Nested approach for X-ray image enhancement based on contrast adaptive using histogram equalization

Mostafa Satea
Department of Computer Techniques Engineering, AlSafwa University College, Karbala, Iraq

Article Info

Article history:

Received Oct 9, 2022
Revised Mar 6, 2023
Accepted Mar 12, 2023

Keywords:

Contrast-limited adaptive histogram equalization
Medical image enhancement
RGB
X-ray images
YCbCr

ABSTRACT

Medical image enhancement is a topic of great interest to researchers due to the rapid evolution of technology and advancements in communication. There are many types of medical images such as X-ray images, computed tomography (CT) scans, magnetic resonance imaging (MRI) scans, ultrasound images, positron emission tomography (PET) scans, single photon emission computed tomography (SPECT) scans, digital radiography images, mammography images and Fluoroscopy images. X-ray imaging is a valuable tool for diagnosis, monitoring, and treatment of many medical conditions, and its non-invasive, widely available, low cost and fast nature makes it a popular choice for many medical professionals. The proposed approach presents an algorithm for enhancing X-ray images, improving their visual appearance and making their content more useful and meaningful. The results of the algorithm show that enhanced images have a more natural look and provide accurate details of the objects in the X-ray images. Overall, this algorithm can aid in the diagnostic process by providing clearer and more detailed images for medical professionals to interpret.

Corresponding Author:

Mostafa Satea
Department of Computer Techniques Engineering, AlSafwa University College
Karbala, Iraq
Email: mustafasatea894@gmail.com

1. INTRODUCTION

Medical image processing is a significant task of image processing because it is directly tied to the lives of patients. Clinicians and medical specialists rely heavily on medical images to diagnose patients and make appropriate treatment decisions [1]. Because of the unexpected variations in image quality and the high priority and sensitivity of the solutions that rely on medical images, we may mention that medical image processing is a crucial scientific area with a low percentage of mistakes [2].

Medical image processing has a major drawback, which is the nature of medical images themselves. The environment in which the images are captured may produce images with low contrast, low visibility, and a lot of noise, which can have a negative effect on the diagnostic procedure's accuracy [2]. Image enhancement is the most important and complex procedure in image processing [3] because because the accuracy of the results of image enhancement is completely dependent on the accuracy of the results of subsequent operations. The major goal of medical image enhancement is to significantly boost the visual appearance of images so that they are more informative and efficient for subsequent procedures, including object detection and/or classification tasks [4].

Generally, image enhancement can be classified based on the targeted domain into two basic types, spatial domain and frequency domain [5]. Spatial image enhancement involves direct manipulation of individual pixels within an image. Conversely, frequency image enhancement involves conversion of the image to the frequency domain through mathematical transformations, processing based on frequency domain attributes, and subsequent reconversion back to the original image space. This approach allows for image processing operations to be performed in the frequency domain, offering potential advantages in terms of image quality and computational efficiency [6].

Contrast enhancement techniques are commonly employed to enhance the visibility of objects in images by increasing the difference in brightness between objects and their backgrounds. This process typically involves two stages, namely contrast stretching and tonal enhancement, although they can be performed concurrently. Contrast stretching improves the uniformity of brightness differences across the entire dynamic range of the image. On the other hand, tonal enhancements alter the brightness differences in the shadow, midtone, or highlight regions, often at the expense of brightness differences in other regions. By utilizing these techniques, the visibility of objects in images can be improved [7].

Many studies proposed contrast enhancement algorithms, contrast enhancement based on human sensitivity was introduced in [8], this study controls image gradient to improve the local image contrast and without need to segment the image into either spatial or frequency domain. This study proposed contrast enhancement is characterized as an optimization task in which the average local contrast of an image is maximized. A perceptual requirement mainly produced from the human supra-threshold contrast sensitivity function is included in the optimization formulation. Then, to represent this optimization task, it presents a greedy heuristic controlled by a single parameter.

Automatic contrast-limited adaptive histogram equalization (CLAHE) was introduced by [9], the primary contribution of this study is the systematic initiation of clip points through the consistency of blocks. Additionally, the study proposes the integration of dual gamma correction into CLAHE for preserving naturalness. The proposed methodology involves three steps. First, the histogram of each block is rearranged based on the dynamic variation within the block. Second, a dual gamma correction technique is developed to enhance luminance, particularly in dark areas, while minimizing over-enhancement artifacts.

Contrast limited dynamic quadri-histogram equalization (CLDQHE) was suggested in [10] as a suitable enhancement technique for retaining brightness and structure. This technique is divided into three steps: i) A suggested threshold splitting an image's original histogram into four sub-histograms; ii) To control the enhancement rate, an adaptive histogram clipping method is proposed, which can adjust the clipping threshold; iii) Each sub-histogram is equalized individually and mapped to a new dynamic range.

A new krill herd (KH)-based improved contrast and sharp edge enhancement framework for medical images was presented in [11]. This research introduces a novel approach for optimizing image enhancement through the use of a threshold limit and fitness function. The threshold limit is adjustable and is based on the minimum, maximum, mean, and median values of the image histogram. The threshold limit is applied to clip the histogram, and the remaining pixels are reassigned to histogram bins with relatively greater vacancy. The proposed approach employs the KH meta-heuristic algorithm to automatically adjust the adjustable parameter using a unique fitness function. This fitness function comprises two distinct objective functions that utilize image features, including edge, entropy, gray level co-occurrence matrix (GLCM) contrast, and GLCM energy, to improve contrast enhancement and visualization of anatomical images. The proposed method aims to provide the best-enhanced image with improved differentiation of characteristic information.

A new approach for enhancing the contrast of medical images, known as quad weighted histogram equalization with adaptive gamma correction and homomorphic filtering (QWAGC-FIL), was proposed by [12]. The proposed technique incorporates three distinct image enhancement methods, namely valley-based segmentation, weighted histogram equalization (HE), and adaptive gain control (AGC) with homomorphic filtering. This technique outperforms other methods in terms of both entropy and visual quality assessments. Specifically, the QWAGC-FIL approach, when compared to individual techniques such as SHE, AGCWD, and adaptive gamma correction and homomorphic filtering (AGC-FIL), effectively enhances low contrast images. Additionally, the proposed approach exhibits superior entropy preservation when compared to other methods such as HE, Brightness preserving Bi-histogram equalization (BBHE), SHE, and AGCWD. Moreover, the QWAGC-FIL approach maintains a natural image presentation.

Color image enhancement approach described in [13] The aim of this study is to enhance the information richness of an image while minimizing viewing artifacts and loss of features. This is achieved by iteratively weighting the input image and the intermediate equalized image until the full range of intensities is covered. Using the efficient golden section search technique, the suitable weighting factor is ideally computed.

For image contrast enhancement, a novel histogram modification approach was developed in [14]. The proposed method involves the following steps: First, the sum and standard deviation of the input histogram are calculated. The resulting sum undergoes gamma correction to produce a modified histogram. Subsequently, a mapping function is generated by applying classic histogram equalization to the modified histogram. The suggested approach aims to improve the image evenly while minimizing computational complexity and preserving the mean brightness.

The triple clipped dynamic histogram equalization based on standard deviation (TCDHE-SD) technique is suggested as a robust contrast enhancement approach in [15]. Based on the standard deviation, the proposed method partitions the histogram of the input image into three sections of equal pixel count and applies a histogram clipping method to each sub-histogram. The resulting histograms are mapped to a new dynamic range and equalized independently. This approach aims to achieve several objectives, including maximizing the entropy, managing enhancement ratio, maintaining brightness, and producing natural, detailed images.

A new image enhancement model based on fractional integral entropy (FITE) was introduced in [2]. This approach combines fractional integral and entropy features to tackle the problem of non-linear image enhancement complexity. The suggested FITE enhances fine features of various medical images dynamically dependent on the image contents. The suggested FITE methodology outperforms existing approaches in the generalized application of image enhancement, according to experimental results on three medical image datasets. It's worth mentioning that some of the comparison techniques may offer superior results under particular settings because they were created expressly to handle the photographs produced under such conditions.

A histogram equalization-based medical image enhancement method was suggested in [16]. Wavelet transform and threshold processing are used to enhance the image at first. The Prewitt operator extracts the enhanced image's detail characteristics and combines them with the original image, after which the histogram is employed to equalize and enhance the image.

A method for improving contrast in color retinal images is presented in [17]. This method does so by taking the image's brightness into account. The AGC method is used to boost the luminance of the given color in the first step. Then, in lab color space, contrast enhancement is performed via a quantile-based histogram equalization approach. On the Messidor database, the suggested technique is evaluated. The results of the enhancement show that, when compared to other ways in various color spaces, the suggested method produces better results, particularly for those color RetImgs with poor quality in the outset. The suggested approach can maintain the images' structural details and naturalness.

Global and local equalization of histogram and dual-image multi-scale fusion, or GLHDF, is a technique for improving underwater image quality that was proposed in [18]. GLHDF is composed of four stages: pixel intensity center regionalization, global histogram averaging, local histogram averaging, and multiscale fusion. As can be seen from the results, GLHDF enhanced images with clear visibility, natural color, high contrast, and texture sharpness. The suggested approach also surpasses other cutting-edge methodologies in both qualitative and quantitative analysis. Additionally, GLHDF can achieve acceptable results in terms of low-light, natural, foggy, sandy, and underwater images acquired with various underwater specialized cameras.

This article examined a novel singular value decomposition-related (SVD) enhancement method based on variational mode decomposition (VMD). The reference images and the processed image were first deconstructed using VMD into distinct modes. Then, in the following phase, the singular matrix's highest value was determined for the chosen mode of each image. Using the singular value matrix (SVM), a correction factor that depends on the image was constructed. Finally, the image is recreated by merely combining the reference image's raw modes with the -corrected mode image. A new weighted factor was applied to both the original and the enhanced image in order to prevent over-enhancement. The suggested approach was evaluated using various kinds of publically accessible low contrast images to validate the algorithm [19].

The present study proposes a novel algorithm for adaptive fuzzy gray level difference histogram equalization in [20]. An input image's gray level difference is initially determined using binary-similar patterns. Then, to address the uncertainties present in the input image, this study proposes a fuzzy gray level difference histogram equalization algorithm. The gray level differences are fuzzified, and a fuzzy clip limit is calculated to limit minimal contrast amplification. The resulting fuzzy clipped histogram is then equalized to obtain the contrast-enhanced MR medical image. The proposed algorithm is evaluated both visually and analytically to compare its performance with other existing algorithms.

This study proposes an effective method for enhancing low contrast medical images using range limited weighted histogram equalization (RLWHE) [21]. The proposed technique combines Otsu's method-based segmentation, weighted HE with range limited BHE (RLBHE) analysis, and AGC with homomorphic filtering for enhancing low contrast medical images. This hybrid technique outperforms individual HE techniques such as RLBHE, AGCWD, and RLBHE with AGC in terms of entropy, peak signal-to-noise ratio (PSNR), and visual quality evaluations. Compared to previous methods, the proposed technique offers superior entropy preservation, better contrast enhancement, and effectively addresses over-enhancement issues, resulting in a more natural appearance of the image.

A revolutionary technique for improving images is presented in [22] that can improve the image's contrast and visual quality. A modified gray world algorithm-based technique is employed for color correction. To assure the improvement of edges and contrast, the processed image is then subjected to unsharp masking and contrast-limited histogram equalization.

2. METHOD

The essential concept behind the proposed approach is to take advantage of the existing of a variety of color spaces. As we all know, there are different color spaces that define colors in image processing, each with its own philosophy or perspective of how we would understand colors. Color spaces are models for displaying colors in digital media, acknowledging that each color will be defined by a collection of rules, equations, and numbers. In image processing, there are many different color spaces, each with its own set of features [23]. The color spaces red, green, and blue (RGB) and YCbCr are employed in this study.

The overview of this approach can be presented by a few words: using multi- color spaces sequentially. With details, the input image will be processed to obtain the components of RGB color spaces, this step can be considered as a preprocessing step to move on to the next step which is applying CLAHE [4] on each one of the three components in RGB. CLAHE is based on the following procedure [24]: divide the input image into several non-overlapping small and equal-size regions, calculate histogram for each region, obtain clip limit for clipping histograms based on contrast expansion, redistribution step will be achieved by preventing all histogram values from exceeding the clip limit. Use the cumulative distribution function (CDF) [25].

The parameters that were used for CLAHE in the implementation the approach were initialized based on two main factors first the previous studies and second the experimental trying. In the proposed approach, the output image obtained from applying CLAHE serves as the input for the next step. The input image is first converted from the RGB color space to the YCbCr color space. The YCbCr color space has three components: Y, Cb, and Cr. The Y component represents the Luma component of the color and is responsible for the light intensity of the color. The human eye is highly sensitive to this component. The Cb component represents the blue component related to the chroma component, i.e., the blue component related to the green component. The Cr component represents the red component related to the chroma component, i.e., the red component related to the green component [23]. Applying CLAHE on Y component only then regroup all components together to produce the final result of this approach.

It is important to mention that the parameters for CLAHE that applied to RGB are completely different from the parameters for CLAHE that applied for YCbCr. These differences result from the effect of applying CLAHE on the image and the variety of used color space. This approach used benchmark dataset X-ray images for hand fractures that provided in Kaggle website [26], this dataset is basically designed for fractures detection and/or classifications whereas is divided into four parts which are: training which is consist of (237) files, training annotation, validations which is consist of (40) files and validation annotation.

The proposed method is broken down into several stages in Figure 1, starting with reading the input X-ray image, extracting the basic RGB color space components, applying CLAHE to each component separately, creating an enhanced image by grouping the RGB from the previous stage, converting the enhanced image from RGB color space to YCbCr color space, extracting the basic YCbCr color space components in preparation for applying CLAHE to each component separately, and generating the final enhanced image by group the components of YCbCr.

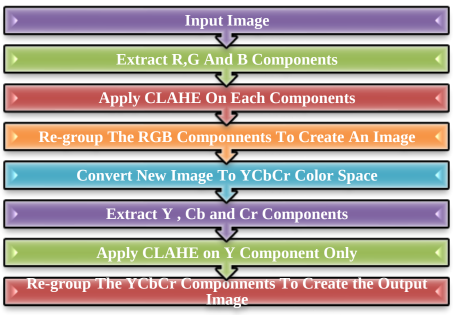


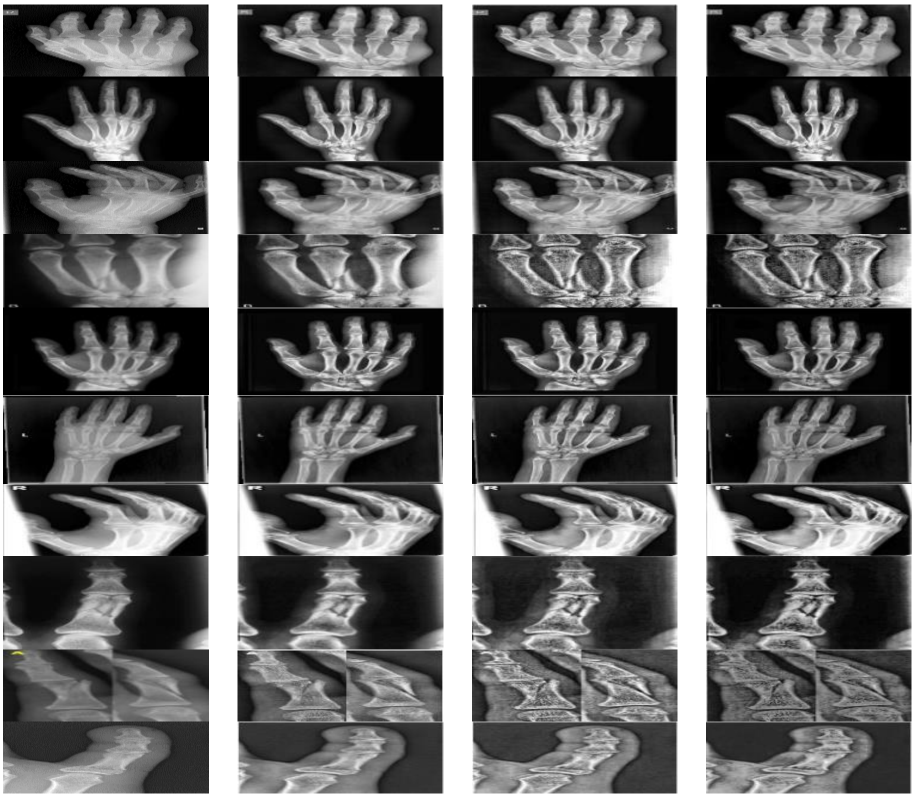
Figure 1. Flow chart of the proposed approach

3. RESULTS AND DISCUSSION

The results of the experiments demonstrate that the proposed approach significantly improves X-ray images by enhancing their visual quality and increasing their level of detail, outperforming traditional methods. Nevertheless, the proposed approach has two primary limitations that need to be addressed in future research. The first limitation is the difficulty in determining optimal values for the CLAHE technique in each step. As a solution to this limitation, future studies may consider using neural networks to optimize the enhancement of each X-ray image. This approach would help to determine the most suitable CLAHE values for each image automatically.

The second limitation of the proposed approach is the limited size of the X-ray dataset used in the study, with the sample sizes being uneven. This issue may affect the generalizability of the results, and future studies should consider using larger and more balanced datasets to verify the effectiveness of the proposed approach. Despite the limitations mentioned above, the proposed approach can serve as a foundation for future research in sequential image enhancement using multiple color spaces. Sequential image enhancement refers to a process that involves the application of several image enhancement techniques in a specific order to improve image quality. The proposed approach could be extended by integrating additional image enhancement techniques, such as denoising, sharpening, and color correction, in the sequence.

Furthermore, future research could explore the use of different color spaces, such as YCbCr, Lab, or HSV, in the sequential image enhancement process. These color spaces have unique properties that can be used to enhance specific aspects of the image, such as brightness, contrast, and color saturation. By incorporating multiple color spaces in the enhancement process, the proposed approach could achieve better results in terms of image quality and detail. Figure 2 illustrates the results for the proposed approach compared with the original image, RGB enhancement, YCbCr enhancement, and the proposed approach, whereas Figure 2(a) presents the original images, Figure 2(b) RGB enhancements, Figure 2(c) YCbCr enhancements, and 2(d) the proposed approach results.



(a) (b) (c) (d)

Figure 2. The results of the proposed approach (a) presents the original images, (b) RGB enhancements, (c) YCbCr enhancements, and (d) the proposed approach results

4. CONCLUSION

The present study proposes a method for improving the quality of X-ray images through the application of CLAHE in a sequential manner, using two distinct color spaces and varying parameters for each step. The findings indicate that this approach results in enhanced visual quality and greater accuracy in detecting specific features compared to conventional methods. The dataset used for evaluation was obtained from Kaggle. In order to further validate the efficacy of the proposed method, a subjective evaluation involving medical experts or radiologists is recommended. This would involve presenting the enhanced images to these professionals and soliciting their opinions on the improvements in image quality and the ability to accurately diagnose medical conditions. The combination of subjective evaluation and objective measurements of image quality will provide a comprehensive assessment of the proposed image enhancement technique.

REFERENCES

[1] N. Salem, H. Malik, and A. Shams, “Medical image enhancement based on histogram algorithms,” *Procedia Computer Science*, vol. 163, pp. 300–311, 2019, doi: 10.1016/j.procs.2019.12.112.

[2] H. A. Jalab, R. W. Ibrahim, A. M. Hasan, F. K. Karim, A. R. Al-Shamasneh, and D. Baleanu, “A new medical image enhancement algorithm based on fractional calculus,” *Computers, Materials and Continua*, vol. 68, no. 2, pp. 1467–1483, 2021, doi: 10.32604/cmc.2021.016047.

[3] T. Rahman *et al.*, “Exploring the effect of image enhancement techniques on COVID-19 detection using chest X-ray images,” *Computers in Biology and Medicine*, vol. 132, p. 104319, May 2021, doi: 10.1016/j.compbiomed.2021.104319.

[4] M. S. Mohammed, H. A. Khater, Y. F. Hassan, and A. Elsayed, “Proposed approach for automatic underwater object classification,” *ICIC Express Letters*, vol. 12, no. 12, pp. 1205–1212, 2018, doi: 10.24507/icicel.12.12.1205.

[5] Y. Qi *et al.*, “A Comprehensive Overview of Image Enhancement Techniques,” *Archives of Computational Methods in Engineering*, vol. 29, no. 1, pp. 583–607, Jan. 2022, doi: 10.1007/s11831-021-09587-6.

[6] R. Szeliski, *Computer Vision*. Cham: Springer International Publishing, 2022, doi: 10.1007/978-3-030-34372-9.

[7] M. J. Corinthios, *Signals, systems, transforms, and digital signal processing with MATLAB®*. CRC Press, 2009.

[8] N. Kumar, A. Kumar, and K. Kumar, “Color image contrast enhancement using modified firefly algorithm,” *International Journal of Information Retrieval Research*, vol. 12, no. 2, pp. 1–18, Jul. 2022, doi: 10.4018/ijirr.299944.

[9] Y. Chang, C. Jung, P. Ke, H. Song, and J. Hwang, “Automatic contrast-limited adaptive histogram equalization with dual gamma correction,” *IEEE Access*, vol. 6, pp. 11782–11792, 2018, doi: 10.1109/ACCESS.2018.2797872.

[10] Z. Huang, Z. Wang, J. Zhang, Q. Li, and Y. Shi, “Image enhancement with the preservation of brightness and structures by employing contrast limited dynamic quadri-histogram equalization,” *Optik*, vol. 226, p. 165877, Jan. 2021, doi: 10.1016/j.ijleo.2020.165877.

[11] P. Kandhway, A. K. Bhandari, and A. Singh, “A novel reformed histogram equalization based medical image contrast enhancement using krill herd optimization,” *Biomedical Signal Processing and Control*, vol. 56, p. 101677, 2020, doi: 10.1016/j.bspc.2019.101677.

[12] M. Agarwal and R. Mahajan, “Medical images contrast enhancement using quad weighted histogram equalization with adaptive gama correction and homomorphic filtering,” *Procedia Computer Science*, vol. 115, pp. 509–517, 2017, doi: 10.1016/j.procs.2017.09.107.

[13] C. Y. Wong *et al.*, “Image contrast enhancement using histogram equalization with maximum intensity coverage,” *Journal of Modern Optics*, vol. 63, no. 16, pp. 1618–1629, Sep. 2016, doi: 10.1080/09500340.2016.1163428.

[14] X. Wang and L. Chen, “An effective histogram modification scheme for image contrast enhancement,” *Signal Processing: Image Communication*, vol. 58, pp. 187–198, Oct. 2017, doi: 10.1016/j.image.2017.07.009.

[15] M. Zarie, A. Pourmohammad, and H. Hajghassem, “Image contrast enhancement using triple clipped dynamic histogram equalisation based on standard deviation,” *IET Image Processing*, vol. 13, no. 7, pp. 1081–1089, 2019, doi: 10.1049/iet-ipr.2018.5395.

[16] L. Yang and Z. Zeng, “Medical image enhancement method based on histogram equalization,” in *International Conference on Computer Graphics, Artificial Intelligence, and Data Processing (ICCAID 2021)*, 2022, vol. 12168, pp. 168-173, doi: 10.1117/12.2631127.

[17] B. Gupta and M. Tiwari, “Color retinal image enhancement using luminosity and quantile based contrast enhancement,” *Multidimensional Systems and Signal Processing*, vol. 30, no. 4, pp. 1829–1837, Oct. 2019, doi: 10.1007/s11045-019-00630-1.

[18] 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, doi: 10.1109/ACCESS.2020.3009161.

[19] L. M. Satapathy and P. Das, “A novel low contrast image enhancement using adaptive multi-resolution technique and SVD,” in *Lecture Notes in Electrical Engineering*, vol. 665, 2020, pp. 1021–1033.

[20] B. Subramani and M. Veluchamy, “Fuzzy gray level difference histogram equalization for medical image enhancement,” *Journal of Medical Systems*, vol. 44, no. 6, p. 103, Jun. 2020, doi: 10.1007/s10916-020-01568-9.

[21] M. Agarwal and R. Mahajan, “Medical image contrast enhancement using range limited weighted histogram equalization,” *Procedia Computer Science*, vol. 125, pp. 149–156, 2018, doi: 10.1016/j.procs.2017.12.021.

[22] K. H. Sanila, A. A. Balakrishnan, and M. H. Supriya, “Underwater image enhancement using white balance, USM and CLHE,” in *International Symposium on Ocean Electronics, SYMPOL*, Dec. 2019, vol. 2019-December, pp. 106–116, doi: 10.1109/SYMPOL48207.2019.9005301.

[23] M. S. Hitam, W. N. J. H. W. Yussof, E. A. Awalludin, and Z. Bachok, “Mixture contrast limited adaptive histogram equalization for underwater image enhancement,” in *2013 International Conference on Computer Applications Technology (ICCAT)*, Jan. 2013, pp. 1–5, doi: 10.1109/ICCAT.2013.6522017.

[24] S. Yelmanov, O. Hranovska, and Y. Romanyshyn, “Image enhancement technique based on power-law transformation of cumulative distribution function,” in *2019 3rd International Conference on Advanced Information and Communications Technologies (AICT)*, Jul. 2019, pp. 120–124, doi: 10.1109/AIACT.2019.8847876.

[25] T. Sağ and M. Çunkaş, “Color image segmentation based on multiobjective artificial bee colony optimization,” *Applied Soft Computing*, vol. 34, pp. 389–401, Sep. 2015, doi: 10.1016/j.asoc.2015.05.016.

[26] Vishal Srinivas, “fracture,” *www.kaggle.com*, 2020. https://www.kaggle.com/datasets/srinivasvishal7/fracture.

BIOGRAPHIES OF AUTHORS

Mostafa Satea received Bachelor of Computer Science from Unviversity of Technology-Iraq, Master of Computer Science/Image processing and machine learning Department of mathematics, Faculty of Science from Alexandaria University-Egypt. He is lecturer in Alsafwa University College since 2020 and his scientific interests focus on image proseccing and machine learning. He can be contacted at email: mustafasatea894@gmail.com.