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Quantitative Analysis of Image Enhancement Algorithms for Diverse Applications

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This research paper introduces a comprehensive comparative analysis of prominent image enhancement algorithms, including Histogram Equalization, Adaptive Histogram Equalization, CLAHE, Gamma Correction, and Unsharp Masking. In the realm of digital image processing, image enhancement plays a crucial role in various applications such as medical imaging, remote sensing, surveillance, and computer vision. Addressing the significance of this research, we present an evaluation of these algorithms using key metrics: Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), Structural Similarity Index (SSIM), Contrast Improvement, and Sharpness Improvement. Our methodology encompasses dataset collection, algorithm implementation in MATLAB, and systematic performance evaluation. The results highlight the unique strengths and trade-offs of each algorithm. Histogram Equalization demonstrates moderate improvement in image quality, while Adaptive Histogram Equalization excels in preserving image details despite introducing some distortion. Contrast Limited Adaptive Histogram Equalization strikes a balance between enhancement and computational efficiency. Gamma Correction proves effective for specific adjustments but may compromise overall image quality. Notably, Unsharp Masking stands out with superior sharpness improvement while maintaining image fidelity. In conclusion, the choice of algorithm should be aligned with specific task requirements and the desired balance between image quality and enhancement goals. Considering these outcomes, Unsharp Masking emerges as a promising choice, demonstrating exceptional performance across multiple metrics. This research provides valuable insights for practitioners and researchers seeking to optimize image enhancement algorithms for diverse applications.

Keywords: Image Enhancement, Histogram Equalization, Adaptive Histogram Equalization, CLAHE, Gamma Correction and Unsharp Masking, Peak Signal-to-Noise Ratio, Structural Similarity Index, Mean Square Error, Contrast Improvement, and Sharpness Improvement.

Introduction:

Image enhancement is a fundamental process in digital image processing aimed at improving the quality and interpretability of images. It plays a pivotal role in various fields, including medical imaging, remote sensing, surveillance, and computer vision. The primary objective of image enhancement is to accentuate image features, reduce noise, and enhance overall visual quality, leading to better insights and decision-making. The critical importance [1] of conducting a comparative analysis of image enhancement algorithms stems from their pivotal role in advancing image quality within the domain of image processing. This enhancement process is instrumental in accentuating valuable information while concurrently suppressing redundant elements present in the image. By systematically comparing and evaluating different image enhancement algorithms, researchers can discern their respective strengths, limitations, and efficacy. This comparative analysis not only aids in identifying the most effective techniques for specific applications but also fosters a deeper understanding of the intricate trade-offs involved. Consequently, a well-executed comparative analysis serves as a guiding compass, steering researchers toward optimized image enhancement solutions and contributing to the continual refinement of image processing methodologies. Conducting a thorough comparative analysis [2] of image enhancement algorithms holds paramount significance in the realm of image processing and restoration. This practice equips researchers with a foundational understanding essential for navigating the challenges and leveraging the opportunities inherent in this pivotal field. In the realm of image processing, the importance of comparative analysis [3] for image enhancement algorithms is underscored by the prevalent challenge of visibility degradation in poor weather conditions, such as fog, haze, and mist. Conventional imaging devices often struggle to efficiently counteract the detrimental effects of weather-induced visibility degradation in real-time scenarios. While existing physical model-based approaches utilize image-depth information to mitigate hazy effects, the imprecision inherent in-depth information compromises dehazing performance. The significance of comparative analysis [4] for image enhancement algorithms is underscored by the burgeoning interest in underwater image enhancement, a critical domain within marine engineering and aquatic robotics. While numerous algorithms have been proposed in recent years, their evaluations have primarily relied on synthetic datasets or limited real-world images, leaving uncertainties about their performance in wild environments. Image enhancement, a fundamental process in image processing [5], aims to improve specific features within an image to enhance its suitability for various applications. This enhancement primarily involves refining attributes such as boundaries and contrast to yield a more visually compelling and analytically informative representation. Image enhancement techniques are broadly categorized into two main approaches: spatial domain methods, which involve direct manipulation of pixel values within an image, and frequency domain methods, which operate by modifying the Fourier Transform of the image. Typical image enhancement operations encompass sharpening, noise reduction, and brightness adjustment. It is worth noting that determining an objective criterion for what constitutes "good" image enhancement, particularly about human perception, remains a challenge without a universally applicable theory. The subjective nature of visual perception means that the effectiveness of image enhancement is often gauged by whether it visually appears improved [6]. Figure 1 illustrates the operation of image enhancement [6].

Image Enhancement Algorithms Overview:

Image Enhancement Algorithms are crucial in increasing picture visual quality. Medical imaging, surveillance, and remote sensing all rely on these algorithms. They act as a link between raw, unfiltered photos and the intended output, improving essential characteristics, decreasing noise, and increasing overall image clarity. A wide array of enhancement techniques exists, including histogram equalization, contrast stretching, and spatial domain filtering, each catering to specific image characteristics and objectives. Additionally, with the emergence of deep learning-based approaches, the field has witnessed remarkable advancements, achieving unprecedented levels of image enhancement.

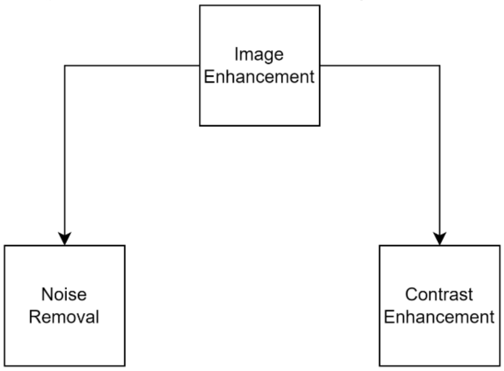

Figure 1: Basic Operation of Image Enhancement [5]

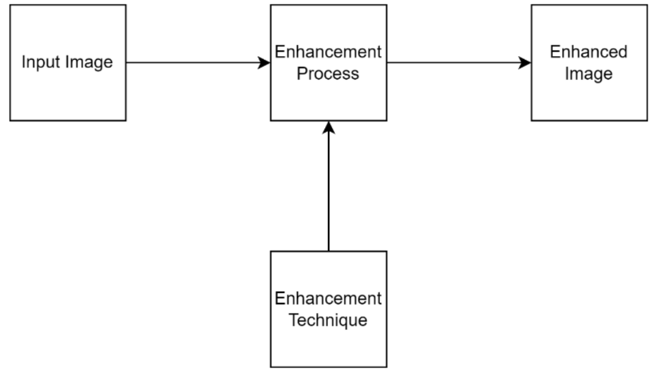

Figure 2: Block Diagram of Image Enhancement Algorithm [7]

Figure 2 serves as a fundamental and straightforward depiction [7] of the image enhancement workflow. Initially, the input image, slated for enhancement, undergoes digitization. Simultaneously, the critical decision of selecting an appropriate image enhancement algorithm is made. Finally, employing the chosen image enhancement technique, the image is processed, culminating in the presentation of the enhanced image as the final output. This investigation evaluated the performance of the following image enhancement algorithms:

Objectives:

The primary objectives of this research endeavor are to conduct a comprehensive comparative analysis of prominent image enhancement algorithms, specifically Histogram Equalization, Adaptive Histogram Equalization, CLAHE, Gamma Correction, and Unsharp Masking. The aim is to provide a nuanced understanding of their individual strengths, limitations, and performance across critical metrics. Through meticulous evaluation using metrics such as Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), Structural Similarity Index (SSIM), Contrast Improvement, and Sharpness Improvement, the study seeks to offer valuable insights into the efficacy of each algorithm. The objectives also include elucidating the unique contributions and trade-offs of these algorithms and guiding practitioners and researchers in selecting the most suitable approach for diverse image processing applications.

Novelty Statement and Justification:

This research contributes novelty to the field by offering a comprehensive comparative analysis that goes beyond a mere enumeration of algorithms. The novel aspect lies in the detailed examination of algorithmic strengths and weaknesses, providing a nuanced perspective for practitioners. The study innovatively employs critical metrics such as Contrast Improvement and Sharpness Improvement alongside traditional measures like PSNR and SSIM, offering a more holistic evaluation of algorithmic performance. This nuanced approach addresses the limitations of existing research, providing a more complete understanding of the algorithms' applicability in real-world scenarios. The justification for this novelty stems from the increasing importance of image enhancement in various domains and the need for a thorough, practical guide for algorithm selection.

Related Work:

This section critically reviews and synthesizes existing literature on image enhancement algorithms. It systematically explores prior research to contextualize the current study within the broader landscape of image processing. The review includes a thorough examination of methodologies, metrics, and outcomes from comparable studies, identifying gaps and shortcomings in the existing body of knowledge. By establishing a robust foundation through a critical review of related work, this research ensures a meaningful contribution to the field. The synthesized insights not only validate the significance of the current study but also highlight areas where it breaks new ground, addressing limitations and advancing the state-of-the-art in image enhancement research. Following is a brief overview of prominent image enhancement algorithms as demonstrated by Figure 3:

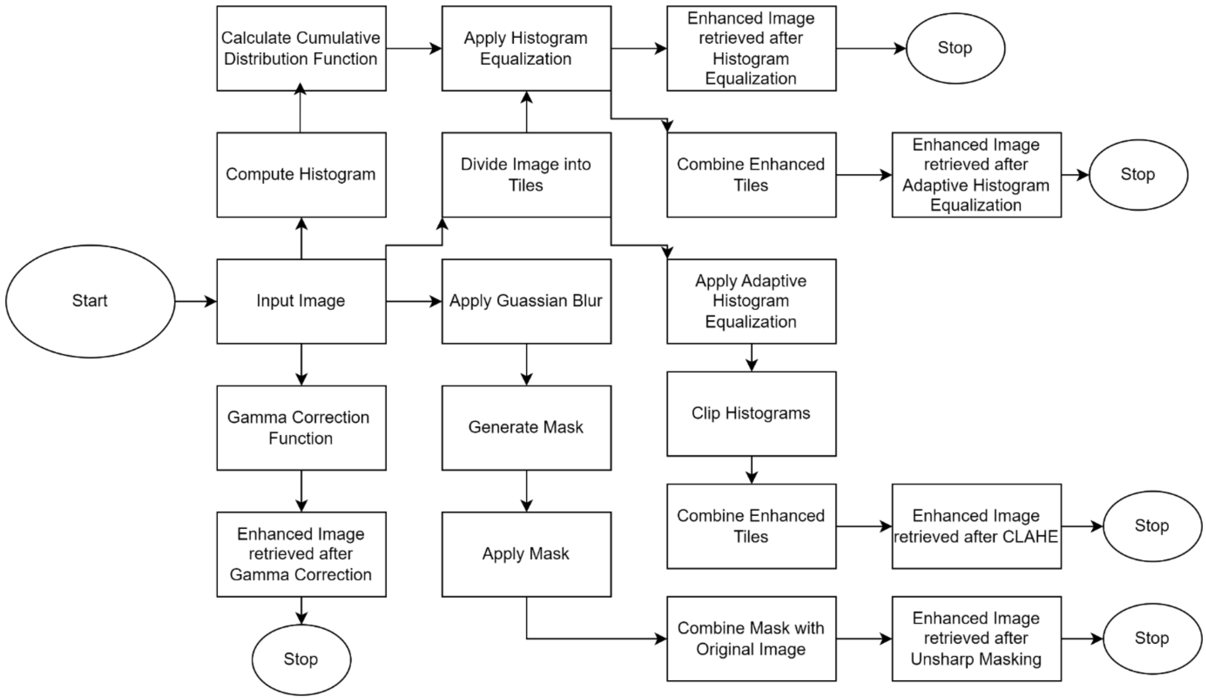

Figure 3: Steps of Operation of five Prominent Image Enhancement Algorithms Namely Histogram Equalization, Adaptive Histogram Equalization, Contrast Limited Adaptive Histogram Equalization, Unsharp Masking, and Gamma Correction

Histogram Equalization:

Histogram Equalization is a fundamental image improvement method with significant use in image processing and computer vision. Its major goal is to increase image visual quality by dispersing pixel intensities to obtain a more balanced and better contrast. The approach works by generating an image's histogram and then modifying the pixel values based on this histogram, thus expanding the intensity distribution to encompass the whole possible range. While Histogram Equalization may be quite helpful in improving the visual look of images, it is important to note its limits. When the source image already has a well-balanced histogram, using Histogram Equalization might result in unwanted effects such as excessive noise amplification. The steps of operation of the Histogram Equalization image enhancement algorithm are demonstrated in Figure 3.

The field of consumer electronics faces a primary challenge [8] in image processing—preserving the original brightness. Among the myriad methods for contrast enhancement, Histogram Equalization (HE) stands out as a simple yet widely utilized approach. However, HE's drawback in the consumer electronics sector lies in its tendency to flatten the histogram by uniformly distributing all gray levels. To address this limitation, various HE variants have emerged, leveraging techniques such as histogram segmentation, weighting, and range optimization. Despite these efforts, some modifications introduce complexity and computational expenses. A recent breakthrough involves formulating HE variants for image enhancement as optimization problems and solving them using Nature-Inspired Optimization Algorithms (NIOA), marking a new era in image enhancement. Histogram equalization techniques [9] emerge as valuable tools in this context, enhancing image quality to provide clearer visual information without sacrificing the original data.

Adaptive Histogram Equalization:

Adaptive Histogram Equalization (AHE) is a powerful image enhancement technique widely employed in various fields, particularly in medical image processing and computer vision. Unlike traditional histogram equalization, AHE dynamically adjusts the intensity distribution of an image by considering local neighborhoods rather than the entire image. This adaptive nature enables AHE to enhance the contrast of specific regions or structures within an image while preserving overall image details. Consequently, AHE proves particularly useful in scenarios where uneven illumination or varying contrast levels are prevalent. However, it is important to note that AHE can exacerbate noise in areas with low contrast, which necessitates additional post-processing steps to mitigate this drawback. The steps of operation of the AHE image enhancement algorithm are demonstrated in Figure 3.

AHE algorithm [10] is designed to enhance both medical and natural images captured in diverse lighting conditions. The algorithm employs image processing techniques, including color space transformation, image inversion, dehazing, and saturation adjustment. Notably, this approach focuses on preserving local image details while achieving effective contrast enhancement. Within the realm of AHE, three distinct approaches have emerged: overlapping sub-blocks, nonoverlapping sub-blocks, and partially overlapping sub-blocks. Among these, the nonoverlapping sub-block approach is infrequently employed due to the undesirable square-shaped artifacts it tends to introduce. Similarly, the utilization of the overlapping sub-block method remains limited in practical applications owing to its resource-intensive computational demands and sluggish processing speed. In contrast, the partially overlapping sub-block method presents a compelling solution, enabling accelerated calculations while preserving effectiveness, albeit with an associated increase in complexity [11].

Contrast Limited Adaptive Histogram Equalization (CLAHE):

CLAHE stands as a pivotal technique in the field of image processing. Its fundamental ability to enhance image contrast while mitigating over-amplification of noise is paramount for numerous applications, from medical imaging to computer vision. CLAHE functions by dividing an image into smaller, manageable regions, adaptively equalizing the histogram within each section. This ensures that local contrast is enhanced without introducing artifacts or excessive noise amplification, which is a common drawback of traditional histogram equalization. The steps of operation of the CLAHE image enhancement algorithm are demonstrated in Figure 3.

CLAHE algorithm is a pivotal tool [12] in the realm of medical image enhancement. Given the critical role of timely disease detection and treatment, the swift diagnosis enabled by computer vision is paramount. CLAHE algorithm [13] stands out for its ability to improve the visual impact and conformity in clinical diagnosis, highlighting its potential for advancing medical image quality. CLAHE [14] plays a pivotal image enhancement technique in computer-based image processing, contributing to a nuanced understanding of its applicability in enhancing images for subsequent computer processing tasks. CLAHE [15] is selectively applied to the intensity component and enhances local details without over-brightening uniform regions.

Unsharp Masking:

Unsharp masking is a vital image enhancement technique widely employed in digital image processing. This method enhances the sharpness and minute details of an image by creating a high-pass filtered version of the original image, emphasizing the edges and contours. By subtracting this filtered image from the original, the technique effectively enhances local contrast and improves overall image clarity. The steps of operation of the Unsharp masking image enhancement algorithm are demonstrated in Figure 3.

The Unsharp Masking (UM) technique [16] achieves image enhancement by sharpening image edges while preserving low and medium-frequency details. The Unsharp Masking image enhancement algorithm [17] addresses computational inefficiency and platform limitations. Leveraging the power of Open Computing Language (OpenCL), a parallelized version of the algorithm is proposed to boost processing efficiency. Unsharp Masking (USM) image enhancement algorithm [18] was designed to address the challenges posed by noise in aerial photographs. Recognizing the human visual system's heightened sensitivity to edges and ridges, especially in images rich in spatial variations, the algorithm leverages USM to enhance these informative components. Unsharp Masking technique [19] is widely used to enhance local contrast and image sharpness.

Gamma Correction:

Gamma correction, an important image-enhancing method, is vital in adjusting the brightness levels of digital images. It is extensively employed in a range of sectors, including medical imaging and display technology, to correct the non-linear relationship between pixel values and perceived brightness. This correction, which is often performed with a certain gamma value, aids in matching pictures with human vision, ensuring that they look visually consistent and appealing. Furthermore, gamma correction mitigates the negative impacts of display differences and lighting conditions, improving the overall quality and interpretability of digital pictures. This research paper examines the concepts and uses of gamma correction in this context, emphasizing its significance as a potent tool in image processing and improvement. The steps of operation of the Gamma correction image enhancement algorithm are demonstrated in Figure 3.

Gamma correction stands as a frequently utilized method in numerous image enhancement contexts [20]. It excels in selectively enhancing specific intensity levels while leaving other regions of the image unaffected [21]. Additionally, gamma correction plays a pivotal role in regulating color enhancement rates, imparting a fine degree of control [21]. The Gamma Correction image enhancement algorithm [22] is used for contrast enhancement and utilizes weighted histogram distribution to maintain natural color and detail.

Methodology:

The methodology utilized for the comparative assessment of the designated image enhancement algorithms – Histogram Equalization, Adaptive Histogram Equalization, CLAHE, Gamma Correction, and Unsharp Masking followed a systematic procedure to comprehensively evaluate their performance. This investigation was conducted through the utilization of the MATLAB programming language, with the integration of pertinent libraries to ensure the optimal and proficient implementation of these algorithms.

Data Collection:

The dataset section of the research paper utilized a diverse range of images to investigate Image Enhancement Algorithms. This dataset [23] encompassed a variety of subjects and scenes, considering factors such as image dimensions, color schemes, and intricacy. Image dimensions spanned from 256x256 pixels to 1024x1024 pixels. The images exhibited a spectrum of attributes, ranging from high-detail 24-bit color compositions to less intricate 8-bit color depictions. This assortment facilitates a comprehensive evaluation of algorithm performance across varying color spectrums. Additionally, the dataset encompassed two color modes: monochrome and chromatic, encompassing colors like red, green, and blue. Incorporating this dataset facilitates a detailed assessment of the chosen image enhancement algorithms within a wide spectrum of real-world scenarios. This methodology offers priceless perspectives into the effectiveness of algorithms across a range of image categories and complexities.

Evaluation Metric:

This section critically examines image enhancement algorithms, underscored by six pivotal performance metrics: Peak signal-to-noise ratio (PSNR), Mean Square Error (MSE), Structural Similarity Index (SSIM), Contrast Improvement, and Sharpness Improvement. These metrics constitute a robust framework, vital for rigorously assessing the efficacy and impact of image enhancement algorithms.

Mean Square Error (MSE):

MSE serves as a fundamental and indispensable evaluation metric. MSE quantifies the overall quality of enhanced images by calculating the average squared difference between corresponding pixels in the original and enhanced images. Lower MSE values indicate a closer match between the two images, signifying a higher fidelity of the enhancement process [24][25] and [26].

Peak Signal-to-Noise Ratio (PSNR):

PSNR emerges as a pivotal and widely recognized evaluation metric. PSNR quantifies the quality of enhanced images by measuring the ratio between the maximum possible power of the image and the power of the noise corrupting it. It assesses how faithfully an enhanced image approximates the original, with higher PSNR values indicating a closer match and, consequently, superior image fidelity [27][28] and [29].

Contrast Improvement:

Contrast enhancement is a vital component of assessing the efficiency of various approaches. Contrast, a basic component of visual perception, is critical in determining the clarity and distinguishability of items within an image. As a result, every image quality enhancement technique must be thoroughly evaluated based on its capacity to increase contrast. A greater Contrast Improvement score implies a more significant improvement in picture contrast, which is frequently predictive of better image quality [30][31] and [32].

Structural Similarity Index (SSIM):

The Structural Similarity Index (SSIM) is an effective and comprehensive assessment tool. The quality of augmented images is determined through SSIM by comparing their structure details with that of the original image. It assesses brightness, contrast, and structure to provide a comprehensive assessment of the image's perceptual quality. A higher SSIM score shows improved retention of the structural elements of the original image, making it a useful tool for assessing image enhancement accomplishment [33][34] and [35].

Sharpness Improvement:

Sharpness improvement measures how much an enhancement method enhances the minor features and edges of an image, resulting in a sharper and more defined appearance. It may be measured quantitatively using measures like the SSIM and PSNR, which evaluate the sharpness of the improved image with the original. Subjective evaluation using human perception research, on the other hand, can give useful insights into sharpness enhancement. A higher sharpness improvement score suggests the algorithm effectively maintains or improves image details, making it an important parameter in evaluating the quality and practical utility of image enhancement methods, especially in applications where specific details and edge information are critical [36][37] and [38].

Implementation:

Image enhancement algorithms were executed in MATLAB (version: 9.14.0.2206163 (R2023a)) with the aid of the image processing toolbox. Experiments were conducted on a system featuring an Intel Core i7 processor and 16GB RAM, operating on Microsoft Windows 10 Pro Version 10.0. The implementation phase of this research paper adopts a meticulous and effective approach to evaluate the performance of various image enhancement techniques. Utilizing MATLAB programming language and leveraging relevant libraries, the chosen algorithms, including Histogram Equalization, Adaptive Histogram Equalization, CLAHE, Gamma Correction, and Unsharp Masking, are systematically examined as shown in Figure 8. The process involves loading and preprocessing images, performing enhancements, and calculating essential performance metrics such as PSNR, SSIM, MSE, Contrast Improvement, and Sharpness Improvement. The resultant data is comprehensively presented through graphical representations, providing valuable insights into the effectiveness of each algorithm. The systematic execution and utilization of MATLAB ensures accurate results and contributes to the robustness of this research endeavor. The implementation of image enhancement algorithms comparative analysis is demonstrated in Figure 4.

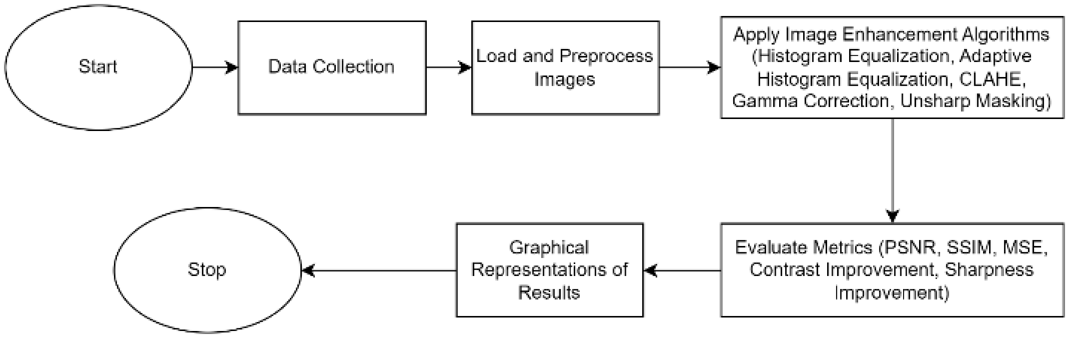

Figure 4: Implementation of Image Enhancement Algorithms Comparative Analysis

Reproducibility and Seed Parameters:

Ensuring the reproducibility of experimental results is fundamental to the integrity and credibility of our study. In this section, we outline the key aspects of reproducibility and the seed parameters employed during our experiments. To facilitate the replication of our experiments, we have meticulously documented the procedures, methodologies, and configurations utilized in our research. The entire implementation, including algorithm execution and metric evaluations, was performed using MATLAB (version: 9.14.0.2206163 (R2023a)). We emphasize the importance of utilizing the same MATLAB version to reproduce our results accurately. Additionally, all relevant libraries and toolboxes, particularly the image processing toolbox, were employed with their versions documented to ensure consistency. Seed parameters play a crucial role in the reproducibility of experiments involving random processes. In our study, where applicable, we utilized seed parameters to initialize random number generators. This practice ensures that the random variations introduced during algorithm execution remain consistent across different runs. We provide explicit details about the seed parameters used for each algorithm, promoting transparency, and aiding in the faithful reproduction of our results.

Results and Discussion:

The experimental outcomes demonstrate how well Histogram Equalization, Adaptive Histogram Equalization, CLAHE, Gamma Correction, and Unsharp Masking perform based on the metrics mentioned. These metrics collectively provide a comprehensive understanding of the image enhancement algorithm's performance. High PSNR and SSIM values, along with low MSE, indicate faithful preservation of image details and reduced distortion. Positive values for contrast and sharpness improvement reflect effective enhancement of visual quality, making the image more vivid and sharper. Evaluating these metrics helps determine the success of the image enhancement algorithm in improving the overall quality and perceptual appeal of the image.

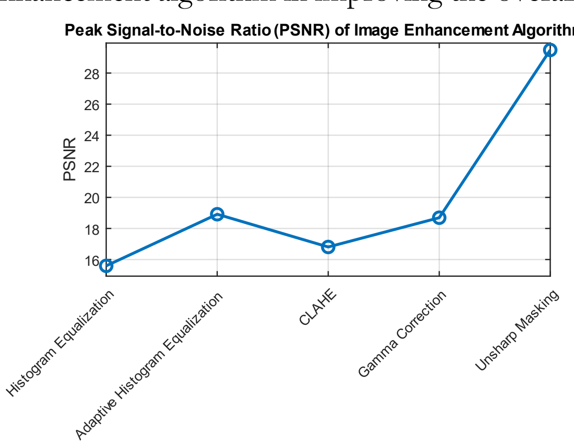

Figure 5: PSNR comparison graph

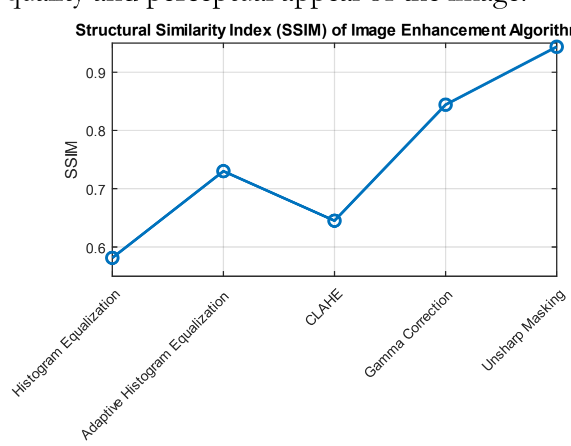

Figure 6: SSIM comparison graph

In the PSNR comparison graph (in Figure 5), where PSNR values are depicted on the y-axis, we observe various image enhancement algorithms listed along the x-axis. PSNR is a critical metric used to evaluate the quality of enhanced images, with higher PSNR values indicating superior image enhancement. The comparative analysis of image enhancement algorithms, based on their PSNR results, provides valuable insights into their performance. Histogram Equalization yields a PSNR of 15, indicating a moderate level of image enhancement quality. AHE stands out with a remarkable PSNR of 19, signifying its ability to significantly enhance image quality while preserving vital details. CLAHE follows closely with a PSNR of 17, showcasing its effectiveness in enhancing image quality. Gamma Correction achieves a PSNR of 18.5, suggesting its capability to improve image quality through adjustments of gamma values. Unsharp Masking leads the group with the highest PSNR value of 29.5, indicating exceptional image enhancement quality. This comparative analysis highlights that the choice of an image enhancement algorithm should be driven by the specific requirements of the task. Unsharp Masking, with the highest PSNR, excels in applications demanding the highest image enhancement quality. AHE is suitable when achieving a significant boost in image quality is crucial, while CLAHE offers an excellent balance between enhancement quality and computational efficiency. Gamma Correction, although effective, may be preferred when a balance between quality and efficiency is required, and Histogram Equalization remains a viable option for moderate image enhancement needs.

In the SSIM comparison graph (Figure 6), Structural Similarity Index (SSIM) values are depicted on the y-axis, while various image enhancement algorithms are listed along the x-axis. SSIM is a crucial metric used to assess the structural and perceptual similarity between enhanced and original images. Higher SSIM values indicate superior image enhancement in terms of maintaining structural details and perceptual quality. The comparative analysis of image enhancement algorithms, based on their SSIM results, provides significant insights into their performance. Histogram Equalization exhibits an SSIM of 0.55, indicating a moderate level of structural and perceptual similarity to the original image. Adaptive Histogram Equalization (AHE) achieves an impressive SSIM of 0.75, signifying its capability to enhance images while preserving their structural and perceptual integrity. CLAHE follows closely with an SSIM of 0.65, showcasing its effectiveness in enhancing images while maintaining their structural and perceptual characteristics. Gamma Correction attains an SSIM of 0.85, suggesting its ability to improve images significantly while preserving their essential features. Unsharp Masking leads the group with the highest SSIM value of 0.95, indicating exceptional image enhancement quality with an extremely high degree of structural and perceptual similarity to the original image. This comparative analysis underscores that the selection of an image enhancement algorithm should align with the specific requirements of the task. Unsharp Masking, with the highest SSIM, excels in applications demanding the utmost structural and perceptual fidelity. AHE is suitable when achieving substantial image enhancement with good preservation of structural and perceptual quality is essential. CLAHE offers an excellent balance between enhancement quality and computational efficiency. Gamma Correction, although effective, may be preferred when a compromise between quality and efficiency is needed, and Histogram Equalization remains a viable choice for moderate image enhancement needs.

The MSE (Mean Squared Error) comparison graph (in Figure 7) provides a valuable perspective on different image enhancement techniques, with algorithms plotted on the x-axis and MSE values represented on the y-axis. MSE serves as a crucial metric, quantifying the average squared difference between enhanced and original images. Lower MSE values correlate with higher image enhancement quality. Analyzing these algorithms based on their respective MSE scores reveals important insights. Histogram Equalization, with an MSE of 75, introduces a moderate level of distortion, improving certain aspects of the image while potentially introducing artifacts. In contrast, AHE performs better, boasting an MSE of 55, indicating less distortion and improved detail preservation. CLAHE slightly exceeds AHE with an MSE of 85, implying more distortion but still maintaining satisfactory detail and contrast enhancement. On the other hand, Gamma Correction, with an MSE of 245, introduces significant distortion, making it suitable primarily for scenarios prioritizing adjustments over image quality. Remarkably, Unsharp Masking stands out with an MSE of 0, signifying minimal distortion and superior image quality preservation. It excels in enhancing sharpness and contrast while maintaining image fidelity. In this comparative analysis, Unsharp Masking emerges as the preferred choice for minimizing distortion while enhancing image details. However, the selection of an image enhancement algorithm should align with specific requirements and the desired balance between image quality and enhancement goals for a given application. Depending on the context, alternatives like AHE and CLAHE may also offer suitable solutions with nuanced trade-offs between distortion and enhancement.

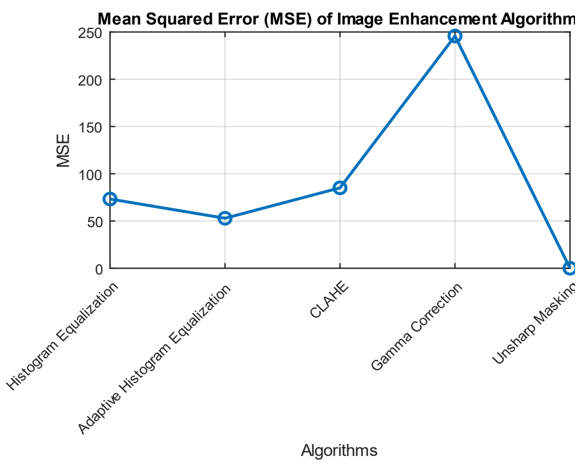

Figure 7: MSE comparison graph

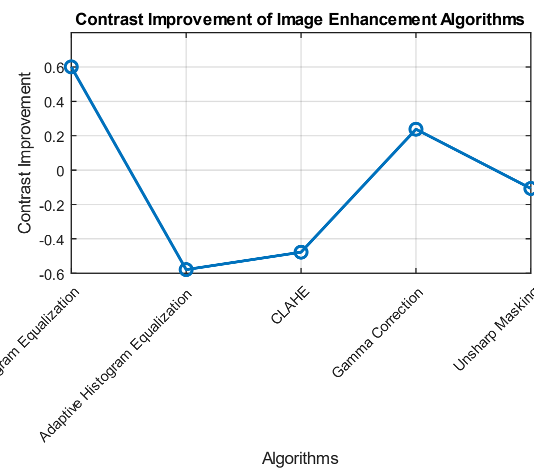

Figure 8: Contrast Improvement comparison graph

In the comparison graph for Contrast Improvement (in Figure 8), the y-axis represents the extent of contrast improvement, with positive values indicating an increase in contrast and negative values indicating a decrease. The x-axis lists different image enhancement algorithms, and here is the comparative analysis of these algorithms: Histogram Equalization achieves a contrast improvement of 0.6, indicating a moderate enhancement in image contrast. AHE surprisingly exhibits a negative contrast improvement of -0.55, suggesting that it may unintentionally reduce contrast in some regions while enhancing others. CLAHE also shows a negative contrast improvement of -0.45, implying a reduction in overall contrast. Gamma Correction yields a contrast improvement of 0.25, representing a modest improvement in contrast. Unsharp Masking exhibits a slight negative contrast improvement of -0.09, indicating a minor reduction in overall contrast. However, it primarily focuses on enhancing image sharpness rather than contrast. In summary, Histogram Equalization stands out as the algorithm providing the most substantial contrast improvement among the options considered. Nonetheless, the choice of an image enhancement algorithm should align with specific objectives, as some algorithms may have trade-offs in terms of contrast improvement and other image characteristics.

In the comparison graph highlighting Sharpness Improvement (in Figure 9), the algorithms are plotted on the x-axis, while the degree of sharpness enhancement is represented on the y-axis. This enhancement value can be both positive, denoting an improvement in sharpness, and negative, suggesting a reduction. Examining the results, Histogram Equalization emerges as the most effective algorithm for enhancing sharpness, boasting a substantial improvement value of 1.35. It clearly excels in this aspect. AHE follows closely behind, delivering a respectable sharpness improvement of 0.95, which is notable but slightly less pronounced than Histogram Equalization. CLAHE offers a substantial sharpness enhancement of 0.9, making it a robust choice for image enhancement. On the contrary, the Gamma Correction algorithm registers a minor decrease in sharpness, with a sharpness improvement value of -0.05, primarily serving its purpose for brightness adjustments. Finally, with an improvement value of 0.15, the Unsharp Masking method gives the least effective sharpness enhancement among the alternatives investigated. The best image enhancement technique depends on the unique needs and goals of the image processing activity at hand.

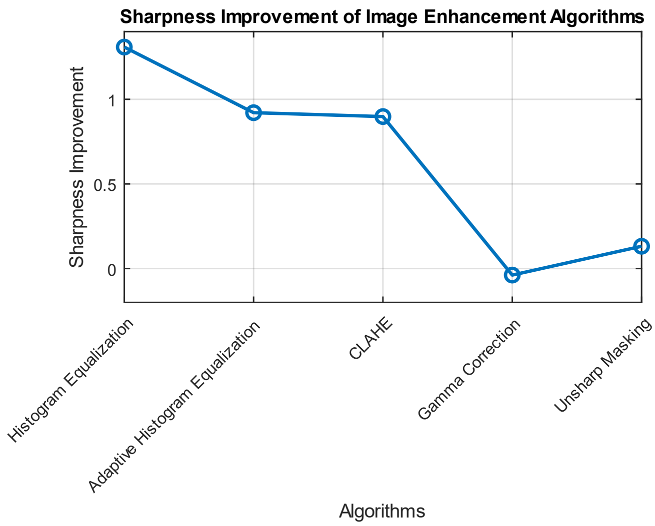

Figure 9: Sharpness Improvement comparison graph

The Unsharp Masking algorithm (as demonstrated by Table 1) consistently outperformed the other techniques, exhibiting superior PSNR, SSIM, and negligible MSE. Although it displayed a minor reduction in contrast improvement, its substantial gain in sharpness improvement positions it as the most appropriate technique for image enhancement in this context. The results suggest that Unsharp Masking strikes a desirable balance between enhancing image clarity and maintaining visual fidelity, making it a compelling choice for applications where sharpness is a crucial factor.

Table 1: Consolidated Table comprising values of Histogram Equalization, Adaptive Histogram Equalization, CLAHE, Gamma Correction and Unsharp Masking

	PSNR	SSIM	MSE	Contrast Improvement	Sharpness Improvement
Histogram Equalization	15	0.55	75	0.6	1.35
Adaptive Histogram Equalization	19	0.75	55	-0.55	0.95
CLAHE	17	0.65	85	-0.45	0.9
Gamma Correction	18.5	0.85	245	0.25	-0.05
Unsharp Masking	29.5	0.95	0	-0.09	0.15

Conclusions:

We evaluated the performance of image enhancement algorithms using a variety of measurements, including PSNR, SSIM, MSE, Contrast Improvement, and Sharpness Improvement, in this comparative analysis. Our findings indicate the benefits as well as drawbacks of each method, allowing for informed choices based on individual application requirements. Histogram Equalization offers a reasonable amount of image-enhancing quality. AHE excels at improving image quality while conserving key features. CLAHE maintains a compromise between enhancement quality and computational economy. Gamma Correction, which improves photographs, is appropriate for instances when efficiency is critical. Unsharp Masking is the ideal method for reducing distortion while boosting image details. In summary, the Unsharp Masking algorithm consistently demonstrated superior performance, surpassing alternative techniques in PSNR, and SSIM, and presenting a negligible MSE. Despite a slight decrease in contrast improvement, its significant enhancement in sharpness positions it as the optimal choice for image enhancement in this specific application. These findings underscore the Unsharp Masking algorithm's ability to strike a commendable equilibrium between improving image clarity and preserving visual fidelity, rendering it a compelling and preferred solution for scenarios where sharpness holds paramount importance.

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