Quantifying the Impact: Evaluating Image Contrast Enhancement Methods in Modern Applications

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ABSTRACT
In the realm of digital image processing, enhancing contrast is a fundamental step in improving visual quality and aiding in subsequent analysis tasks. This research paper delves into a comprehensive evaluation of contemporary image contrast enhancement techniques, aiming to provide a nuanced understanding of their efficacy in modern applications. The study scrutinizes six prominent methods, including Histogram Equalization, Probability and Statistics-based Segmentation, DCT-based Compression, Fourier Transforms, Image Restoration and Denoising, and Integration Techniques. Each technique is dissected, highlighting its mathematical foundation, crucial parameters, and experimental setup. The comparative analysis encompasses considerations of computational cost, user-friendliness, versatility, and potential synergies between methods. The findings illuminate the diverse strengths and limitations of each approach, empowering practitioners to make informed choices based on specific image processing requirements. This research contributes a comprehensive framework for quantifying the impact of image contrast enhancement techniques, fostering advancements in fields reliant on high-quality visual data.

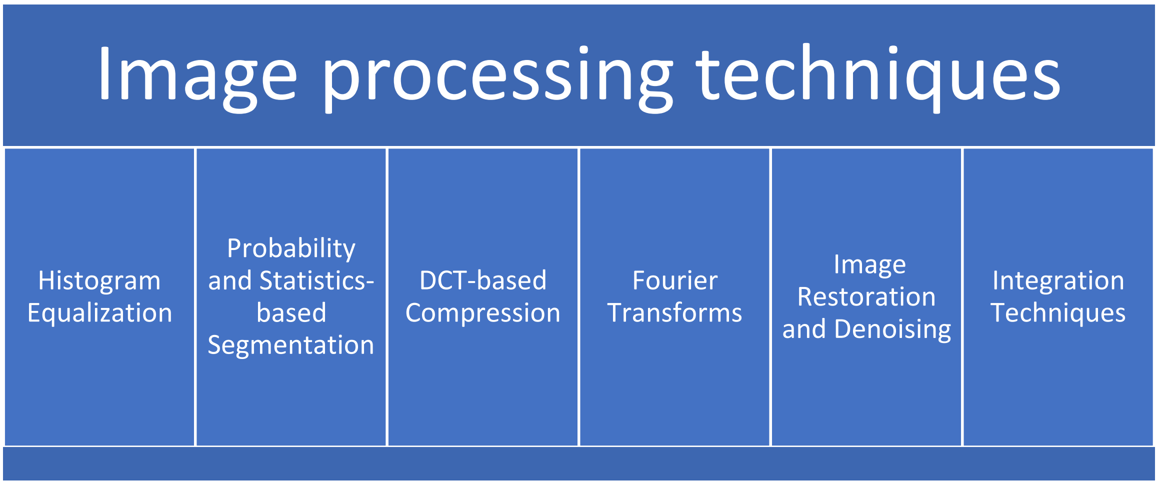
KEYWORDS: Image Enhancement, Noise Reduction, Histogram Equalisation, Contrast, Performance Metrics

1. INTRODUCTION

The ubiquity of digital images in today's information age has underscored the importance of image quality and clarity in a myriad of applications. From medical diagnostics and satellite imaging to entertainment and social media, the ability to enhance image contrast is a foundational step in improving visual fidelity and facilitating downstream analysis. In this era of information abundance, the value of robust image processing techniques cannot be overstated.

This research paper embarks on a comprehensive journey into the realm of image contrast enhancement, a pivotal domain within the broader field of digital image processing. The objective is clear: to assess and evaluate the effectiveness of modern image contrast enhancement methods and their applicability in contemporary scenarios.

We explore six prominent image processing techniques, each with its unique mathematical foundation and parameters. These techniques encompass Histogram Equalization, Probability and Statistics-based Segmentation, DCT-based Compression, Fourier Transforms, Image Restoration and Denoising, and Integration Techniques. By delving into the intricacies of these methods, we aim to provide practitioners and researchers with a comprehensive understanding of their strengths, limitations, and contexts of use.



The comparative analysis presented in this paper goes beyond mere technicalities; it seeks to gauge the economic and computational efficiency, user-friendliness, versatility, and the potential for synergy among these techniques. Our objective is to empower decision-makers in image processing to make informed choices, guided by the specific demands of their applications.

In a world where images convey information and emotions more powerfully than words alone, the quality of image processing techniques can have far-reaching consequences. By quantifying the impact of image contrast enhancement methods, this research seeks to contribute a valuable framework for advancing fields reliant on high-quality visual data, such as medical imaging, remote sensing, and computer vision. Through this journey, we invite the reader to explore the intricacies and potential of image contrast enhancement in the context of modern applications.

2. LITERATURE REVIEW

Image enhancement is a crucial aspect of digital image processing, aiming to reveal hidden details or increase contrast in low contrast images. Contrast is a visual property that distinguishes objects from background. In real-world perception, contrast is determined by the color and brightness difference between the darker and lighter pixels. This paper compares various image contrast techniques, primarily histogram adjustment methods, with common objective quality metrics on different image sets.

The field of image enhancement has witnessed significant strides in recent years, with researchers introducing innovative techniques to address a range of challenges associated with digital images.

Ngernplubpla (2018) proposed a pioneering method that leverages Neuro-fuzzy techniques for generating gradient profiles. This approach involves the collection of natural gradient priors and their subsequent analysis using a Neuro-fuzzy model [1]. The results demonstrated marked improvements in both quantitative metrics and perceptual performance.

Xiong (2021) explored histogram equalization techniques to improve visual perception in digital images, addressing noise and lighting variations[2]. Chen (2015) introduced a hierarchical correlation histogram analysis method for Parkinson's disease diagnosis, enhancing contrast for specific objects and reducing recognition time[3]. Acharya (2020) introduced a contrast enhancement algorithm using skewness and mode-based histogram equalization techniques, resulting in superior image contrast enhancement[4]. These studies demonstrate the effectiveness of histogram equalization in various fields, including medical imaging, CAD processes, and impulse noise detection.

Singh (2015) addressed the artifact issues introduced by Histogram Equalization (HE) through techniques like Dual Histogram Equalization (DHE) and Contrast Limited Adaptive Histogram Equalization (CLAHE)[5]. DHE was found to outperform CLAHE in mitigating intensity saturation and noise amplification. Singh (2013) introduced the Exposure-based Sub-Image Histogram Equalization (ESIHE) method for enhancing contrast in low-exposure grayscale images[6]. By dividing the image into sub-images with varying intensity levels and limiting enhancement based on gray level occurrences, this technique achieved superior visual quality.

Pushpavalli (2013) presented a hybrid filter combining a nonlinear switching median filter with a neuro-fuzzy network for denoising and enhancing digital images affected by noise[7]. The filter demonstrated exceptional performance in preserving fine details while eliminating noise, particularly under noisy conditions. Lastly, Li (2018) introduced the Robust Retinex Model, a low-light image enhancement technique incorporating noise maps and innovative regularization terms[8]. This model effectively enhanced low-light images by employing the L1 norm for smoothness, a fidelity term for reflectance gradients, and a novel approach for noise estimation.

The field of image enhancement has seen remarkable progress, with various approaches tailored to specific challenges. Chen (2018) introduced a method employing two-way generative adversarial networks (GANs) and enhancing the U-Net architecture with global features, along with an adaptive weighting scheme for faster convergence[9]. This technique demonstrates effectiveness in both quantitative and visual assessments.

Patvardhan (2012) focused on denoising and binarizing document images affected by white Gaussian noise and impulse noise[10]. By utilizing the Curvelet Transform's sparse representation and edge preservation capabilities, the study significantly improved OCR performance. This approach outperformed comparable methods based on wavelet transforms.

Rahman (2021) introduced a novel UNet model for lung segmentation, achieving high accuracy, precision, sensitivity, and specificity[11]. Zhang (2019) introduced Kind, a network designed to mitigate low-light image degradations such as noise and colour distortion[12]. Lore (2017) presented a deep autoencoder-based method for identifying signal features in low-light images, crucial for real-time enhancement of brightness, contrast, and noise reduction[13]. Guo (2017) introduced the Low-Light Image Enhancement (LIME) method, which estimates pixel illumination and refines it using a structural constraint[14]. Guo (2020) proposed Zero-DCE, a light enhancement method utilizing a deep neural network, potentially benefiting applications such as face detection in low-light situations[15]. Mustafa (2017) examined various histogram-based algorithms for enhancing the visual quality of medical images[16], while Ma (2018) introduced a fusion algorithm for underwater image enhancement[17]. Salem (2019) examined various histogram-based algorithms for improving the visual quality of medical images[18], while Shi (2019) presented a method to enhance sand-dust images[19]. Vijayalakshmi (2020) explored contrast enhancement techniques in spatial domains[20]. Arora (2023) proposed a breakthrough method for automatic defect diagnosis in Industry 4.0, leveraging advanced image processing techniques for quality control[21]. Also, Arora (2023) focused on the progress of Industry 4.0 technologies, with a specific emphasis on image processing AI, and explores their applications in the post-COVID-19 era[22]. Chahar

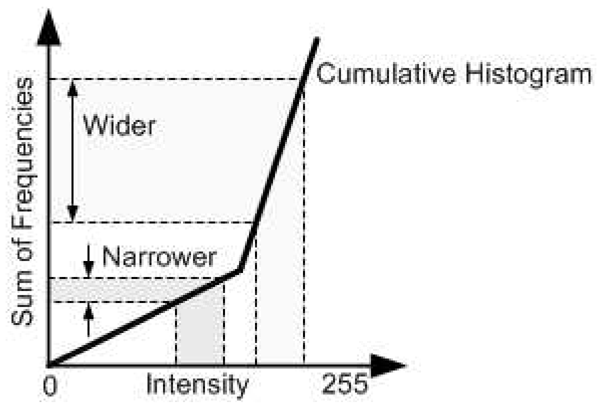
(2023) reviewed AI-based Model for Physio-Psycho Behavior of University Students using ANN Model[23].

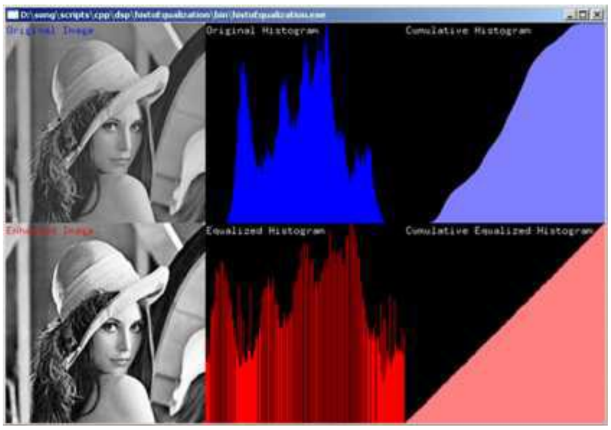
Asamoah (2018) focused on three contrast enhancement techniques for image enhancement which are: Histogram Equalization (HE), Adaptive Histogram Equalization (AHE) and Contrast Limited Adaptive Histogram Equalization (CLAHE) which are then compared with the help of the eight (8) quality image measurement metrics which are: i.e. the Mean squared error (MSE), Root Mean squared error (RMSE), Peak signal noise ratio (PSNR), Mean absolute error (MAE), Signal to noise ratio (SNR), Image Quality Index (IQI), Similarity Index (SI) and Pearson Correlation Coefficient (r). The paper concluded that Histogram Equalization (HE), is the one best contrast enhancement technique, as it recorded high percentage values for all the eight quality image measurement metrics[24].

(a) Histogram equalization

The idea behind this technique for improving contrast is to more evenly distribute the pixel values in the given image across the whole histogram. In this manner, the spectator can notice more of the scene's invisible intricacies. Thus, HE transforms the input image's histogram into its ideal uniform form.

The process of creating a histogram involves figuring out the pixel frequencies for the whole dynamic range of the supplied image. The frequency of a certain pixel indicates how frequently a particular gray level appears in the input image. The histogram equalization approach requires less processing effort. It is also evident that this approach transforms higher-frequency pixel values into extremely wide gray level intervals. This implies that minute details vanish in between objects when





Let's assume that, unlike the discrete situation in digital photos, the intensity levels of the image are continuous. We restrict the range of values that r can take to be between 0 and L-1, or 0 r L-1. Black is represented by r = 0 and white by r = L-1. Let's think about a random transformation function:

Where s stands for the image's intensity levels after processing. We have some restrictions on T(r).

T(r) must be an increasing function strictly speaking. It is an injective function as a result.

0 ≤ T(r) ≤ L-1. T(r) is consequently surjective.

T(r) is a bijective function because of the first two requirements. We are aware that these functions can be inverted. Thus, we may retrieve the values of r from s. A function that has r = T-1(s) can exist.

To ensure that the preceding step is true, we carefully specify the initial condition of T(r). Since s is the output image's intensity value and must fall between o and (L-1), the second condition is required.

$$F_s(x) = P(S \leq x) = P\{T(r) \leq x\} = P\{r \leq T - 1(x)\} = F_r\{T - 1(x)\}$$

$$S = T(r) = (L - 1)\int_0^T \mathrm{P_r}(x)\, dx$$

$$\frac{ds}{dr} = (L-1)\frac{d}{dr}\int_0^r \mathrm{P_r}(x)\,dx = (L-1)\,\mathrm{P_r}(r)$$

Used Leibnitz's integral rule

$$P_s(s) = \mathrm{P_r}(r)\frac{ds}{dr} = \mathrm{P_r}(r)\frac{1}{(L-1)\,\mathrm{P_r}(r)} = \frac{1}{L-1}$$

Thus, the pdf of s is constant. What we desire is this.

We now convert the aforementioned continuous case to a discrete case. The summation is a natural substitute for the integral sign. The histogram equalization transformation function that remains is as follows.

Therefore, by differentiating $F_s(x)$ with respect to x, it is possible to generate a pdf of s. inferring the

relationship, we find: Let us now say that the probability density function (pdf) of r is $p_r(x)$ and the cumulative distribution function (CDF) of r is $F_r(x)$. Now the CDF of s will be:

$$S_k = T_r(k) = (L-1)\sum_{j=0}^{k} \mathrm{P_r}(\mathrm{r_j}) = \frac{(L-1)}{N2}\sum_{j=0}^{k} n_j$$

Any non-integer number derived from the aforementioned function is rounded to the closest integer because s must only have integer values.

(b) Adaptive Histogram Equalization

Image Adjustment is an extension of traditional Histogram Equalization, enhancing image contrast by transforming intensity values. It operates on small data regions (tiles) and uses bilinear interpolation to eliminate artificial boundaries. This method has better output performance but higher computational load. Contrast can be limited in homogeneous areas to avoid image noise.

(c) Contrast-Limited Adaptive Histogram Equalization

The CLAHE technique algorithm is used for contrast enhancement in medical images. It separates the original image into nonoverlapping subimages and deduces histograms for each. The subimage histograms are trimmed to reduce augmentation before equalization. The foreground and background are boosted simultaneously, creating a high contrast image. CLAHE reduces noise in medical pictures, enhances local characteristics, and maintains crisp edges and detail. It requires less computing time than Histogram Equalization.Fuzzy systems can be effectively used in histogram-based image processing techniques to handle uncertainties and ambiguities in image data. Here's an overview of how fuzzy systems can be applied in this context.

(d) Fuzzy Histogram Equalization:

Fuzzy set theory enhances image contrast by assigning pixel degrees of belongingness to various intensity levels. Fuzzy logic is used for histogram specification, segmentation, and C-means clustering. Fuzzy thresholding allows pixels to belong to multiple classes, reflecting uncertainty in classification. Fuzzy C-means clustering partitions images into different clusters, allowing for robust edge detection in noisy images. Fuzzy logic defines gradients and edge strength with membership, allowing for more robust edge detection. Fuzzy filtering techniques smooth or enhance images, such as a fuzzy median filter. Fuzzy logic can represent uncertainty in the contribution of each source in multi-sensor scenarios. Fuzzy set theory is applied in morphological operations, representing and analyzing textures in images. Fuzzy logic can adaptively enhance different regions of an image based on local characteristics and detail preservation. Implementing fuzzy systems for histogram-based image processing requires defining membership functions and rules, tuning parameters, and validating results through experimentation.

(e)The Generalized Laplacian-Gaussian (GLG) method

GLG method aims to enhance edges and fine details in digital images by accentuating high-frequency components, which are typically associated with edges. It combines two fundamental operations: Laplacian filtering and Gaussian smoothing. The Laplacian operator is used to emphasize regions of rapid intensity change (edges) in an image. Gaussian smoothing helps to reduce noise and artifacts by suppressing high-frequency noise components.

The extent of smoothing and the strength of the Laplacian filter can be adjusted using parameters like the standard deviation of the Gaussian kernel and the scaling factor for the Laplacian.

The Generalized Laplacian-Gaussian (GLG) method involves convolving an image with a Gaussian kernel for smoothing and a Laplacian kernel for edge enhancement. The mathematical operations can be represented as follows:

The Gaussian function is given by:

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

where: x and y are spatial coordinates.σ is the standard deviation of the Gaussian, controlling the extent of smoothing. The 2D Gaussian kernel is computed by discretizing this function and is used to convolve with the original image.

The Laplacian operator is used to highlight regions of rapid intensity change (i.e., edges) in an image. In discrete form, it is represented as:

$$\nabla^2 I(x, y) = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2}$$

In 2D discrete space, the Laplacian kernel can be represented as:

$$\nabla^2 I(x, y) = \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

This kernel is applied to the image after the Gaussian smoothing step. After applying the Laplacian operator, the result is added back to the original image:

$$\textbf{Enhanced Image= Original Image}+\boldsymbol{\nabla^2 I(x, y)}$$

Where k is a scaling factor that controls the strength of the edge enhancement.

3. OBJECTIVE

The primary objective of this research paper is to conduct a comprehensive evaluation of contemporary image contrast enhancement techniques and their applicability in modern contexts. Specifically, the study aims to:

- Provide a detailed understanding of six prominent image processing techniques, namely Histogram Equalization, Probability and Statistics-based Segmentation, DCT-based Compression, Fourier Transforms, Image Restoration and Denoising, and Integration Techniques.
- Examine the mathematical foundations and critical parameters associated with each technique, enabling a nuanced assessment of their strengths and limitations.
- Conduct a comparative analysis, considering factors such as computational cost, user-friendliness, versatility, and potential synergies between methods, to empower practitioners in making informed choices based on specific image processing requirements.
- Illuminate the potential impact of image contrast enhancement techniques in diverse applications, including but not limited to medical imaging, satellite imagery analysis, computer vision, and entertainment media.
- Contribute a comprehensive framework for quantifying the effectiveness of these techniques, fostering advancements in fields reliant on high-quality visual data.

4. METHODOLOGY

(a) **Performance measures**

Quantitative performance measures are very important in com- paring different image enhancement algorithms. Besides the visual results and computational time, Contrast Improvement Index (CII) and Tenengrad measure are the two important quantitative measures used here for the performance analysis.

Contrast improvement index (CII)

The Contrast Improvement Index (CII), the most well-known benchmark image enhancement metric, is used to compare the outcomes of contrast enhancement methods in order to assess how competitive the new fuzzy method is against existing contrast enhancement techniques. CII can be calculated as a ratio to assess contrast improvement [26]. The formula for the contrast improvement index is CII = as:

$$CII = \frac{\lambda_{expected}}{\lambda_{actual}}$$

where λ is the average value of the local contrast measured with 3 × 3 window as per the instruction

$$\frac{Max - Min}{Max + Min}$$

$\lambda_{expected}$ and λ_{actual} are the average values of the local contrast in the output and original images, respectively.

(b) Tenengrad Measurement

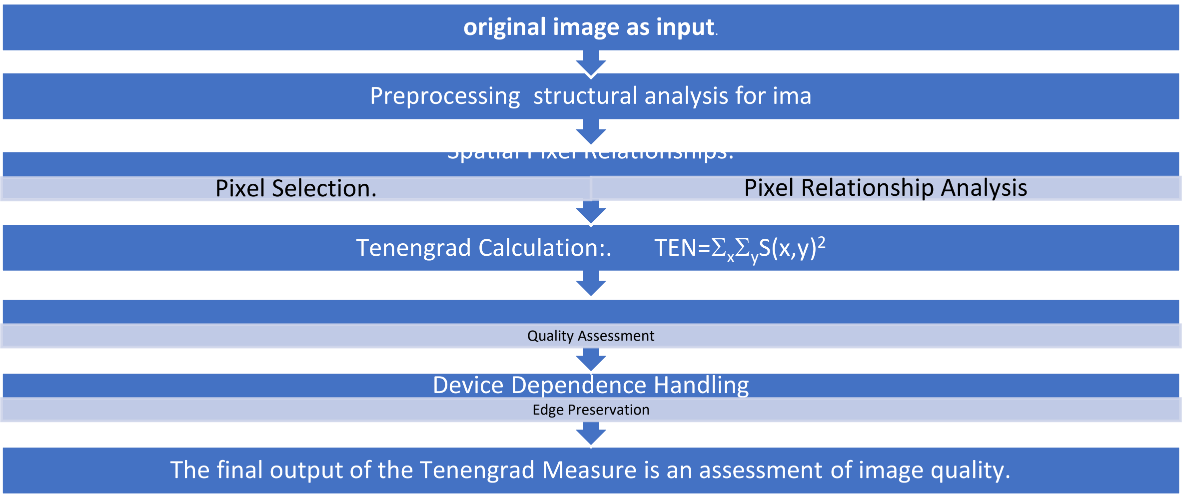
Maximising the gradient magnitude is the foundation of the Tenengrad criterion. It is regarded as one of the most reliable and functionally accurate measurements of image quality. A high-pass filter, such the Sobel operator, and the convolution kernels ix and iy are used to generate the partial derivatives of the gradient I(x, y) at each pixel (x, y), which is how the Tenengrad value of an image, I, is determined. The gradient's size is indicated as

$$S(x,y) = \sqrt{(ix * I(x,y))2 + (iy * I(x,y))2}$$

and the Tenengrad criterion is formulated as

$$TEN = \sum_x \sum_y S(x,y)^2 \qquad (2)$$

where T is a threshold, and S(x, y) > T. When an image's Tenengrad rating is higher, it is typically thought to be of higher quality. Tenengrad measure has been used to assess whether structural information in the enhanced image has improved or not, despite being less effective than CII as a performance measure for image enhancement.



Protocol for Tenengrad Measure

5. RESULT & DISCUSSION

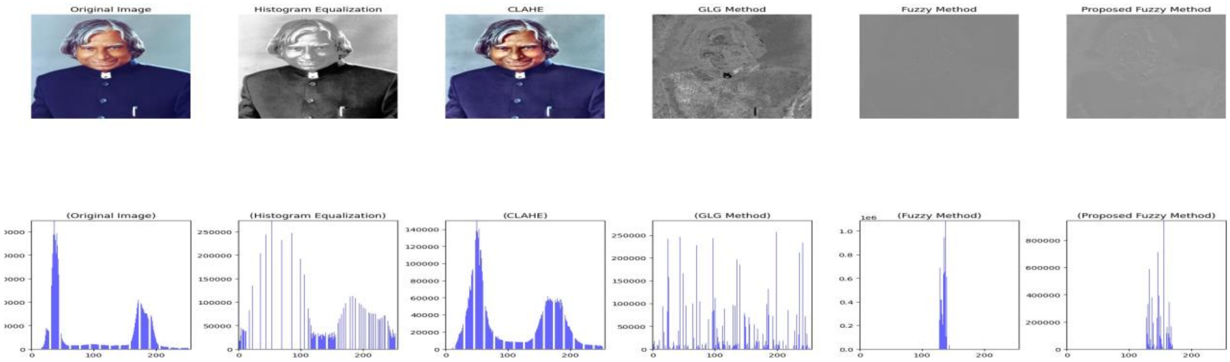
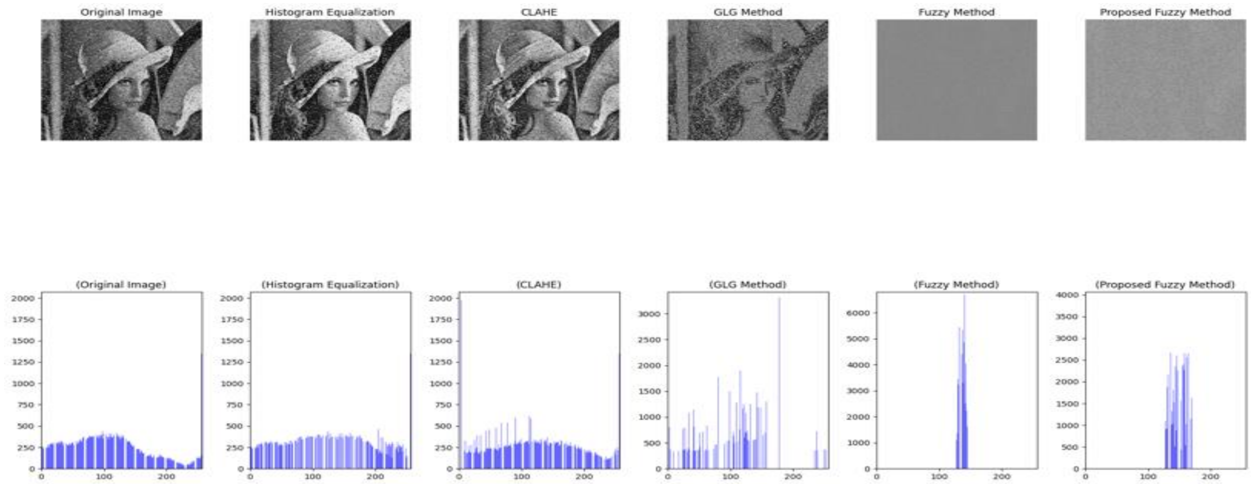


Image: 1

Image: 2



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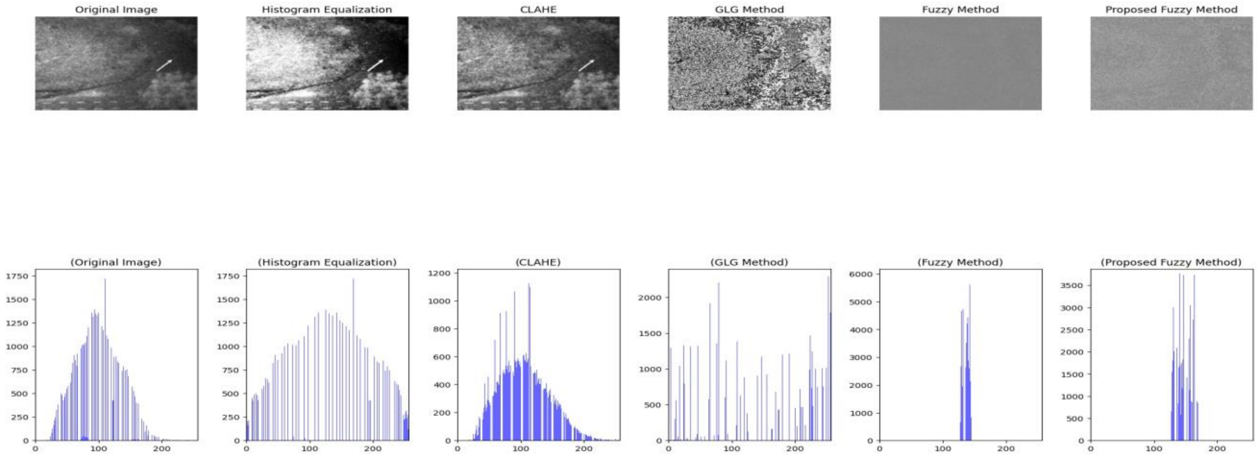

Image: 4

		HE	CLAHE	GLG	FUZZY	PROPSED FUZZY
Image I	**CII**	0.23	0.26	0.34	0.28	0.40
	Tenengrad	8.7e+07	8.7e+07	1.3e+09	3.56e+06	2.99e+07
	Time	0.002	0.097	0.027	1.42	1.43
Image II	**CII**	0.17	0.038	0.184	0.238	0.356
	Tenengrad	8.5e+07	8.56e+07	1.44e+09	3.76e+06	3.06e+07
	Time	0.002	0.024	0.025	1.43	1.41
Image III	**CII**	0.26	0.11	0.200	0.328	0.451
	Tenengrad	1.43e+07	2.56e+07	1.33e+09	4.05e+06	3.07e+07
	Time	0.002	0.002	0.026	1.40	1.41
Image IV	**CII**	0.32	0.06	0.34	0.40	0.53
	Tenengrad	3.81e+07	4.46e+07	1.33e+09	4.65e+06	3.27e+07
	Time	0.002	0.099	0.025	1.43	1.41

Table:1

The performance measure values demonstrate that the proposed method outperforms both conventional and cutting-edge improvement strategies in terms of results. The proposed method is significantly more suitable for real-time applications because it requires less calculation time than other sophisticated methods. The suggested approach is quick to compute and effective in terms of quality.
The several low-contrast and low-brightness images used in this paper's performance analysis are displayed in Images 1-4 through (d). Prof. Abdul Calam.jpg, M.S. Dhoni.jpg, Madam.jpg, and Sky.jpg, and they have resolutions of 283 432, 283 432, 360 236 and respectively.
2.12 104, 3.67 104, 6.26 104, and 4.58 104 are the sizes of the beach photos, respectively.
After using histogram equalisation, adaptive histogram equalisation, GLG, the fuzzy technique, and the proposed fuzzy method, the contrast and brightness enhanced the images (1-4). jpg images are shown in Fig. 4(a)–(e), accordingly. The corresponding V component histograms of the upgraded image (1-4) JPG photos are displayed in Figs. According to Fig. 1, the histogram of the V component has been stretched while maintaining the basic form of the histogram of the original image (1–4). jpg in order to boost contrast and brightness.
Table 1 displays the results of applying several enhancement techniques to the photos: Prof. Abdul Calam.jpg, M.S. Dhoni.jpg, Playground.jpg, and Sky.jpg, respectively. It is clear from the table values that the suggested fuzzy method outperforms both traditional and cutting-edge picture enhancement techniques in terms of CII value. The suggested method's higher Tenengrad values demonstrate that it improves the structural information in the source images. Although the Tenengrad values produced by the GLG and histogram equalisation methods are greater, the visual quality of the resulting photos cannot be compared to that of the suggested method. The table data make it abundantly clear that the proposed method, as opposed to GLG and the fuzzy method, is computationally quick. The suggested approach requires 20–30% and 30–40% less computational time, respectively

6. CONCLUSION

This study suggests a simple and efficient method for improving colour images using fuzzy data. A comparison of the proposed method with conventional histogram-based contrast enhancement techniques (such as histogram equalisation, adaptive histogram equalisation), as well as the more recent histogram-based Grey Level Grouping method and the Fuzzy Logic method, was done in order to ascertain which of these methods is best suited for automatic contrast enhancement of colour images. The Tenengrad and CII values have risen while the visual quality has improved utilising the fuzzy logic method we recommend in this study, according to comparison analysis. The process is substantially quicker when compared to the advanced enhancing methods that are currently accessible. One drawback of this approach is that it can only be applied in specific Using the fuzzy logic approach we propose in this work, it can be deduced that the Tenengrad and CII values have grown while the visual quality has improved. The process is substantially quicker when compared to the advanced enhancing methods that are currently accessible.

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