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Proceedings of ICICIT-2024

16-17, April 2024
Bangkok, Thailand

STAMFORD INTERNATIONAL UNIVERSITY

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X-ray Image Contrast Enhancement Approach

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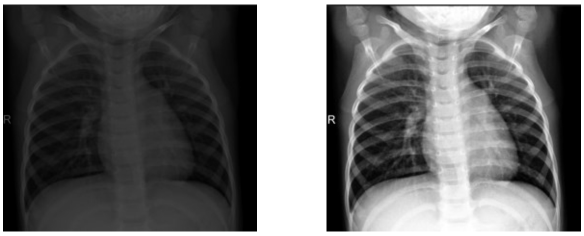
***Abstract*— Contrast enhancement algorithms are important in improving the quality of X-ray images, helping medical professionals diagnose and treat patients more accurately. Most of the contrast enhancement algorithms available today are applied to the entire image without taking into account local features and differences in contrast in different areas of the image. This can lead to undesirable consequences such as loss of detail in the dark areas of the image or saturation in the bright areas. In this regard, in this work, a contrast enhancement approach is proposed, which provides contrast enhancement in each fragment of the image, taking into account the local features of the X-ray image. This approach is based on dividing the image into small fragments and applying different contrast enhancement algorithms to each fragment. Each fragment was evaluated according to the RMS criterion, and the algorithm that gave the largest value was selected as the optimal one for this fragment. In addition, the research paper analyzed the effectiveness of the approach developed based on the test results of X-ray images.**

Keywords*— *X-ray image, Image quality, Medical diagnosis, Histogram equalization, Contrast stretching, Contrast enhancement algorithm, Image processing, Brightness, Pixel, RMS value.

I. Introduction

Today, X-ray diagnosis plays a key role in medical practice, as it allows medical professionals to obtain important information about the state of the patient's internal organs and tissues [1]. However, the quality of X-ray images can be degraded by various factors such as low light, noise, or low contrast between tissues [2]. In such cases, contrast enhancement algorithms are important to improve diagnostic accuracy and image quality.

Contrast enhancement algorithms are image processing techniques designed to increase the difference between the brightness of different areas of the image [3]. Application of these algorithms allows us to see more clearly the important details and structures of the image. Contrast enhancement in X-ray diagnosis can be a decisive factor in identifying pathologies or other abnormalities. Using contrast enhancement algorithms helps improve the visual appearance of various tissues and structures, such as bones, organs, and blood vessels, and provides a more accurate image interpretation (Fig. 1). Therefore, among image preprocessing algorithms and approaches [4-6], the role of contrast enhancement algorithms is incomparable.



A) B)

Fig. 1. A) Original X-ray image with low contrast, B) Result of applying contrast enhancement algorithm to the original image

Although many improved and new methods of contrast enhancement have been proposed in recent years [7-13], they have their limitations. For example, they are usually applied to the entire image without taking into account local features and differences in contrast in different areas of the image. This can lead to undesirable consequences such as loss of detail in the dark areas of the image or saturation in the bright areas. In this regard, this article proposes a contrast enhancement approach that provides contrast enhancement in each fragment of the image, taking into account the local features of the X-ray image. This approach is based on dividing the image into small fragments and applying different contrast enhancement algorithms to each fragment independently of the others.

This research work describes selected image contrast enhancement algorithms based on a literature review, results of testing them for the whole image and its fragments, as well as the advantages and limitations of the proposed approach.

II. Related Work

Algorithms for increasing the contrast allow to improve the image's visual appearance. However, they may differ depending on the type of image. For example, a method or algorithm that is effective for enhancing the contrast of a satellite image may not be effective for an X-ray image.

As the object of this study, only X-ray images were taken, and factors such as insufficient radiation during their acquisition, patient behavior, and limitations of imaging equipment led to insufficient X-ray image contrast. In this case, it is advisable to increase the contrast of the X-ray image obtained so that the patient does not receive additional radiation without involving him in repeated examinations. Below is an analysis of much literature on image contrast enhancement. It is reported in [14] that the implementation of the histogram equalization algorithm is simple and convenient, so it is popular among contrast enhancement algorithms. Also, this algorithm is recognized as the most optimal option for increasing the contrast of medical images [15]. Because the histogram equalization algorithm does not have adjustable parameters and it can perform calculations quickly [12].

As an improved variant of the histogram equalization algorithm, the CLAHE (Contrast Limited Adaptive Histogram Equalization) algorithm was proposed in [16], and its main advantage is the thresholding of the histogram. The algorithm increases the image's contrast by redistributing the brightness in the part that exceeds the specified threshold. X-ray image contrast enhancement by proposing an Otsu threshold instead of a threshold value in the CLAHE algorithm was tested in [17] and this approach was found to be effective. Also, comparisons of this algorithm with adaptive histogram equalization and global histogram are presented in [18], among which the CLAHE algorithm is superior in contrast enhancement of X-ray images.

A contrast stretching algorithm that uses the largest and smallest image brightness values to fill the range of image brightnesses is presented in [19]. The contrast stretching algorithm [20] was used to increase the contrast of low-contrast images created under adverse conditions such as fog, resulting in improved visual images and comparisons with evaluation criteria such as MSE and SSIM. Also, the problem of recognizing a person's face image taken in dark conditions or at night was considered in [21], where the contrast stretching algorithm was used to normalize the contrast.

It is very important to evaluate the performance of contrast enhancement algorithms in image analysis. Image contrast assessment is based on subjective and objective criteria. In this case, a lot of time is spent on the subjective evaluation of the X-ray image by a medical expert, and therefore, it is appropriate to use non-standard objective criteria for contrast evaluation in the automation of image processing. Usually, objective criteria without references are used more in practice. Because in various fields, especially X-ray images taken directly from X-ray imaging equipment, there will be no original reference image intact. In this work, no-reference criteria for X-ray image contrast evaluation were analyzed.

Weber's criterion is one of the first criteria for evaluating image contrast. When calculating this criterion value, the brightness of the object and the background in the image are taken into account. However, it was shown in [9] that the Weber criterion does not work well when it is difficult to distinguish the background from the objects.

One of the widely used criteria for evaluating image contrast is the Michelson criterion. This criterion uses the maximum and minimum brightness values of the pixels that make up the image to evaluate the contrast. However, it was pointed out in [10] that this criterion is unsatisfactory for evaluating text contrast in a gray image. Also, since the largest and smallest brightness values in X-ray images are often 0 and 255, the Michelson criterion is not suitable for evaluating the contrast of X-ray images [6]. In addition, various distortions and noises in the image prevent the correct assessment of contrast.

Many literatures use the RMS criterion to evaluate image contrast [22-24]. In particular, the RMS criterion was presented in [25] as a standard model for image contrast evaluation, and based on its value, the CLAHE algorithm was proven to be effective. In [26], the RMS criterion was used to evaluate the contrast, which is considered an important parameter determining the quality of the image, in which RMS is recognized as a criterion equivalent to the standard deviation of the brightness of the image. Also, RMS is presented in works [27,28] as the most reliable and widely used criterion for image contrast evaluation. This criterion is considered to be the one that gives the closest prediction to the observers' sensitivity in viewing images [29].

As a result of the literature analysis, histogram equalization, CLAHE, contrast stretching algorithms to enhance the contrast of X-ray images, and the RMS criterion were selected as the most reliable criteria for contrast evaluation and were used in the experiments.

III. METHODOLOGY

Algorithms selected for use in the study cannot adapt to the local characteristics of the image, and because they are applied only to the entire image, they increase the contrast in some parts of the image, which is their main disadvantage. Therefore, it is necessary to develop a new approach to increase the image contrast, taking into account the local characteristics of the image. For this, an approach to increase image contrast by dividing the image into fragments is proposed.

In this work, the approach to increase the contrast of X-ray images is carried out in the following steps:

- Step 1. Separation of the image into fragments is carried out;
- Step 2. An appropriate contrast enhancement algorithm is applied to each fragment;
- Step 3. Each fragment is evaluated according to the RMS (Root mean square) criterion;
- Step 4. An optimal algorithm is determined according to the RMS value for each fragment, and the whole image is formed by combining the fragments.

The first step of the proposed approach is to divide the original X-ray image into small fragments. This is done for each fragment to adapt the contrast enhancement algorithms to that fragment, regardless of the rest of the fragments. Fragment sizes can be chosen differently depending on the desired detail and the nature of the image. Typically, fragment sizes should be small enough to account for differences in image contrast, but large enough to be statistically significant in the analysis. In this research, the case where the image is divided into 2^n equal fragments is studied.

The contrast enhancement algorithms used in the study are designated as A_1 – Histogram equalization, A_2 – CLAHE, A_3 – Contrast Stretching, and their description is detailed below:

A. Histogram equalization

This algorithm is used to evenly distribute the pixel intensities in the image over the entire range of intensity values [14]. It helps reduce the difference between the brightest or darkest pixels in the image, which helps improve image contrast [15]. The following formulas form the foundation of this algorithm:

$$f(s_k) = \frac{z_k}{z}, k = 0,1,...,B-1 \quad (1)$$

$$g_k = T(s_k) = (B-1)\sum_{j=0}^{k} f(s_j) = (B-1)\sum_{j=0}^{k}\frac{z_j}{z} \quad (2)$$

where s_k – initial and g_k – output brightness, B – range of brightness, z_j – number of brightness pixels, z – overall number of pixels.

In formula (3), the relationship between s_k and g_k is valid as follows:

$$s_k = T^{-1}(g_k), k = 0,1,...,B-1 \quad (3)$$

B. CLAHE (Contrast Limited Adaptive Histogram Equalization)

This algorithm improves image contrast by analyzing pixel intensities in small windows of the image [16]. It effectively takes into account the local features of the image and allows to preserve of details in places with different brightness levels.

C. Contrast stretching.

In contrast stretching, the contrast in the image is stretched from the range of intensity values it contains to cover the desired range of values [17,18] and it is also called normalization. When applying this method to the original image, the following formula is used:

$$L_c(i,j) = 255\frac{L_{org}(i,j)-\min}{\max-\min}, i=\overline{1,P}, j=\overline{1,Q} \quad (4)$$

$\max$ – the maximum brightness value in the image, $\min$ – the minimum brightness value in the image, P and Q – image sizes, L_c – is the image after the contrast was adjusted.

D. RMS criterion

The RMS criterion based on the standard deviation of the image brightness was used to evaluate the contrast enhancement algorithms presented above [19]. The global contrast is estimated by RMS, and its computation process is quick and easy. It has been demonstrated that this metric is a trustworthy predictor of the human contrast detection threshold in scenes with natural lighting [20]. RMS is calculated using the following formula:

$$RMS = \sqrt{\frac{1}{m}\sum_{j=1}^{m}\left(L_j - \bar{L}\right)^2}, \bar{L} = \frac{1}{m}\sum_{j=1}^{m} L_j \quad (5)$$

where L_j – j pixel intensity.

IV. RESULTS

Computational experiments used open base X-ray images available at www.kaggle.com to test the proposed approach. The results of applying the contrast enhancement algorithms individually to the entire original image are shown in Fig.1.

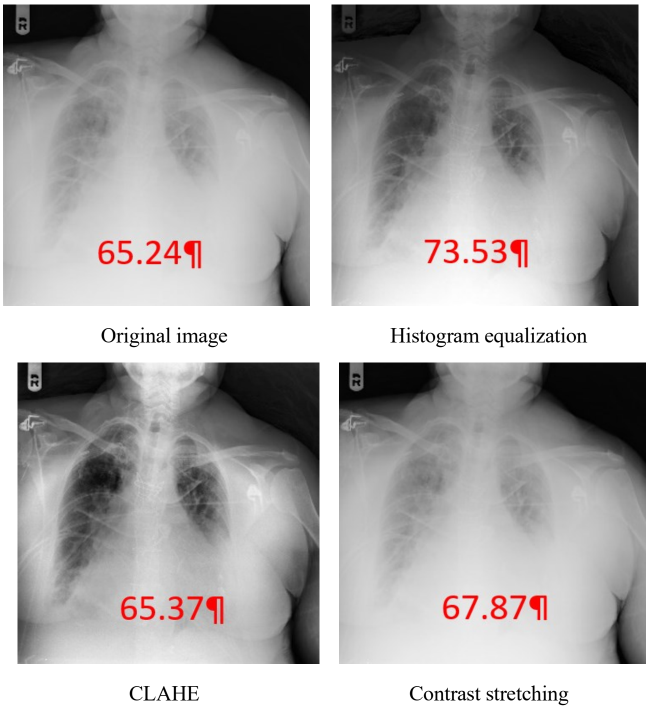
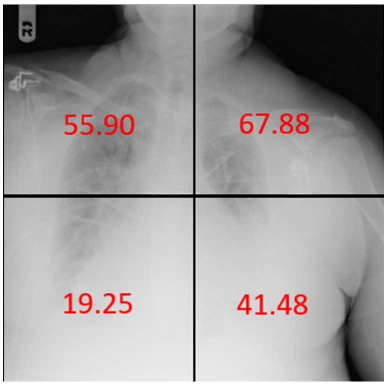
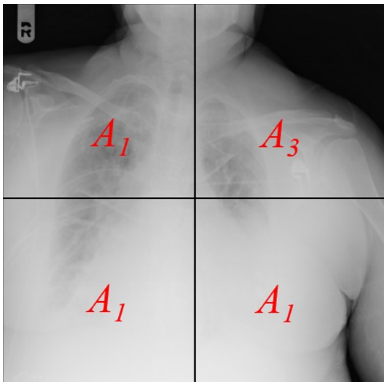


Fig.1. The original image and the results of applying contrast enhancement algorithms to it and their corresponding RMS values

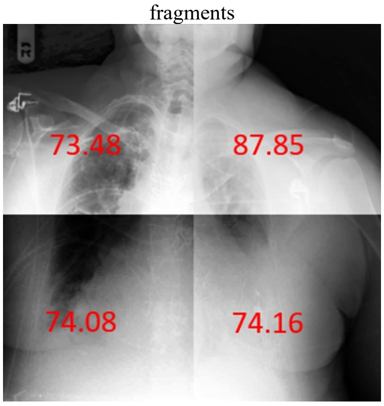
The original X-ray image is divided into 2^n equal fragments. Below are sample images for $n=2$ and $n=4$ cases. Each fragment isolated in these samples is represented along with its RMS value.



Original image fragments RMS values
RMS=65.24

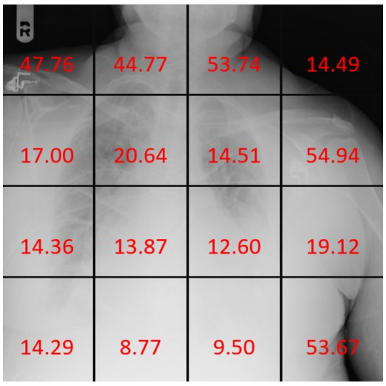


Optimal algorithms for processed image fragments

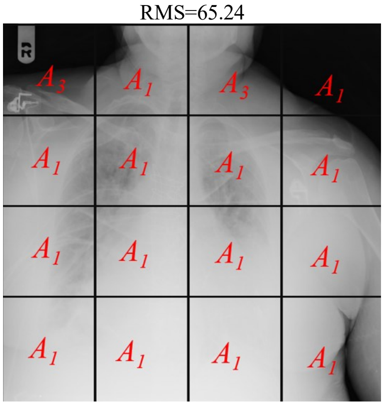


Processed image fragments RMS values RMS=77.68

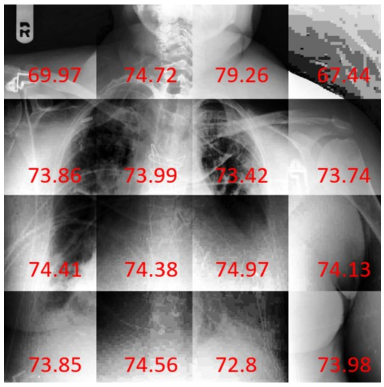
Fig.2. The result of dividing the original image into fragments in case $n = 2$



Original image fragments RMS values RMS=65.24



Optimal algorithms for processed image fragments



Processed image fragments RMS values RMS=75.06

Fig.3. The result of dividing the original image into fragments in case $n = 4$

The obtained results showed that the proposed approach for contrast enhancement in X-ray images is significantly improved compared to the application of existing algorithms to the entire image. By adapting the algorithms to each fragment of the image, high contrast and clarity of the images was achieved, which helps to make a more accurate diagnosis. Also, in future studies, the accuracy of the research results can be improved by doing the following:

• optimization of parameters of algorithms used in research;

• using advanced methods of image contrast enhancement;

• after increasing the contrast of image fragments, research results can be further improved by developing an efficient way to combine them.

V. The Strengths and Weaknesses of the Approach

The main advantages of the proposed approach are:

- increase the accuracy of the diagnosis: due to the increase in contrast, the details allow medical specialists to interpret the images more accurately and make a more informed diagnosis;
- efficient use of algorithms: application of algorithms adapted to each image fragment allows to maximize their capabilities and achieve optimal results;
- short processing time: parallel processing of image fragments and subsequent merging of optimal results can significantly reduce processing time, which is especially important in a clinical environment.
- preservation of details and structures: the approach preserves details and textures in images, allowing doctors to analyze images more fully and accurately.

It is also necessary to highlight some limitations of the developed approach, including:

- the computational complexity of the proposed approach may be high and may not show good results when applied to some types of images. Also, after applying contrast enhancement algorithms to image fragments, when combining them again, the formation of lines between fragments is recognized as a disadvantage of the approach proposed in the work;
- the need to develop specialized software: the successful application of the method requires the

development of specialized software, which may require significant time and financial costs;

- dependence on the quality of the original images: the effectiveness of the approach may depend on the quality of the original radiographs, which may be a limiting factor in some clinical situations;
- the need to train medical professionals: for the approach to be successful, it is necessary to train medical professionals in the use of new software and image processing techniques.

VI. CONCLUSION

In this research, a new approach to contrast enhancement in X-ray images was presented. Using existing contrast enhancement algorithms on a fragment-by-fragment basis has been shown to significantly improve image contrast and clarity, both quantitatively and qualitatively. The developed approach not only increased the intensity differences between different areas of the image, but also preserved the details and structures in the images, which serves to increase their informativeness.

The advantages of the proposed approach include increased diagnostic accuracy, efficient use of algorithms, reduced processing time, and preservation of details and structures in images. However, this approach has certain limitations, including the dependence on the quality of the original images and the need to train medical personnel. However, the efficiency and accuracy of the approach can be improved by improving contrast enhancement algorithms or developing new ones.

REFERENCES

[1] S.Jokar, S.Khazaei, H.Behnammanesh, M.Laranjo, D.Beiki, and M.Botelho, “X-ray-based cancer diagnosis and treatment methods”, Electromagnetic Waves-Based Cancer Diagnosis and Therapy. 2023, Chapter 5. pp. 239-294.

[2] O. P. Lakhwani, V. Dalal, M. Jindal, and A. Nagala, “Radiation protection and standardization,” Journal of Clinical Orthopaedics and Trauma, vol. 10, no. 4, pp. 738–743, Jul. 2019.

[3] N. Mamatov, N. A. Niyozmatova, M. Jalelova, A. Samijonov, and Sh. X. Tojiboyeva, “Methods for improving contrast of agricultural images,” E3S Web of Conferences, vol. 401, p. 04020, Jan. 2023.

[4] N. Mamatov, M. Jalelova, A. Samijonov, and B. Samijonov, “Algorithm for improving the quality of mixed noisy images,” Journal of Physics: Conference Series, vol. 2697, no. 1, p. 012013, Feb. 2024.

[5] N. Mamatov, M. Jalelova, B. Samijonov, and A. Samijonov, “Algorithms for contour detection in agricultural images,” E3S Web of Conferences, vol. 486, p. 03017, Jan. 2024.

[6] N. Mamatov, M. Jalelova, B. Samijonov, and A. Samijonov, “Algorithm for extracting contours of agricultural crops images,” ITM Web of Conferences, vol. 59, p. 03015, Jan. 2024

[7] R. Rosnelly, B. S. Riza, L. Wahyuni, S. Suparni, A. Prasetio, and R. Rahim, “Improvement of Hybrid Image Enhancement for Detection and Classification of Malaria Disease Types and Stages with Artificial Intelligence,” TEM Journal, pp. 535–542, May 2022.

[8] I. M. O. Widyantara, I. M. D. P. Asana, N. M. A. E. D. Wirastuti, and I. B. P. Adnyana, “Image enhancement using morphological contrast enhancement for video based image analysis,” ICODSE, Oct. 2016

[9] Y.I. Golub, F.V.Starovoitov, “Study of local estimates of the contrast of digital images in the absence of a standard” System analysis and applied informatics. no. 2. 2019.

[10] A. Beghdadi, M. A. Qureshi, S. A. Amirshahi, A. Chetouani, and M. Pedersen, “A critical analysis on perceptual contrast and its use in visual information analysis and processing,” IEEE Access, vol. 8, pp. 156929–156953, Jan. 2020.

[11] P. Gade and P. Walsh, “Use of GCF aesthetic measure in the evolution of landscape designs.,” IJCCI, pp. 83–90, Jan. 2013.

[12] R. M. Dyke and K. Hormann, “Histogram equalization using a selective filter,” The Visual Computer, vol. 39, no. 12, pp. 6221–6235, Nov. 2022.

[13] N. Nahrawi, W. A. Mustafa, S. N. A. M. Kanafiah, M. A. Jamlos, and W. Khairunizam, “Contrast enhancement approaches on medical Microscopic Images: a review,” in Lecture notes in electrical engineering, 2020, pp. 715–726.

[14] A. Aosiman, A. Abulijiang, A. Abulikemu, T. A. Turki, and M. Maimaiti, “Medical image enhancement algorithm based on histogram equalization and dyadic wavelet transform.,” Computer Systems: Science & Engineering, pp. 181–185, Jan. 2020.

[15] B. Mnassri, A. Echtioui, F. Kallel, M. Dammak, C. Mhiri, and A. B. Hamida, “Image Enhancement Techniques Applied to Magnetic Resonance Images: Multiple sclerosis,” 2022 6th International Conference on Advanced Technologies for Signal and Image Processing (ATSIP), May 2022.

[16] R. L. Levien, “Resolution-dependence of perceived contrast of textures,” Proceedings of SPIE, Dec. 2003.

[17] A. A. Riadi, E. Wijayanti, W. H. Sugiharto, A. Latubessy, and A. C. Murti, “Automated contrast improvement of X-Ray image using OTSU threshold on Contrast-Limited Adaptive Histogram Equalization Algorithm,” Proceedings of the 1st International Conference on Computer Science and Engineering Technology Universitas Muria Kudus, Jan. 2018.

[18] S. Wu, Q. Zhu, S. Yu, Q. Li, and Y. Xie, “Multiscale X-ray image contrast enhancement based on limited adaptive histogram equalization,” N Proceedings of the Fifth International Conference on Internet Multimedia Computing and Service (ICIMCS ’13), pp. 231–236, Aug. 2013.

[19] R. C. Gonzalez, R. E. Woods, and B. R. Masters, “Digital Image Processing, third edition,” Journal of Biomedical Optics, vol. 14, no. 2, p. 029901, Jan. 2009.

[20] N. Dadhich, M. Mathur, “Contrast Stretching and Improved Dark Channel Prior Method Based Image Defogging,” World Journal of Research and Review (WJRR), vol.9, no. 1, pp. 19-25, July 2019.

[21] W. Wang, X. Wang, W. Yang, and J. Liu, “Unsupervised face detection in the dark,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 45, no. 1, pp. 1250–1266, Jan. 2023.

[22] G. Popov, M. Korneev, “Method of adaptive regulation of the contrast level of a digital image when preparing it for recognition” Modern science: current problems of theory and practice, pp. 48–53, 2018.

[23] C. Ionescu, C. Foşalău, and D. Petrişor, “A study of changes in image contrast with various algorithms,” EPE 2014 - Proceedings of the 2014 International Conference and Exposition on Electrical and Power Engineering, pp. 100–104, Oct. 2014.

[24] P. Oak, “Contrast Enhancement of brain MRI images using histogram based techniques,” Medicine, Computer Science, Jan. 2013.

[25] A. Mishra, “Contrast Limited Adaptive Histogram equalization (CLAHE) approach for enhancement of the microstructures of friction stir welded joints,” Research Square (Research Square), Jun. 2021.

[26] Md. A.-A. Bhuiyan and A. R. Khan, “Image quality assessment employing RMS contrast and histogram similarity.,” The International Arab Journal of Information Technology, vol. 15, pp. 983–989, Jan. 2018.

[27] K.Lemya, M. Naoji, M. Ahmed, C. André, “Predicting perceived complexity using local contrast statistics and fractal information,” Courier du Savoir, no. 16. pp. 89-97, 2013.

[28] S. Yousefi, J. Qin, Z. Zhi, and K. Wang, “Uniform enhancement of optical micro-angiography images using Rayleigh contrast-limited adaptive histogram equalization.,” PubMed, Feb. 2013.

[29] W. J. Harrison, “Luminance and contrast of images in the THINGS database,” Perception, vol. 51, no. 4, pp. 244–262, Mar. 2022.

[30] 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.

[31] M. S. S. Hameed, W. A. Mustafa, S. Z. S. Idrus, M. A. Jamlos, and H. Alquran, “Contrast enhancement on pap smear cell images: A comparison,” AIP Conference Proceedings, Jan. 2023.

[32] R. Rosnelly, B. S. Riza, L. Wahyuni, S. Suparni, A. Prasetio, and R. Rahim, “Improvement of Hybrid Image Enhancement for Detection and Classification of Malaria Disease Types and Stages with Artificial Intelligence,” TEM Journal, pp. 535–542, May 2022.

[33] S. K. Saroj, “An efficient hybrid approach for medical images enhancement,” Electronic Letters on Computer Vision and Image Analysis, vol. 21, no. 2, pp. 62–76, Oct. 2022.

[34] P. J. Bex and W. Makous, ‘‘Spatial frequency, phase, and the contrast of natural images,’’ J. Opt. Soc. Amer. A, Opt. Image Sci., vol. 19, no. 6, pp. 1096–1106, 2002. G. Popov, M. Korneev, “Method of adaptive regulation of the contrast level of a digital image when preparing it for recognition” Modern science: current problems of theory and practice, pp. 48–53, 2018.