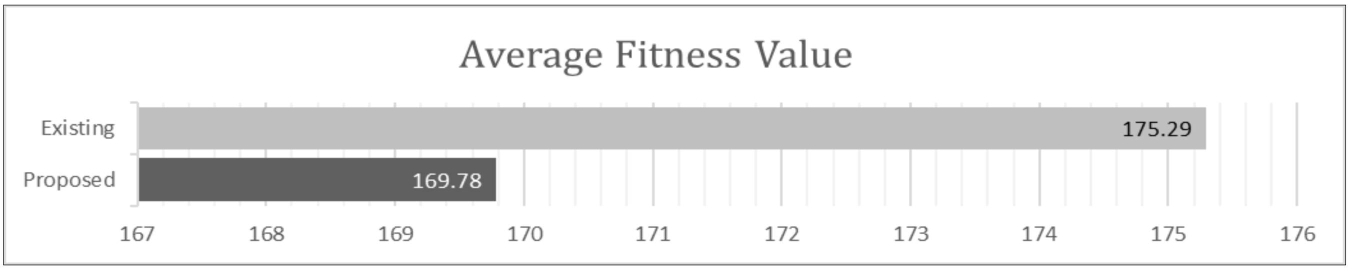

Figure 13 Calculated Average Fitness Value for both existing and proposed algorithms

3.5 Peak Signal to Noise Ratio (PSNR)

PSNR measures the quality of the reconstructed image compared to the original, with higher values indicating better image retention. While the difference between Cauchy and Levy Flights is relatively small, Figure 14 shows Cauchy consistently maintains a slightly higher average PSNR, indicating that it preserves image quality marginally better.

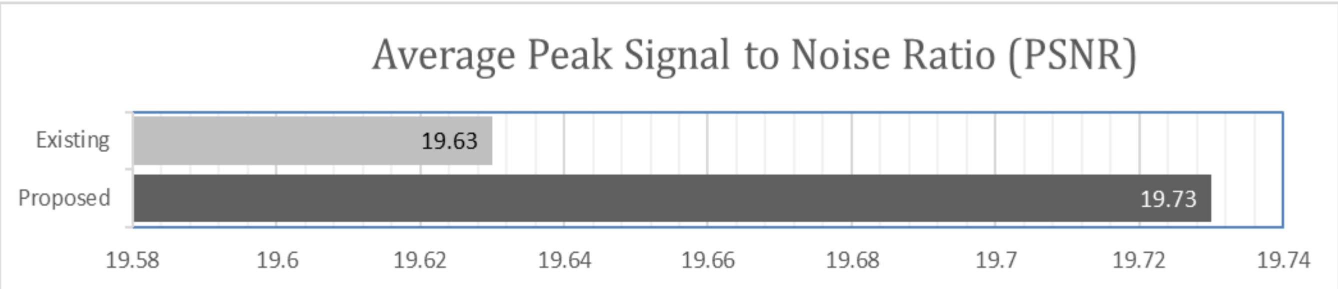

Figure 14 Calculated Average PSNR for both existing and proposed algorithms

3.6 Number of Detected Edges

While the number of detected edges may lean slightly towards Levy Flights in Figure 15, it's important to consider the broader context. The Cauchy Operator, despite detecting marginally fewer edges, could still offer superior performance in certain scenarios. Its precision in edge detection might signify a more nuanced approach, emphasizing quality over quantity. Thus, while Levy Flights may excel in sheer volume, the Cauchy Operator's ability to discern crucial edges with precision could render it the preferred choice in applications where accuracy is paramount.

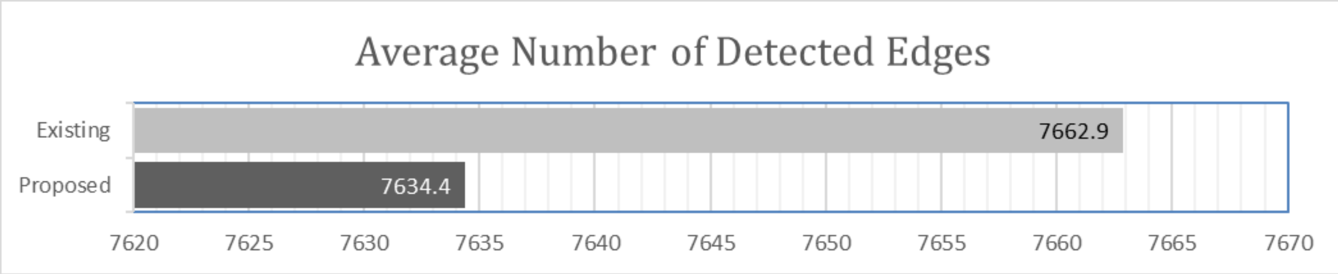

Figure 15 Calculated Average Number of Detected Edges for both existing and proposed algorithms

3.7 Entropy

Entropy measures the randomness or uncertainty in the image, with lower values suggesting higher predictability and organization. Figure 16 shows Cauchy maintains marginally lower average entropy values compared to Levy Flights, implying that it produces images with slightly less randomness or disorder.

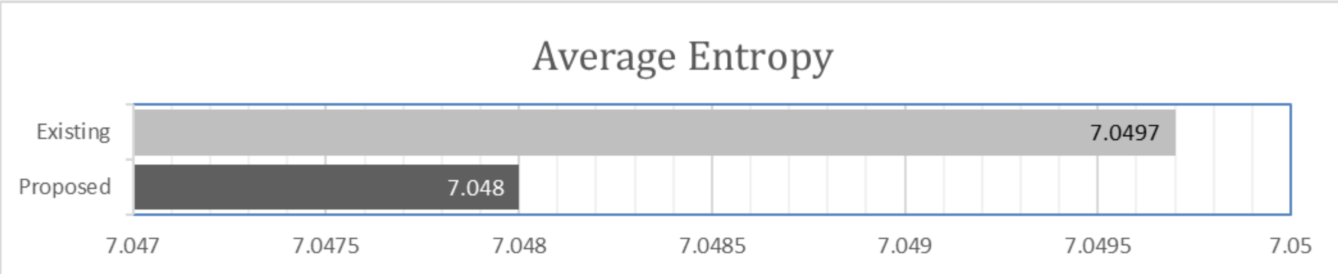

Figure 16 Calculated Average Entropy for both existing and proposed algorithms

3.8 Feature Similarity Index (FSIM)

FSIM quantifies the structural similarity between the generated and original images, with higher values indicating better similarity. Figure 17 shows Cauchy consistently demonstrates a slightly lower FSIM compared to Levy Flights, suggesting a slightly lesser similarity to the original images. In most cases this means better for the proposed algorithms as most images that are enhanced should be different from the original image.

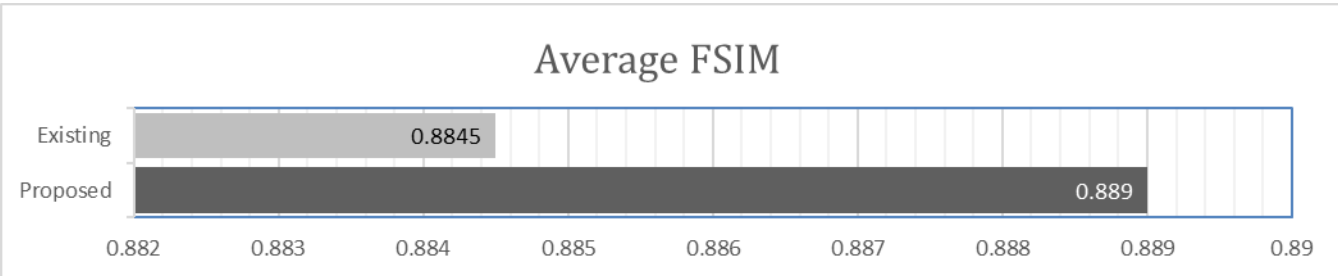

Figure 17 Calculated Average FSIM for both existing and proposed algorithms

4. Conclusion

The goal of this study is to improve the overall performance of the Cuckoo Search Algorithm, minimize execution time and bottleneck during implementation, and fine-tune parameters without sacrificing important image details. All of these have been accomplished by the suggested adjustment in almost all cases. The proposed Cuckoo Search Algorithm in this paper is proven to be better in terms of execution time. In terms of overall performance according to five performance metrics, it consistently produces solutions with lower fitness values, slightly higher PSNR, competitive detected edges, lower entropy, and comparable feature similarity index. Therefore, based on these metrics, the Cauchy operator exhibits slightly superior performance in image optimization tasks compared to Levy Flights.

4.1 Reducing Execution Time

The proposed algorithm consistently demonstrates faster execution times when compared to the previous algorithm, as evidenced by the data presented in Figure 2 and Table 1. These figures provide evidence supporting the efficiency and effectiveness of the algorithm in reducing execution times during image enhancement.

4.2 Balanced Enhancement

As demonstrated in Figures 3 through 12. This indicates that the proposed algorithm applied in image enhancement has effectively maintained the balance and distribution of pixel intensities of the images. Consequently, the visual quality of the images has been adequately enhanced while preserving finer details. Also, While CLAHE seems like the better image enhancement algorithm, when it comes to human features / photos that includes people (Figure 4), it struggles to preserve its detail and oversaturates the features leading to a more photoshopped appearance.

4.3 Improving Overall Performance

Data to evaluate the overall performance of the proposed algorithm is sourced from Table 2 and Figures 13 to 17. Performance measured by the five performance metrics proved the current algorithm to be better than its predecessor.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

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