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Evaluation of Intensity Transformation and Histogram-Based Methods for Image Enhancement

Adhitya Januarizky Hadi Putra[1].
[1]Department of Computer Science, Universitas Nusa Mandiri, Depok, Indonesia

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ABSTRACT

Digital image enhancement is an important process in image processing because it improves visual quality and supports further image analysis. Images captured by digital devices often suffer from degradation caused by sensor limitations, uneven illumination, low contrast, and non-uniform intensity distribution. This study evaluates several grayscale image enhancement techniques based on intensity transformation and histogram analysis using an interactive Python-based application. The methods include image negative transformation, power-law transformation (gamma correction), gray level slicing, histogram equalization, histogram matching, and Contrast Limited Adaptive Histogram Equalization (CLAHE). Evaluation was performed through visual comparison, histogram analysis, and quantitative measurements, including mean intensity, entropy, Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), standard deviation, and Contrast Improvement Index (CII). The dataset consisted of six standard grayscale images from the Gonzalez and Woods image database: Lena, Cameraman, Boat, House, Peppers, and Baboon. All images were converted to grayscale and resized to 512 × 512 pixels.The results show that each method has different characteristics depending on the image condition. Histogram equalization effectively enhances global contrast but may cause over-enhancement. CLAHE provides more stable local contrast improvement and preserves image details. Power-law transformation offers flexible brightness adjustment, while gray level slicing highlights specific intensity ranges. The developed application supports real-time parameter adjustment and visualization of processed images, histograms, and evaluation metrics, providing an effective framework for image enhancement analysis and learning digital image processing

Corresponding Author:
Adhitya Januarizky Hadi Putra,
Department of Computer Science,
Universitas Nusa Mandiri,
Jl. Sepakat Raya, RT.002/RW.001, Jatirasa, Kec. Jatiasih, Kota Bks, Jawa Barat 17424,
Email: adhitya.januarizky93@gmail.com

INTRODUCTION

Digital image processing has become an important component in various fields, including computer vision, remote sensing, security systems, multimedia applications, and automated visual inspection. In many practical cases, digital images acquired through digital devices do not always have optimal visual quality. Image degradation may occur due to sensor limitations, uneven illumination, environmental conditions, low contrast, noise, or inappropriate intensity distribution.

Image enhancement is one of the fundamental stages in digital image processing. Enhancement techniques do not necessarily recover the original physical condition of an image.

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Intensity transformation is a basic spatial domain technique that directly maps the original pixel intensity into a new intensity value. Several commonly used intensity transformation methods include image negative transformation, power-law transformation or gamma correction, and gray level slicing. Image negative transformation reverses intensity values so that dark areas become bright and bright areas become dark.

In addition to intensity transformation, histogram-based methods are also widely applied for image enhancement. A histogram represents the frequency distribution of gray levels in an image. By analyzing the histogram, image contrast and intensity spread can be observed more objectively. Histogram equalization is a common technique used to improve global contrast by redistributing intensity values across the available gray-level range. However, this method may produce excessive contrast enhancement in certain image conditions. Histogram matching is used to transform the histogram of a source image so that it resembles the histogram of a reference image.

Several previous studies have shown that image enhancement is widely used to improve visual quality, contrast readability, and structural visibility before further image analysis. Enhancement methods can be implemented through intensity transformation, spatial-domain processing, histogram modification, and adaptive local enhancement approaches (Acharya & Ray, 2005; Liu et al., 2019; Simon & Rosenfeld, 1980; Vyas et al., 2018). However, image enhancement remains a context-dependent process because one method may improve brightness or contrast but may also reduce naturalness, structural similarity, or local detail preservation (Arora et al., 2018; Puniani & Arora, 2015; Qi et al., 2022; Suganya, 2013). Previous studies have discussed the effectiveness of intensity transformation and histogram-based enhancement methods for improving visual quality, contrast distribution, and structural visibility in digital images.(Pizer et al., 1990)

Classical image processing references explain that contrast enhancement strongly depends on image characteristics and the selected transformation function. Histogram equalization is effective for images with narrow intensity distribution, but it can generate over-enhancement when applied to images with complex intensity variations. Histogram equalization remains one of the most commonly used contrast enhancement methods because of its simplicity and computational efficiency. Nevertheless, conventional histogram equalization may cause brightness shift, washed-out appearance, over-enhancement, artifact introduction, or loss of structural details when applied globally to images with complex intensity distributions (Ayaz & Shehryar, n.d.; Das, 2015; Dyke & Hormann, n.d., 2023; Kim, 1997; Mustafa et al., 2018). CLAHE is considered more adaptive because it enhances local regions and limits excessive contrast amplification. However, many previous discussions still present these methods separately as mathematical concepts, algorithmic procedures, or individual enhancement techniques. Integrated and interactive evaluation that combines multiple enhancement methods, histogram visualization, and objective image quality metrics remains useful, especially for educational and introductory experimental purposes. CLAHE was included because it applies adaptive local contrast enhancement by processing image regions or tiles and limiting excessive contrast amplification using a clip limit parameter. Previous studies show that CLAHE can improve local detail visibility more effectively than global histogram equalization, although its performance is affected by parameter selection such as clip limit and tile grid size (Journal et al., 2022; Lee et al., 2015; Mohammed, 2025; Pizer et al., 1990).

An interactive application can help users understand image enhancement methods more intuitively. Through real-time parameter adjustment and direct visualization, users can observe how changes in gamma value, selected intensity range, histogram equalization, histogram matching, and CLAHE parameters affect image appearance and intensity distribution. This approach is useful not only for practical image processing experiments but also for learning digital image processing concepts. Therefore, this study develops and evaluates an interactive Python-based application that integrates several image enhancement methods, histogram visualization, and quantitative evaluation (Wang & Bovik, 2005).

The novelty of this study does not lie in proposing a new image enhancement algorithm, since intensity transformation and histogram-based methods have been widely established in digital image processing literature. Instead, the main contribution of this study is the development of an integrated comparative evaluation framework through an interactive Python-based application. The proposed framework combines multiple enhancement methods, real-time parameter exploration, side-by-side visual comparison, histogram visualization, and objective quality metrics, including mean intensity, entropy, Mean Squared Error, Peak Signal-to-Noise Ratio, Structural Similarity Index, standard deviation, and Contrast Improvement Index. This integration provides a structured experimental environment that supports introductory image enhancement analysis and educational understanding of the relationship between transformation parameters, histogram distribution, and visual image quality.
Based on this background, the objectives of this study are: (1) to evaluate the visual and statistical effects of intensity transformation and histogram-based enhancement methods on grayscale images; (2) to compare the characteristics of each method using

histogram distribution and objective quality metrics; and (3) to develop an interactive Python-based application that supports parameter exploration, visualization, and comparative analysis for digital image processing learning

RESEARCH METHOD

Research Design

This study used an experimental research design with qualitative and quantitative evaluation approaches. The qualitative approach was conducted through visual comparison between original and enhanced images, while the quantitative approach was performed using histogram analysis and objective image quality metrics. The study focused on grayscale image enhancement because grayscale images provide a direct representation of pixel intensity values and simplify the analysis of contrast, brightness, and histogram distribution. The research procedure consisted of several stages, namely image acquisition, preprocessing, implementation of enhancement methods, visualization of enhancement results, histogram analysis, quantitative evaluation, and comparative analysis. All processes were implemented using a Python-based interactive application. The application allows users to load images, select enhancement methods, adjust parameters, display processed images, visualize histograms, and calculate quantitative indicators.

Dataset

The dataset used in this study consisted of six standard grayscale images obtained from the Gonzalez and Woods digital image processing image database. The images used in this study were Lena, Cameraman, Boat, House, Peppers, and Baboon. These images are commonly used as benchmark images in digital image processing experiments because they provide different intensity, contrast, texture, and structural characteristics.

The six images were selected to represent diverse visual characteristics required to evaluate grayscale image enhancement methods. Lena was used to observe smooth intensity transition and facial detail preservation. Cameraman was used to evaluate object boundary visibility and dark-region enhancement. Boat was used to analyze natural texture and moderate contrast. House was used to evaluate structural detail and edge visibility. Peppers was used to observe global contrast enhancement on object-based images. Baboon was used to evaluate enhancement performance on complex texture and local detail.

The use of the Gonzalez and Woods image database was intended to support reproducibility and allow consistent comparison among enhancement methods. Before preprocessing, the images had different original dimensions depending on the source file. To ensure experimental consistency, all images were converted into grayscale format and resized to 512 × 512 pixels. The selection criteria included image diversity, variation in intensity distribution, object structure visibility, texture complexity, and suitability for evaluating both intensity transformation and histogram-based enhancement methods.

Table 1. Dataset Description

No	Image	Source	Main Characteristic	Testing Purpose
1	Lena	Gonzalez and Woods Image Database	Smooth intensity transition and facial details	Histogram equalization and global contrast evaluation
2	Cameraman	Gonzalez and Woods Image Database	Clear object boundary and dark regions	Gray level slicing and structural emphasis evaluation
3	Boat	Gonzalez and Woods Image Database	Natural texture and moderate contrast	Gray level slicing and structural emphasis evaluation
4	House	Gonzalez and Woods Image Database	Object structure and edge details	CLAHE and structural detail evaluation
5	Peppers	Gonzalez and Woods Image Database	Moderate texture and object variation	Histogram equalization and contrast distribution evaluation
6	Baboon	Gonzalez and Woods Image Database	Complex texture and local details	CLAHE and local texture enhancement evaluation

Preprocessing

Preprocessing was performed to ensure that all images had a consistent format and size before the enhancement stage. This stage aimed to reduce external variables that could affect the experimental results. Three preprocessing steps were applied in this study.

First, RGB images were converted into grayscale images. Grayscale conversion was performed because the methods evaluated in this study operate on intensity values. By using a single-channel grayscale representation, the analysis focused on gray-level distribution rather than color components. Second, all images were resized into a standard resolution of 512 × 512 pixels. Image resizing was required to ensure that each method was tested under comparable resolution conditions. This step also simplified histogram computation and quantitative evaluation. Third, pixel values were represented in the standard 8-bit grayscale range from 0 to 255. The pixel data type was converted into unsigned 8-bit integer format to ensure compatibility with OpenCV and the quantitative evaluation process.

Image Enhancement Methods

The enhancement methods evaluated in this study were divided into two groups: intensity transformation methods and histogram-based methods. The intensity transformation methods consisted of image negative transformation, power-law transformation, and gray level slicing. These methods were included because they directly modify pixel intensity values and are suitable for evaluating grayscale image behavior. Image negative transformation reverses pixel intensity values, while power-law transformation or gamma correction adjusts brightness through nonlinear mapping. Gray level slicing emphasizes selected intensity ranges and is useful for highlighting specific gray-level regions (Acharya & Ray, 2005; Baidoo, 2018; Rahman et al., 2016).

The histogram-based methods consisted of histogram equalization, histogram matching, and CLAHE. These methods were included because they modify the intensity distribution of an image. Histogram equalization improves global contrast by redistributing gray-level values, while histogram matching adjusts the input image distribution according to a reference histogram. However, the effectiveness of histogram matching depends on the suitability of the reference image distribution (Chen & Chen, 2015; Çiftçi, 2025; Saravanan & Siva, 2015).

Image negative transformation reverses the intensity value of each pixel. If the original pixel intensity is represented by r and the maximum intensity level is $L - 1$, the transformed intensity s can be expressed as:

$$s = L - 1 - r \quad (1)$$

where s is the output intensity, r is the input intensity, and L represents the number of gray levels. For an 8-bit grayscale image, L = 256, so the maximum intensity value is 255. This transformation is useful for enhancing details in images with dark backgrounds or images where bright objects need to be visually inverted.

Power-law transformation, also known as gamma correction, is used to adjust image brightness by applying a nonlinear mapping function. The transformation is expressed as:

$$s = cr^{\gamma} \quad (2)$$

where s is the output intensity, r is the normalized input intensity, c is a scaling constant, and γ is the gamma value. If γ is less than 1, the image becomes brighter. If γ is greater than 1, the image becomes darker. In this study, the gamma value was set to 0.5 for the main experiment to improve visibility in darker regions.
Gray level slicing is used to emphasize a specific range of intensity values. Pixels within a selected intensity range are highlighted, while pixels outside the range are either suppressed or preserved. This method is useful for detecting or emphasizing objects that occupy a particular gray-level interval. In this study, the selected intensity range was set from 80 to 180.

Histogram equalization improves global contrast by redistributing gray-level values across the available intensity range. This method uses the cumulative distribution function of the original histogram to map pixel values into new intensity values. Histogram equalization is particularly effective for images with narrow intensity distribution. However, in some cases, it may produce over-enhancement or reduce local detail visibility. Histogram matching adjusts the intensity distribution of a source image so that it follows the distribution of a reference image. Unlike histogram equalization, which attempts to spread intensity values uniformly, histogram matching depends on the histogram characteristics of the selected reference image. This method is useful when the objective is to standardize the visual appearance of several images.

Contrast Limited Adaptive Histogram Equalization, or CLAHE, is an adaptive enhancement technique that applies histogram equalization locally to small regions of an image. CLAHE limits contrast amplification using a clip limit parameter to prevent excessive noise enhancement. In this study, the clip limit was set to 2.0 and the tile grid size was set to 8 × 8 pixels. CLAHE is particularly suitable for images with uneven illumination and fine local structures.

Interactive Application Design

The interactive application was developed using Python, OpenCV, NumPy, Matplotlib, PIL, and Tkinter. The application interface provides several main functions, including loading the original image, loading the reference image for histogram matching, selecting the enhancement method, adjusting the gamma value, displaying the original and processed images, visualizing histograms, and calculating quantitative values.

The workflow of the application begins with image input. The image is then converted into grayscale format and resized into a standard resolution. After preprocessing, the user selects an enhancement method through the application interface. The selected method is applied to the grayscale image, and the result is displayed together with its histogram and quantitative values. The user can adjust selected parameters in real time and observe the effect of each parameter on image quality.

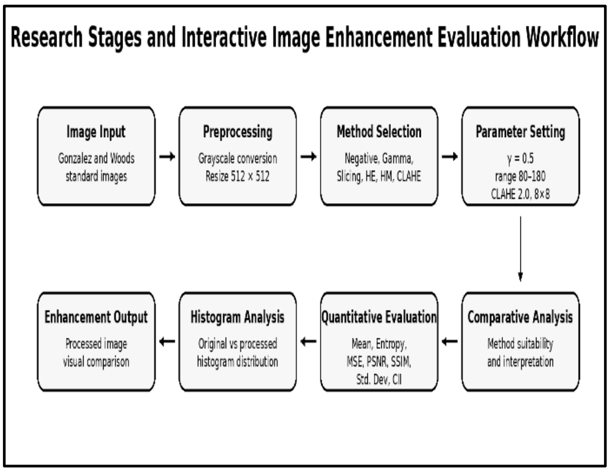

Figure 1 shows the research stages and workflow of the proposed interactive image enhancement evaluation system.

Experimental Parameters and Reproducibility

To improve reproducibility, the experimental environment and parameter settings were defined consistently for all test images. All images were processed using the same preprocessing procedure and evaluated using the same quantitative metrics. The main experiment used fixed parameters, while the interactive application also allowed users to adjust selected parameters in real time for exploratory analysis.

Table 2. Experimental Parameters and Reproducibility Details

Component	Specification
Programming language	Python 3.x
Image processing library	OpenCV 4.x
Numerical computation	NumPy
Visualization	Matplotlib
GUI framework	Tkinter
Image handling	PIL / Pillow
Image format	8-bit grayscale
Standard image size	512 × 512 pixels
Gamma value	0.5
Gray level slicing range	80–180
CLAHE clip limit	2.0
CLAHE tile grid size	8 × 8
Parameter strategy	Fixed parameters for the main experiment; interactive adjustment available in the application
Operating system	Windows 11
Hardware	Intel Core Ultra 9 185H (22CPU) RAM 32 GB
Source code availability	Public GitHub repository: https://github.com/Adhitya-Januarizky-Hadi-Putra/Interactive-Image-Enhancement-App

To support reproducibility, the source code of the interactive Python-based image enhancement application is available in a public GitHub repository: https://github.com/Adhitya-Januarizky-Hadi-Putra/Interactive-Image-Enhancement-App.

Evaluation Metrics

The evaluation was conducted using visual comparison, histogram analysis, and objective image quality metrics. Visual comparison was used to observe brightness, contrast, object visibility, and detail preservation. Histogram analysis was used to examine intensity distribution before and after enhancement. Quantitative evaluation was performed using mean intensity, entropy, Mean Squared Error, Peak Signal-to-Noise Ratio, Structural Similarity Index, standard deviation, and Contrast Improvement Index.

Objective evaluation metrics were used to reduce subjectivity in visual assessment. MSE and PSNR were used to measure pixel-level differences and reconstruction quality, while SSIM was used to evaluate structural similarity between the original and enhanced images. SSIM considers luminance, contrast, and structural components, where a value closer to 1 indicates stronger similarity between images (Grigoryan & Agaian, 2004; Rabeya et al., 2025). Standard deviation was used as a contrast indicator, entropy was used to observe information distribution, and CII was used to measure contrast improvement after enhancement(Arora et al., 2018; Grigoryan & Agaian, 2004; Mohammed, 2025; Puniani & Arora, 2015).

Mean intensity was used to measure the average brightness level of an image. It is calculated as:

$$\mu = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N} I\,(x, y) \qquad (3)$$

where $I(x, y)$represents the intensity value at coordinate (x, y), M is the image height, and N is the image width.
Entropy was used to observe the complexity and variation of intensity distribution. It is calculated as:

$$H = -\sum_{i=0}^{L-1} p\,(i) \log_2 p\,(i) \quad (4)$$

where p(i) is the probability of the i-th gray level and L is the number of gray levels.

Mean Squared Error measures the average squared difference between the original image and the enhanced image. It is calculated as:

$$MSE = \frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} [I(x, y) - K(x, y)]^2 \quad (5)$$

where $I(x, y)$is the original image and $K(x, y)$ is the enhanced image.

Peak Signal-to-Noise Ratio measures the quality level of the enhanced image based on the MSE value. It is calculated as:

$$PSNR = 10 \log_{10} \left(\frac{MAX_I^2}{MSE} \right) \quad (6)$$

where MAXI is the maximum possible pixel value. For 8-bit grayscale images, MAXI = 255.

Structural Similarity Index measures the structural similarity between the original image and the enhanced image. It is calculated as:

$$SSIM(x, y) = \frac{(2\mu_x \mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (7)$$

where μx and μy are the mean values, σx^2 and σy^2 are the variances, and σxy is the covariance between the original and enhanced images.

Standard deviation was used as a contrast indicator. It is calculated as:

$$\sigma = \sqrt{\frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} [I(x, y) - \mu]^2} \quad (8)$$

Contrast Improvement Index was used to measure the degree of contrast improvement after enhancement. It is calculated as:

$$CII = \frac{C_{enhanced}}{C_{original}} \quad (9)$$

where Cenhanced is the contrast value after enhancement and Coriginal is the contrast value before enhancement.
These metrics were not interpreted separately, but were analyzed together with visual observation and histogram distribution. This approach was used because a single metric cannot fully represent image enhancement quality. For example, an increase in mean intensity may indicate a brighter image, but it does not always indicate better contrast. Similarly, a higher contrast value may improve visual separation but may also reduce structural similarity if over-enhancement occurs.

RESULTS AND DISCUSSION

Dataset Description

The dataset consisted of six grayscale images with various contrast, texture, and illumination characteristics. Lena, Boat, and Peppers were used to evaluate global contrast enhancement because they contain smooth intensity transitions and moderate texture details. Cameraman and House were used to evaluate structural emphasis because they contain distinct object boundaries and visible edge structures. Baboon was used to evaluate local detail enhancement because it contains complex texture and dense local patterns.
All images were converted into grayscale format and resized to 512 × 512 pixels before enhancement. This preprocessing ensured that all methods were applied to images with identical format and comparable resolution. The use of standard grayscale images from the Gonzalez and Woods image database also allowed histogram distribution and quantitative values to be compared consistently

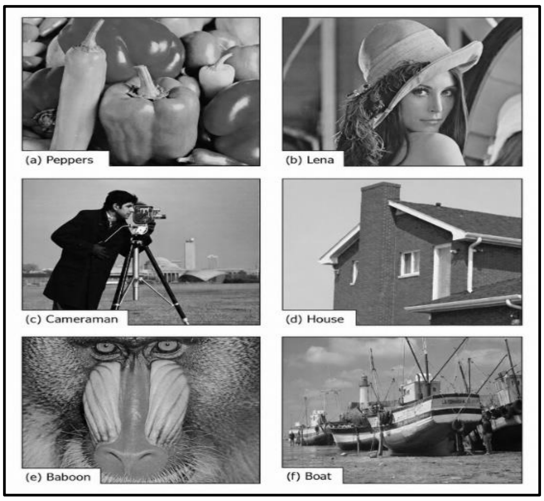

Figure 2. Examples of test images used in the experiment after grayscale conversion and resizing.

Figure 2 illustrates the six standard grayscale test images used in this study, namely Peppers, Lena, Cameraman, House, Baboon, and Boat. These images were selected because they represent different visual characteristics, including smooth intensity transition, object boundary visibility, natural texture, structural detail, complex local texture, and moderate contrast. The image diversity supports objective evaluation of intensity transformation and histogram-based enhancement methods.

Performance of Intensity Transformation Methods

The results show that intensity transformation methods produce different effects depending on the characteristics of the original image. Image negative transformation does not directly improve contrast in the statistical sense. Instead, it reverses intensity values, making bright regions dark and dark regions bright. This method is useful for visualization purposes, particularly in images with dominant dark regions or strong intensity inversion needs. However, image negative transformation does not necessarily increase image information complexity because the distribution of intensity values is only inverted.

Power-law transformation provides flexible brightness adjustment. With the gamma value set to 0.5, darker regions become brighter, and hidden details in low-intensity areas become more visible. This result indicates that gamma correction is effective for images with insufficient brightness or smooth intensity gradation. However, inappropriate gamma values may cause excessive brightness or loss of detail in bright regions. Therefore, gamma correction requires careful parameter selection based on the initial image condition.

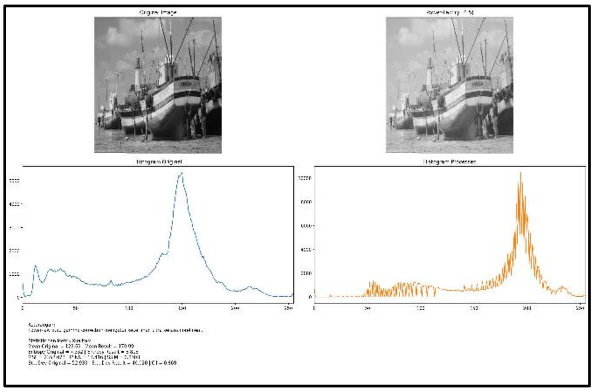

Figure 3. Visual comparison of the original Boat image and power-law transformation resul
t using $\gamma = 0.5$.

Figure 3 shows that power-law transformation improves the visibility of darker image regions in the Boat image. The method shifts the intensity distribution toward brighter values and increases visual brightness without completely changing the main structural information of the image. This result supports the role of gamma correction as a brightness adjustment technique.

Gray level slicing emphasizes specific intensity ranges. In this study, the intensity range of 80 to 180 was used to highlight object structures located within the selected gray-level interval. This method is useful for emphasizing specific objects or regions, but it is less suitable for general contrast enhancement because values outside the selected range are suppressed or not emphasized.

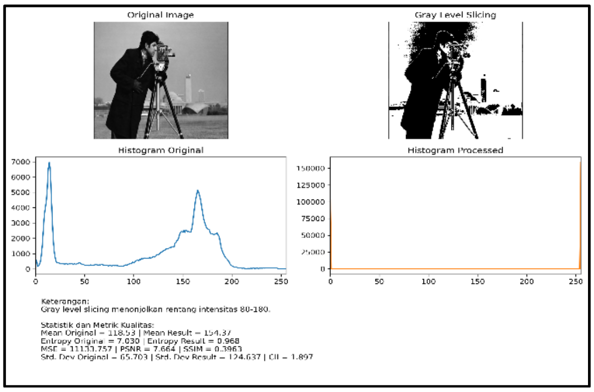

Figure 4. Visual comparison between the original Cameraman image and gray level slicing result using the intensity range 80–180.

Figure 4 shows that gray level slicing emphasizes selected intensity regions in the Cameraman image. The method highlights object structures within the specified gray-level interval and makes certain boundaries more visible. This result indicates that gray level slicing is more appropriate for feature emphasis than for general image quality enhancement.

Performance of Histogram-Based Methods

Histogram equalization produced a significant improvement in global contrast. Images with narrow intensity distribution became visually clearer after the intensity values were redistributed across a wider gray-level range. The histogram after equalization showed a more distributed intensity pattern compared with the original histogram. This result confirms that histogram equalization is effective for enhancing low-contrast images. Histogram equalization is widely used for global contrast enhancement because of its simplicity and ease of implementation. However, conventional histogram equalization may cause brightness shift, over-enhancement, artifact introduction, and loss of structural details (Ayaz & Shehryar, n.d.).

However, the experiment also showed that histogram equalization may produce over-enhancement. In images that already contain strong intensity variation, global equalization may exaggerate contrast and reduce local detail visibility. This limitation indicates that histogram equalization is not always suitable for all image types.

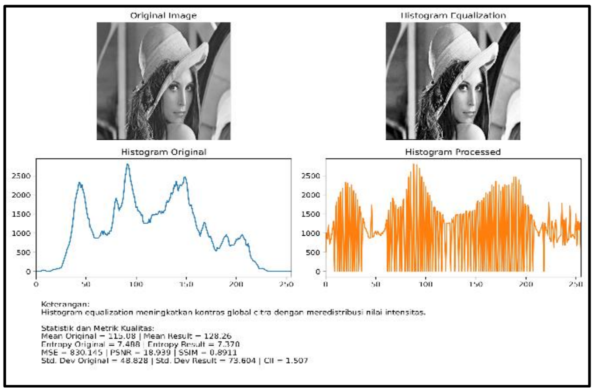

Figure 5. Visual comparison between the original Lena image and histogram equalization result.

Figure 5 demonstrates the effect of histogram equalization on the Lena image. The processed image shows clearer separation between dark and bright regions because the intensity values are redistributed across a wider gray-level range. This confirms that histogram equalization is effective for improving global contrast, although excessive redistribution may reduce natural appearance in some local regions.

CLAHE produced more stable results than global histogram equalization, especially for images with local structural details. Because CLAHE works on smaller image regions, it enhances local details without forcing the entire image histogram into one global distribution. The clip limit parameter prevents excessive contrast amplification and reduces the risk of noise enhancement.

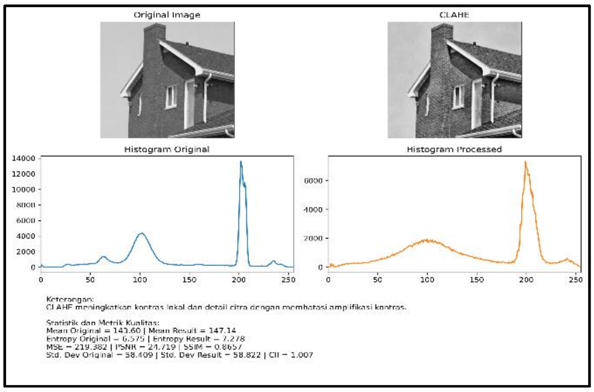

Figure 6. Visual comparison between the original House image and CLAHE result using clip limit 2.0 and tile grid size 8 × 8.

Figure 6 shows that CLAHE improves local contrast in the House image while preserving structural details. Compared with global histogram equalization, CLAHE produces a more controlled enhancement effect because it operates on smaller image regions and limits excessive contrast amplification. This makes CLAHE suitable for images with edge structures and local detail variation.

Histogram matching produced results that strongly depended on the reference image. When the reference image had similar visual characteristics to the source image, histogram matching successfully adjusted the appearance of the source image. However, when the reference image had significantly different intensity distribution, the result could appear unnatural. Therefore, reference image selection is a critical factor in histogram matching.

Histogram Distribution Analysis

Histogram analysis was conducted to observe changes in gray-level distribution after enhancement. The original images generally showed uneven histogram distribution, with intensity values concentrated in certain ranges. Such distribution indicates limited contrast and reduced visibility of image details.

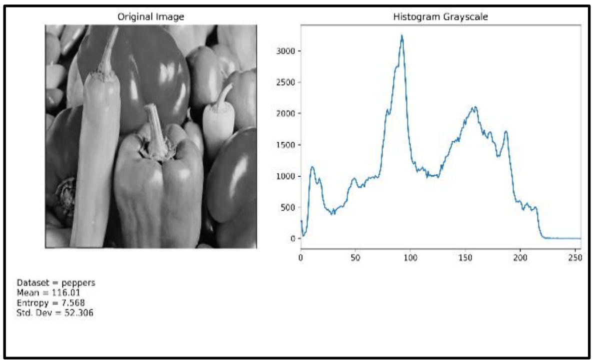

Figure 7. Histogram distribution of the original Peppers image before enhancement.

Figure 7 shows the histogram distribution of the original Peppers image before enhancement. The intensity values are concentrated in certain gray-level ranges, indicating that the image has limited contrast distribution. This provides the basis for evaluating how enhancement methods modify the intensity distribution.

After enhancement, histogram distribution may change depending on the selected method. Histogram equalization tends to redistribute intensity values globally, while CLAHE enhances intensity distribution more adaptively in local regions. Power-law transformation changes the histogram shape based on the gamma value by shifting intensity values toward darker or brighter ranges.

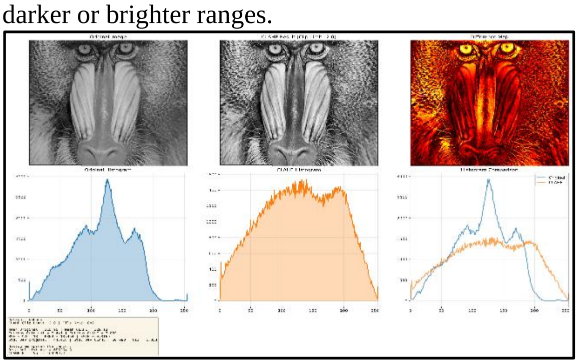

Figure 8. Histogram distribution
of the Baboon image after CLAHE enhancement.

Figure 8 shows the histogram distribution of the Baboon image after CLAHE enhancement. The intensity values are redistributed more adaptively across local regions, indicating improved local contrast without excessive global intensity spreading. This supports the suitability of CLAHE for texture-rich images with dense local patterns.

Quantitative Evaluation

Quantitative evaluation was conducted using mean intensity, entropy, Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), standard deviation, and Contrast Improvement Index (CII). Mean intensity was used to observe brightness changes, while entropy was used to observe the variation of intensity distribution. MSE and PSNR were used to measure pixel-level differences between the original and enhanced images. SSIM was used to evaluate structural similarity, standard deviation was used as a contrast indicator, and CII was used to measure the degree of contrast improvement after enhancement.

Table 3. Mean Intensity and Entropy Comparison

No	Dataset	Method	Mean Original	Mean Result	Entropy Original	Entropy Result
1	Lena	Histogram Equalization	115.08	128.26	7.488	7.370
2	Cameraman	Gray Level Slicing	118.53	154.37	7.030	0.968
3	Boat	Power-Law, γ = 0.5	123.69	170.99	7.332	6.815
4	House	CLAHE	143.60	147.14	6.575	7.278
5	Peppers	Histogram Equalization	116.01	128.15	7.568	7.431
6	Baboon	CLAHE	115.95	129.13	7.441	7.859

Table 4. Quantitative Evaluation Using MSE, PSNR, SSIM, Standard Deviation, and CII

No	Dataset	Method	MSE	PSNR	SSIM	Std. Dev Original	Std. Dev Result	CII
1	Lena	Histogram Equalization	830.145	18.939	0.8911	48.828	73.604	1.507
2	Cameraman	Gray Level Slicing	11133.757	7.664	0.3963	65.703	124.637	1.897
3	Boat	Power-Law, γ = 0.5	2352.073	14.416	0.8703	52.930	46.020	0.869
4	House	CLAHE	219.382	24.719	0.8657	58.409	58.822	1.007
5	Peppers	Histogram Equalization	664.565	19.905	0.9093	52.306	73.705	1.409
6	Baboon	CLAHE	926.218	18.464	0.8169	44.418	60.090	1.353

The quantitative results show that each enhancement method produces different numerical characteristics depending on the dataset and transformation method. Power-law transformation with γ = 0.5 increased the mean intensity of the Boat image from 123.69 to 170.99, indicating that gamma correction effectively improves image brightness. However, the CII value decreased to 0.869, which indicates that brightness enhancement does not always increase contrast.

Gray level slicing on the Cameraman image produced the highest MSE value and the lowest SSIM value among the evaluated methods. This result is expected because gray level slicing strongly modifies pixel distribution by emphasizing only the selected intensity range of 80–180. Therefore, this method is more suitable for feature emphasis than for general image quality enhancement.

Histogram equalization increased the standard deviation and CII values in both Lena and Peppers images. This indicates that global contrast was improved by redistributing intensity values across a wider gray-level range. However, the entropy values slightly decreased, showing that higher contrast does not always correspond to higher intensity complexity.

CLAHE produced more controlled enhancement results on House and Baboon images. The House image showed a relatively stable CII value of 1.007, while the Baboon image showed an increased CII value of 1.353 and higher entropy after enhancement. These results indicate that CLAHE is effective for improving local contrast, especially in images with structural details and complex texture.

Overall, the quantitative evaluation confirms that image enhancement quality cannot be judged using only one metric. Mean intensity, entropy, MSE, PSNR, SSIM, standard deviation, and CII should be interpreted together with visual observation and histogram analysis to obtain a more reliable evaluation.

Comparative Analysis of Enhancement Methods

The comparative analysis shows that no single enhancement method performs best for all image conditions. Each method has specific characteristics, advantages, and limitations depending on the image structure, intensity distribution, texture complexity, and selected parameters.

Image negative transformation is suitable for visual inversion and detail observation in images with dominant dark regions. However, this method does not directly improve global contrast or information complexity because it only reverses the intensity values. Power-law transformation is effective for brightness correction. In this study, the use of γ = 0.5 increased the brightness of the Boat image, as indicated by the increase in mean intensity. However, the decrease in CII shows that brightness adjustment does not always improve contrast.

Gray level slicing is useful for emphasizing specific intensity regions. The result on the Cameraman image shows that this method can highlight selected structures using the intensity range of 80–180. However, because many pixel values outside the selected range are suppressed, this method may produce higher MSE and lower SSIM. Therefore, gray level slicing is more appropriate for feature emphasis than for general image quality enhancement.

Histogram equalization is effective for improving global contrast, especially in images with limited intensity distribution. The results on Lena and Peppers show that histogram equalization increased the standard deviation and CII values, indicating stronger contrast distribution. However, global redistribution may also reduce natural appearance or structural similarity in some local regions when over-enhancement occurs.

CLAHE provided a relatively balanced enhancement effect for images with structural details and complex texture. The results on House and Baboon show that CLAHE improved local contrast while limiting excessive contrast amplification. Compared with global histogram equalization, CLAHE is more suitable for images that require local detail preservation. However, its performance still depends on the selected clip limit and tile grid size parameters. Histogram matching is useful when the desired visual appearance is determined by a reference image. Its effectiveness depends strongly on the suitability of the reference histogram. If the reference image has a very different intensity distribution, the output image may appear unnatural. Therefore, reference image selection is an important factor in histogram matching.
Table 5. Comparative Performance of Enhancement Methods

Role of the Interactive Application

The developed interactive application supports a more comprehensive evaluation process. Through the application, users can directly compare original and enhanced images, observe histogram changes, adjust selected parameters, and read quantitative metrics. The parameter control feature allows users to examine how gamma value, gray level slicing range, CLAHE clip limit, and CLAHE tile grid size affect the enhancement results. Python and OpenCV are widely used in image processing implementation because they provide practical functions for grayscale conversion, histogram computation, enhancement operations, visualization, and quantitative image analysis workflows.

From an educational perspective, the application helps students and users understand image enhancement concepts more intuitively. Instead of only studying mathematical formulas, users can directly observe the relationship between transformation functions, parameter changes, histogram distribution, and visual image quality. Therefore, the application functions not only as an experimental tool but also as an interactive learning medium for digital image processing. Python-based image processing applications can support efficient computational workflows because Python provides extensive libraries for image analysis, feature extraction, model development, and validation. Therefore, the use of a Python-based interactive application in this study supports reproducibility and practical implementation of image processing experiments (Jamaluddin et al., 2024).

CONCLUSION

This study evaluated grayscale image enhancement methods based on intensity transformation and histogram-based techniques using an interactive Python-based application. The evaluated methods included image negative transformation, power-law transformation, gray level slicing, histogram equalization, histogram matching, and CLAHE. The evaluation was conducted using visual comparison, histogram analysis, and objective quantitative metrics, including mean intensity, entropy, MSE, PSNR, SSIM, standard deviation, and CII. SSIM was used to evaluate structural similarity between the original and enhanced images because this metric considers luminance, contrast, and structural components. A higher SSIM value indicates that the enhanced image maintains stronger structural similarity with the original image
The results show that each enhancement method has different characteristics depending on the dataset and parameter settings. Power-law transformation with $\gamma = 0.5$ increased the mean intensity of the Boat image from 123.69 to 170.99, indicating that gamma correction is effective for brightness adjustment. Gray level slicing using the intensity range of 80–180 emphasized selected structures in the Cameraman image, but it produced a lower SSIM value because many pixels outside the selected range were suppressed. This confirms that gray level slicing is more suitable for feature emphasis than for general image quality enhancement.

Histogram equalization improved global contrast in Lena and Peppers by increasing the standard deviation and CII values. However, this method may produce over-enhancement when applied to images with complex intensity variation because the redistribution process is performed globally. CLAHE provided more controlled local contrast enhancement in House and Baboon images. The results indicate that CLAHE is suitable for images with structural details and complex texture because it improves local contrast while limiting excessive contrast amplification.

The addition of objective metrics, including MSE, PSNR, SSIM, standard deviation, and CII, strengthens the evaluation by providing a more comprehensive interpretation of image quality. The results also confirm that mean intensity and entropy alone are insufficient to represent enhancement quality comprehensively. Therefore, visual observation, histogram analysis, and objective quantitative metrics should be interpreted together to obtain a more reliable evaluation.

The developed interactive application supports real-time parameter exploration, visual comparison, histogram visualization, and quantitative analysis. The application allows users to observe the effect of gamma value, gray level slicing range, CLAHE clip limit, and tile grid size on the enhancement results. Thus, the application can be used not only as an experimental tool but also as an interactive learning medium for understanding digital image enhancement methods.

Future research may extend the application to color image enhancement, larger and more diverse image collections, domain-specific datasets, and machine learning-based enhancement methods. Further studies may also include additional perceptual quality metrics and user-based evaluation to strengthen the interpretation of visual enhancement results.

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