Empirical Study of Contrast Enhancement Techniques for Handicraft Bell Metal Product Images

***Abstract*:** Handicraft Bell metal products hold great cultural and artistic importance in Assamese society, especially in the Sarthebari region, where they are crafted using traditional techniques passed down through generations.However, studying and classifying images of these intricate products using modern machine learning methods comes with challenges. Variations in pixel intensity, caused by changes in brightness and color during photography, can lower image quality. Additionally, the detailed textures and complex backgrounds of these products make it difficult for computers to separate the main object from its surroundings. A dataset of fifty handicraft bell metal product images was collected directly from production units in Sarthebari area using digital camera. Image pre-processing is essential to increase the model performance. This study examines five contrast enhancement techniques-Histogram Equalization (HE), Adaptive Histogram Equalization (AHE), Unsharp Masking (UM), Contrast Limited Adaptive Histogram Equalization (CLAHE), and Triangular Fuzzy Membership Contrast Limited Adaptive Histogram Equalization (TFM-CLAHE). The performance of these techniques was evaluated using four quantitative metrics: Mean Squared Error (MSE), Signal-to-Noise Ratio (SNR), Peak Signal-to-Noise Ratio (PSNR), and Similarity Index (SI) . The results show that UM and TFM-CLAHE are the most effective methods for enhancing image details while maintaining clarity. These techniques help to highlight the intricate designs of bell metal products, making them useful for automated classification and quality control. By applying these methods, technology can better support the preservation and promotion of this ancient Assamese craft.

Keywords: Handicraft, Bell metal images,Contrast Enhancement, TFM-CLAHE , Performance Metrics.

1. Introduction

Bell metal products are very important in Assamese culture because they come from ancient traditions. In the Sarthebari area of Assam, these products are made on a large scale, and the region is well known for this unique craft. Bell metal items are not only useful, but they also carry deep cultural and artistic values. They are crafted by skilled artisans who use techniques that have been passed down from generation to generation.When it comes to using modern technology, such as machine learning, to study or classify images of these beautiful products, several challenges arise. One of the main issues is that during the process of taking pictures, random changes in the brightness and color of pixels can occur. These changes or variations in pixel intensity, leads to degrade thequality of the image. When the image quality is poor, it becomes much harder for a computer to correctly identify or classify the product.Another challenge is that many bell metal products have very detailed and busy backgrounds. The items themselves often feature intricate textures and complex motifs. These detailed designs, while beautiful to the human eye, can confuse computer systems. The computer might have difficulty distinguishing between the product and its background because both may have similar patterns and colors. This makes the task of automatically classifying these products even more complicated[1,3,6].

Because of these difficulties, it is an utmost important to prepare, or pre-process, the images before they are used in machine learning tasks. Pre-processing means cleaning up the images to improve their quality. This might involve correcting the brightness, reducing the noise from random pixel changes, and making the product stand out more clearly from its background. With better quality images, machine learning systems can more accurately learn the important features of the bell metal products[7].

The process of pre-processing helps to remove the unwanted changes in the image and focuses on the key details that define the product. This is essential not only for classifying the products but also for any further research or automated quality control in manufacturing. By using these techniques, the rich heritage of bell metal craftsmanship can be preserved and promoted in the modern world. In summary, while bell metal products are a treasured part of Assamese society, careful image preparation is a necessary step to ensure that modern technology can appreciate and support this ancient art form[8,9].

Five(05) different contrast enhancement[8] techniques are analyzed in this study such asHistogram Equalization (HE), Adaptive Histogram Equalization (AHE), Unsharp Masking (UM) , Contrast Limited Adaptive Histogram Equalization (CLAHE)[8] and Triangular Fuzzy Membership-Contrast Limited AdaptiveHistogram Equalization (TFM-CLAHE) [10]on Fifty numbers of different handicraft bell metal product images these methods are applied. From the experimental result analysis it is observed that UM and TMF-CLAHE[8,10]emerges as the most effective technique for preprocessing handicraft bell metal product images. It strikes a balance between detail enhancement, making it ideal for highlighting the intricate textures and designs characteristic of these products[8,10].

The structure of the remaining article is outlined as in Section 2, we investigate into a review of previous studies related to contrast enhancement problem. Section 3 & 4 presents the overall motivation , background, and the proposed methodology of the five different techniques. In Section 5, we have presented the experimental results, while Section 6 concludes the paper and outlines direction for future work.

2. Literature Review

Recently, multiple methods for enhancing image contrast have been implemented to assess their usefulness in various areas. Tiwari*et al*.[3] presented a fast histogram equalization method based on quantiles (HSQHE), designed for high-contrast digital images . The effectiveness of the technique in improving contrast is evaluated by PSNR and Entropy measurements.B. SreeVidya *et al*. [10] put up the TFM-CLAHE technique, which improves the image by boosting the contrast and automatically calculating the clip limit based on the input image to reduce noise amplification..Ritika*et al.*[6] did a depth study that compared various image contrast enhancement techniques and comparing these methods and evaluating their suitability for various application fields.Shakeri*et al.* [2] put forward a technique for improving contrast using local histogram equalization, which segments histograms based on density. This process consists of three steps: initially, it predicts the amount of clusters in brightness levels of the image; next, it groups these brightness levels together; ultimately, it enhances contrast for each cluster individually.Lidong*et al.* has suggested a technique called CLAHE-DWT which integrates CLAHE and Discrete Wavelet Transform (DWT) [9]. This algorithm begins by breaking down the initial image into low- and high-frequency parts using DWT in three stages. Next, CLAHE is used on the low-frequency coefficients, with the high-frequency elements remaining unaltered. The enhanced image is reconstructed with the inverse discrete wavelet transform, resulting in a significant contrast enhancement.Parihar*et a*l. [4] introduced a dynamic sub-histogram equalization algorithm based on entropy that improves contrast throughout the full dynamic range. Bora.D *et al* [12] applied a two-phase enhancement method combining a Type-2 fuzzy set-based local contrast enhancement technique with unsharp masking. Their findings indicate that this approach effectively reduces vagueness, improves contrast, and preserves brightness and hue, outperforming traditional and state-of-the-art method . Li.C *etal* [15] found that the deep learning-optimized CLAHE significantly improved image quality, with higher SSIM and PSNR values and reduced LOE compared to standard CLAHE. It also revealed that semantic segmentation and clustering effectively extracted key color features and relationships, enabling the creation of a Suzhou garden color palette generator

3. Background

In this section, some important concepts that are required to understand and implementthe work thoroughly.Image enhancement methods are very important for improving how images look in different fields like medical imaging, photography, and remote sensing. One of the key techniques is contrast enhancement, which helps to make the difference between light and dark areas clearer. This makes it easier to see details in a image. These enhancement techniques play a major role in making images sharper and more detailed, allowing for better analysis and interpretation.[5].

3.1 Histogram Equalization: One popular method for image enhancement that is used to increase contrast in images is histogram equalization.The fundamental idea of this contrast enhancement technique is to distribute pixel values in the specified images more evenly across the whole histogram. A histogram is generated by calculating the pixel frequencies across the entire dynamic range of the input image. The gray level present in the input image are represented by the pixel frequency[6, 8].

3.2 Adaptive Histogram Equalization: Adaptive Histogram Equalization (AHE) is an advanced technique over Histogram Equalization. This technique enhances contrast by working smaller portion known as tiles.In each tile, pixel intensities are adjusted so that the histogram of the portion align more efficiently with a desired distribution.The neighboring tiles are than combined using bilinear interpolation in order to eliminate artificially induced boundaries.In this process,the image can be partitioned into sub portion and enhanced each portion separately, which can help to restore existing details and reduces significant change in gray level. AHE can enhance the details in both areas without over-enhancing one at the expense of the other. However, AHE can sometimes amplify noise in homogeneous regions of the image, which is a drawback that needs to be considered [7, 8].

3.3 Unsharp Masking: Unsharp Masking is widely used to increase the sharpness of an image by enhancing the contrast at the edges. In unsharp masking it makes the edges and detail appear sharper without doing blur to the images. This process uses Gaussian blur to create a blurred or “Unsharp” version of the original image. This blurred image is then subtracted from the original image to isolate the edge details, resulting in an output image where the edges appear more distinct.Unsharp Masking technique is commonly used in digital image processing to make images more familiar and detailed.However,it can sometimes introduce nimbus or ring of light around edges if applied too aggressively,which can lead to look like unnatural [9,12]**.**

3.4 Contrast Limited Adaptive Histogram Equiliztion: Contrast Limited Adaptive Histogram Equalization (CLAHE) [8] is an improved version of AHE that addresses the issue of noise amplification.CLAHE divides the original image into numbers of small and non overlapping sub images and make histograms for each portion.Histogram of sub images are cut at some threshold to limit the amount of enhancement and then equilized. The image details are clearly appear relative to background. At the same time, background is also enhanced. In CLAHE the intensity values are redistributed in a controlled manner, preventing excessive amplification of noise. As a result, CLAHE produces images with enhanced detail and fewer artifacts compared to traditional AHE. Another advantage of CLAHE is that it can be combined with other techniques, such as contrast stretching, to further improve the image quality. Contrast stretching involves linearly transforming the pixel values to map a narrow range of input values to a wider range of output values, thereby increasing the overall contrast of the image[7,8].

3.5 Triangular Fuzzy Membership-CLAHE : The Triangular Fuzzy Membership-CLAHE (TFM-CLAHE) method enhanced image contrast by employing a triangular fuzzy membership (TFM) function to determine the clipping parameter.This technique manages how much amount of contrast is added to an image.In CLAHE method a fixed clip limit is used for all images,but in TFM-CLAHE a different clip limit is calculated for each image using TFM function,which resulting to a more image-specific enhancement instead of uniform enhancement. A Triangular Fuzzy Membership Function is used to adjust the brightness and contrast of the image in a smooth and controlled manner. This allows for better handling of complex patterns and fine details in the image, making them clearer and more visible. This method is gaining popularity in fields such as medical imaging and remote sensing, where accurate and detailed image analysis is essential [2,4,10].

The formula is:

$$\mu(x; a, b, c) = \begin{cases} 0 & x \le a \text{ or } x \ge c \\ \frac{x-a}{b-a} & a < x \le b \\ \frac{c-x}{c-b} & b < x < c \end{cases}$$

where a= lower limit

b= peak(where membership=1)

c= upper limit

4. Methodology

The process for applying image contrast enhancement methods in this research is shown as a block diagram in Figure 1.

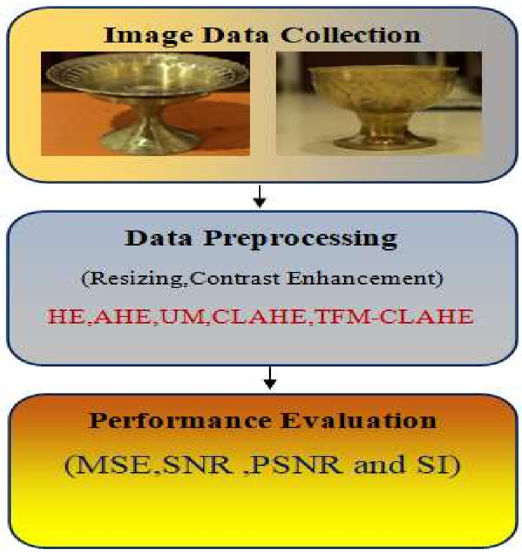


Figure 1: Block diagram of the methodology

The methodology begins with the data collection stage, as the success of any computer model largely depends on the quality of the dataset used. To ensure this, a collection of high-quality images of handicraft bell metal products was prepared. The images were captured using a digital camera from various handicraft bell metal production units in the Sarthebari area. After collecting the image samples, we filtered out blurred, dark, and noisy images to maintain quality. Seven(07) different classes of products were prepared namely(traditional name) Bata, BanKahi ,BanBati ,Bati ,Kahi ,Taal and Lota. In figure 2 sample of some images are shown for reference.

Figure 2: Sample images of Handicraft Bell metal product (a)Bata (b)Bankahi (c)Banbati (d)Bati (e)Kahi (f)Taal (g)Lota

Then the above mentioned five different types of contrast enhancement method i.e., HE, AHE, UM ,CLAHE [8] and TFM-CLAHE[10] are examined. On several handicraft bell metal images those methods are applied to check the visual outputs.

In further, to order the reliability of the methods, four performance metrics are utilized such as, MSE, SNR, PSNR, and SI are applied [8].The aim of this research is to offer a thorough assessment of the strengths and weaknesses of each image enhancement technique. Expected outcome of this research shall help in choosing suitable contrast enhancement methods, based on image quality needs and application demands.

5.**Experimental Result** and Discussion

For consistency in experimental results, all methods are implemented in Python. The experiments were conducted on a system with an Intel Core i5 8300H @ 2.30GHz processor, 8 GB of RAM, running the Windows 11 operating system. The development environment included Jupyter Notebook (IDE) and various useful Python packages.

5.1 Performance Measures

Quantitative performance metrics are essential for comparing various image enhancement methods. It can additionally explain, categorize, and generate change recognition within the image. In this study, the evaluated performance metrics aim to extract specific features of an improved image, which includes Mean Square Error (MSE), Signal to Noise Ratio (SNR), Peak Signal to Noise Ratio (PSNR), and Similarity Index (SI) [7,8].

Mean Square Error (MSE): MSE is a suitable and common distortion measure. MSE between the original image and processed image with a size of(mxn) is expressed as follows-

$$\mathrm{MSE} = \frac{1}{\mathrm{mn}} \sum_{\mathrm{i}=1}^{\mathrm{m}} \sum_{\mathrm{j}=0}^{\mathrm{n}} (\mathrm{Aij} - \mathrm{Bij})^2$$

The value of MSE measeures the difference between a processed image and reference image.The value that is close to zero indicates the better result.

Signal to Noise Ratio (SNR): The signal-to-noise ratio is characterized by the power ratio of a signal compared to the noise. SNR is computed using the formula expressed as-

$$\mathrm{SNR}_{(\mathrm{db})} = 10\log_{10} \frac{\mathrm{Psignal}}{\mathrm{Pnoise}}$$

Higher SNR values indicates the better result for the processed image.

Peak Signal to Noise Ratio (PSNR): To measure the reconstruction quality , PSNR is the most widely used measurement parameter. It represent the ratio of the mximum possible power of asignal to the power of corrupting noise. PSNR can be expressed as follows:

$$\mathrm{PSNR}_{(\mathrm{db})} = 10\log \frac{255}{\mathrm{MSE}}$$

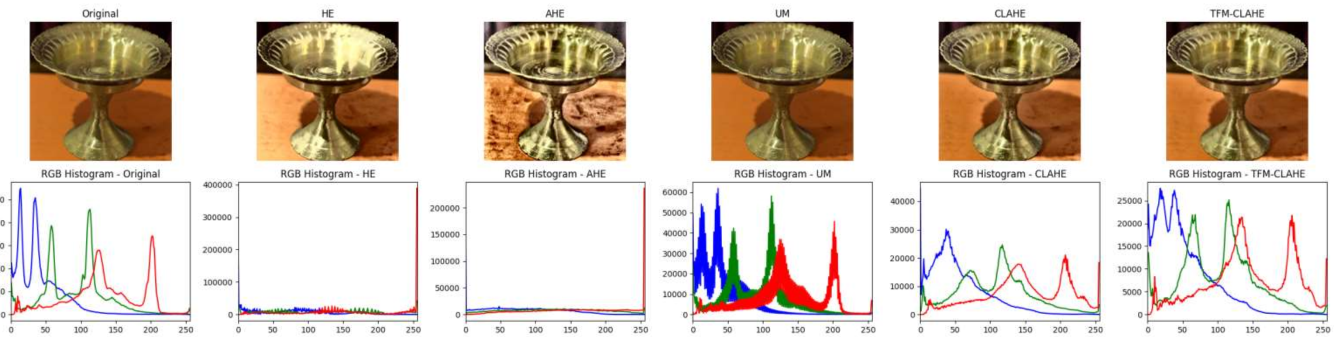
Higher PSNR value indicates the better performance.

Similarity Index (SI): The Similarity Index assesses the uniqueness of the refined image against the original image. It includes comprehensive details regarding the pixel utilization from the original image that generated the improved image [7,8]. A greater SI value signifies a more improved outcome

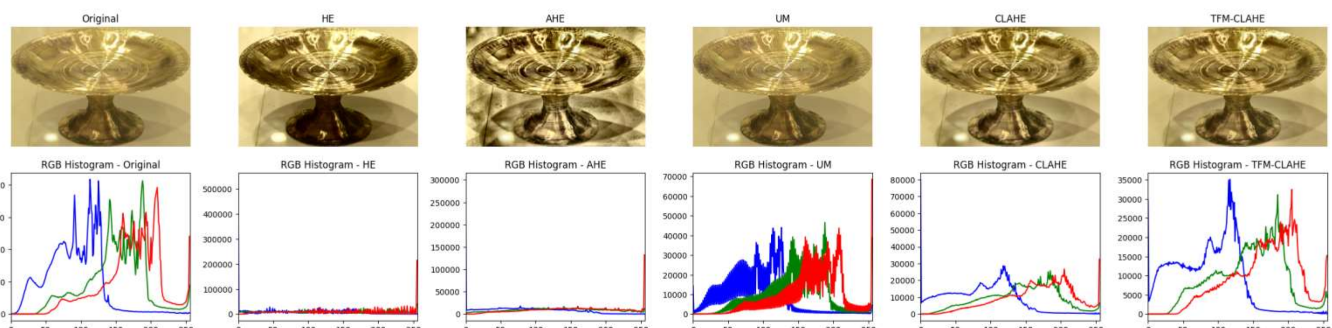
$$\mathrm{SI} = \frac{m_{ab} 2xy 2 m_a m_b}{m_a m_b x^2 + y^2 m_a{}^2 + m_b{}^2}$$

5.2 Comparative analysis of results

In this study, we have used seven types of test bell metal images: Bata, BanKahi, BanBati, Bati, Kahi, Taal and Lota. Each type has fifty images, as shown in Figures 3(a) to 3(g). The unique features of each type create a varied dataset for testing contrast enhancement methods. We checked how well the original and processed images matched, with higher values meaning better detail preservation. The results from different techniques were compared across all image types. It was found that the UM and TFM-CLAHE method gave better results than the other methods.



(a)



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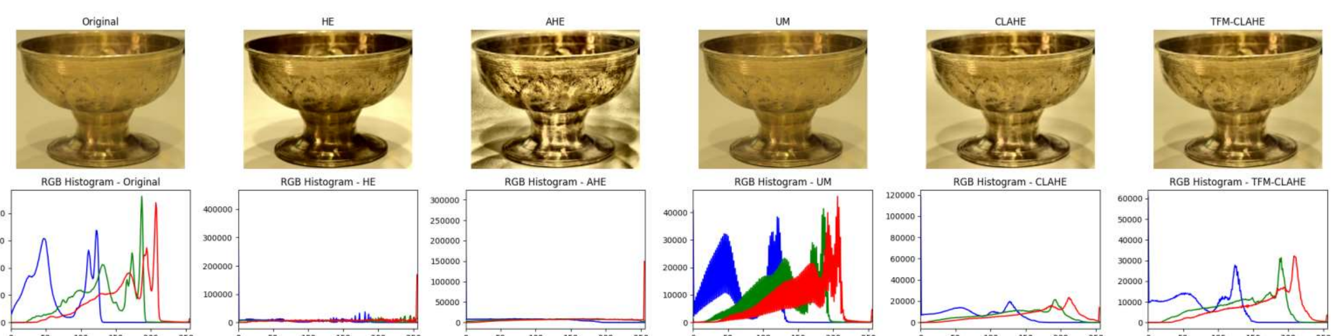
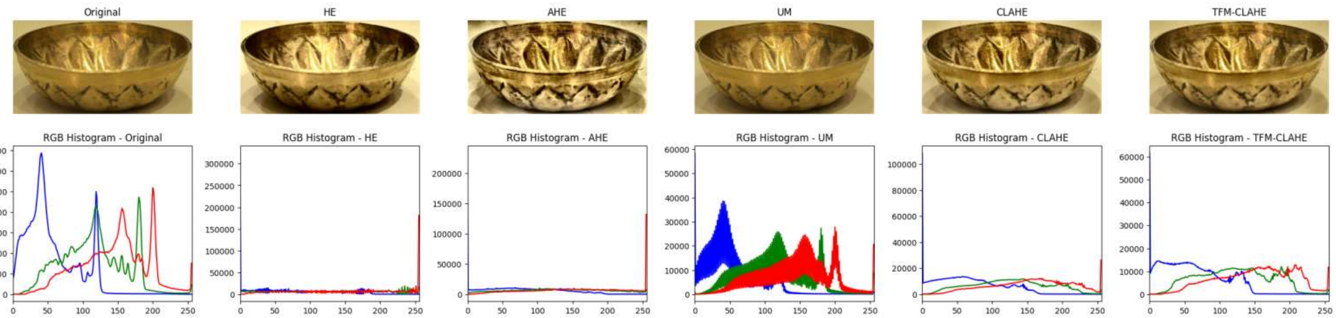
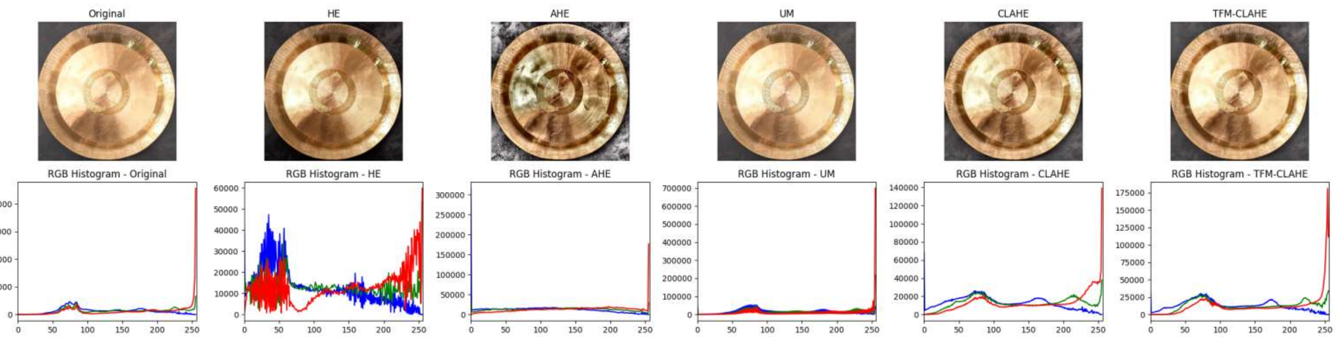


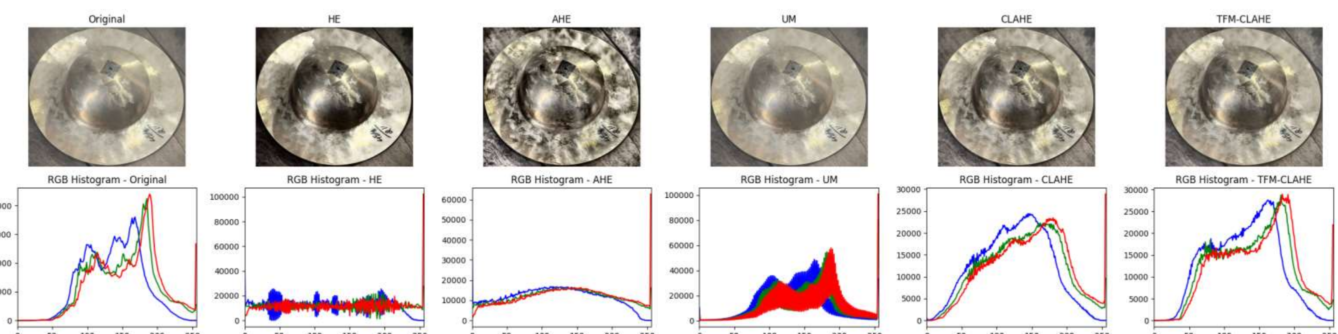
(c)


Original
HE
AHE
UM
CLAHE
TFM-CLAHE
RGB Histogram - Original
RGB Histogram - HE
RGB Histogram - AHE
RGB Histogram - UM
RGB Histogram - CLAHE
RGB Histogram - TFM-CLAHE

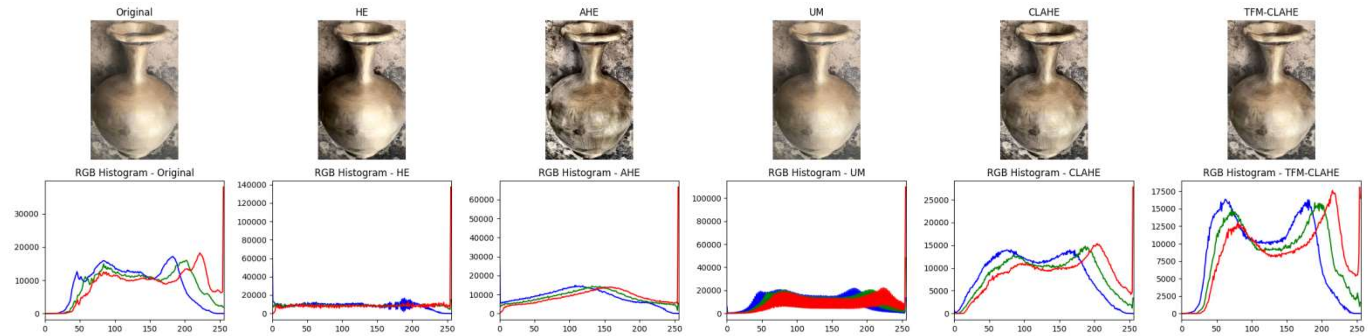
(d)


Original
HE
AHE
UM
CLAHE
TFM-CLAHE
RGB Histogram - Original
RGB Histogram - HE
RGB Histogram - AHE
RGB Histogram - UM
RGB Histogram - CLAHE
RGB Histogram - TFM-CLAHE

(e)


Original
HE
AHE
UM
CLAHE
TFM-CLAHE
RGB Histogram - Original
RGB Histogram - HE
RGB Histogram - AHE
RGB Histogram - UM
RGB Histogram - CLAHE
RGB Histogram - TFM-CLAHE

(f)



(g)

Figure 3: Histogramof the processed test images of (a) Bata (b) Bankahi (c) Banbati (d) Bati (e) Kahi (f) Taal (g) Lota using HE,AHE,UM,CLAHE and TFM-CLAHE

Figure 3(a) to Figure 3(g), test results are shown. The test results areafter applying the various mechanisms the intensities are redistributed, enhancing contrast and often making details more visible. For the TFM-CLAHE results, the transformation results in an image where features are more defined and easier to distinguish, as shown by the broader, more uniform histogram in the processed image compared to the original.The processed images reveals a noticeable improvement especially around edges and fine textures. In the original image, details appear slightly blurred, particularly in areas with complex textures or transitions.

Table 1: Evaluation of Performance on the Test Images of Bata.

Methods	**MSE**	**SNR**	**PSNR**	**SI**
HE	1460.226672	9.381376	16.486601	154.752587
AHE	5090.690962	3.957811	11.063036	2418.704940
UM	238.031247	17.259239	24.364464	103.105132
CLAHE	453.369224	14.461058	21.566283	135.048245
TFM-CLAHE	28.182020	36.525857	49.631082	214.860598

Table 2: Evaluation of Performance on the Test Images of Bankahi.

Methods	**MSE**	**SNR**	**PSNR**	**SI**
HE	1460.226672	9.381376	16.486601	154.752587
AHE	5090.690962	3.957811	11.063036	2418.704940
UM	238.031247	17.259239	24.364464	103.105132
CLAHE	453.369224	14.461058	21.566283	135.048245
TFM-CLAHE	28.182020	36.525857	49.631082	214.860598

Table 3: Evaluation of Performance on the Test Images of Banbati.

Methods	**MSE**	**SNR**	**PSNR**	**SI**
HE	1081.775140	12.035143	17.789434	512.786962
AHE	2028.861636	9.303989	15.058279	4329.604462
UM	260.828073	18.212970	23.967260	521.067486
CLAHE	432.514462	16.016507	21.770797	651.062840
TFM-CLAHE	54.107269	35.043957	39.798247	873.456596

Table 4: Evaluation of Performance on the Test Images of Bati.

Methods	**MSE**	**SNR**	**PSNR**	**SI**
HE	1081.775140	12.035143	17.789434	512.786962
AHE	2028.861636	9.303989	15.058279	4329.604462
UM	260.828073	18.212970	23.967260	521.067486
CLAHE	432.514462	16.016507	21.770797	651.062840
TFM-CLAHE	54.107269	35.043957	39.798247	873.456596

Table 5: Evaluation of Performance on the Test Images of Kahi.

Methods	**MSE**	**SNR**	**PSNR**	**SI**
HE	1081.775140	12.035143	17.789434	512.786962
AHE	2028.861636	9.303989	15.058279	4329.604462
UM	260.828073	18.212970	23.967260	521.067486
CLAHE	432.514462	16.016507	21.770797	651.062840
TFM-CLAHE	54.107269	35.043957	39.798247	873.456596

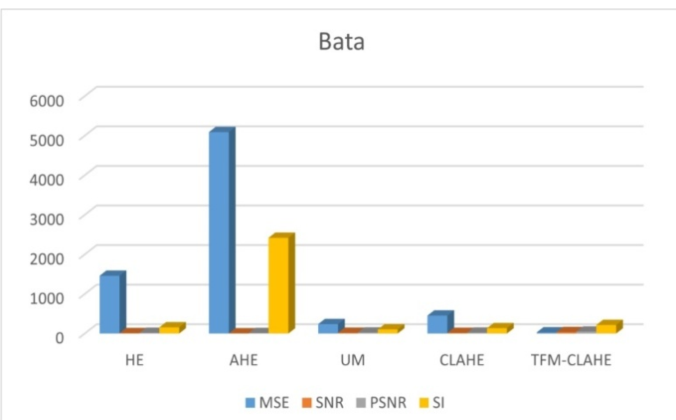
Table 6: Evaluation of Performance on the Test Images of Taal

Methods	**MSE**	**SNR**	**PSNR**	**SI**
HE	1652.910597	11.676746	15.948310	686.564666
AHE	2405.889285	10.046484	14.318047	1652.849962
UM	362.647403	18.264394	22.535958	519.586268
CLAHE	607.171766	16.026124	20.297688	637.692286
TFM-CLAHE	191.654137	27.034058	31.305622	1271.101358

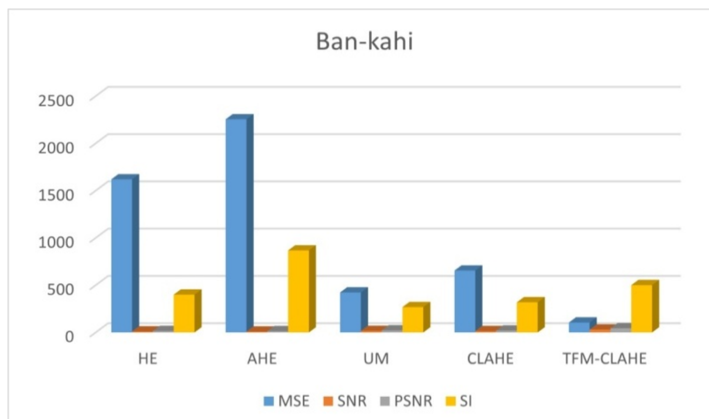
Table 7: Evaluation of Performance on the Test Images of Lota

Methods	**MSE**	**SNR**	**PSNR**	**SI**
HE	1652.910597	11.676746	15.948310	686.564666
AHE	2405.889285	10.046484	14.318047	1652.849962
UM	362.647403	18.264394	22.535958	519.586268
CLAHE	607.171766	16.026124	20.297688	637.692286
TFM-CLAHE	191.654137	27.034058	31.305622	1271.101358

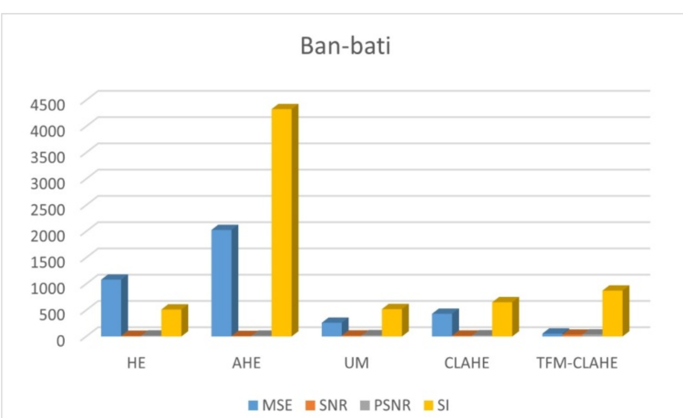
Tables 1 to 7 shows the performance metrics MSE,SNR,PSNR and SI for five contrast enhancement methods viz.,HE, AHE, UM, CLAHE and TFM-CLAHE. Each table provides a comparative analysis of these methods' impact on image quality. Across these metrics, UM and TFM-CLAHE consistently shows superior performance, with lower MSE values indicating reduced distortion, and higher SNR and PSNR values reflecting improved image quality. The SI values for UM and TFM-CLAHE are also notably higher. These results collectively highlight TMF-CLAHE as the most effective method among those tested for contrast enhancement.



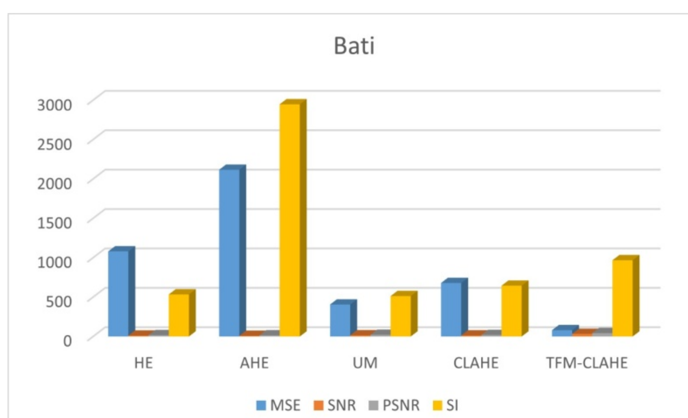
(a)



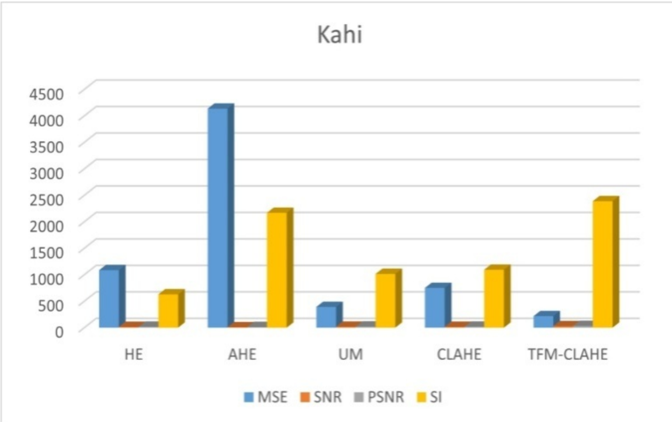
(b)



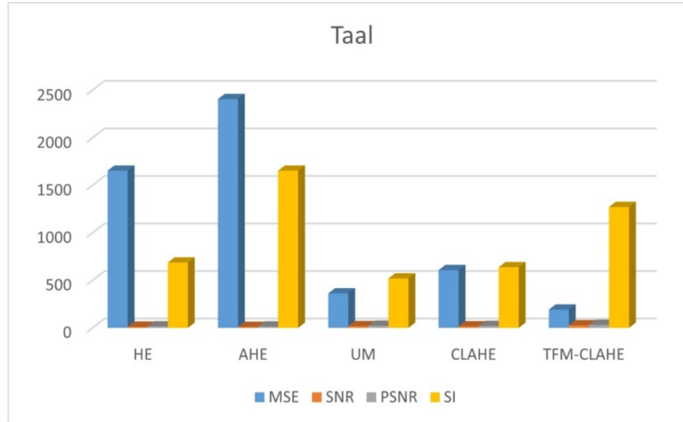
(c)



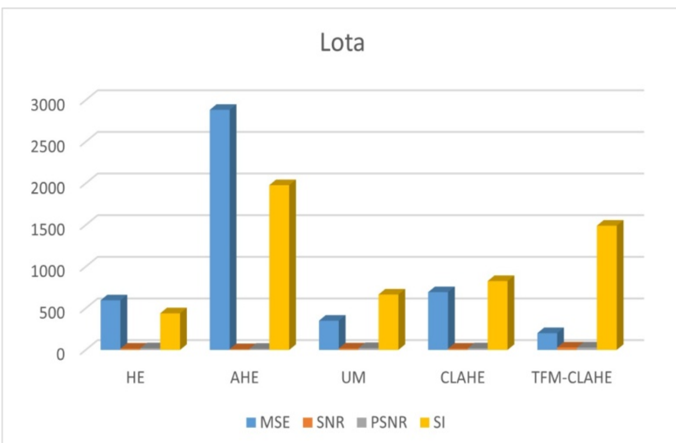
(d)



(e)



(f)



(g)

Figure 4 : Barchart Comparison of Test Image (a) Bata (b) Bankahi (c) Banbati (d) Bati (e) Kahi (f) Taal (g) Lota

Fig 4(a) to 4(g) shows the bar chart comparison of the performance of five image enhancement techniques HE , AHE , UM , CLAHE and TFM-CLAHE created using performance metrics like Mean Squared Error (MSE), Signal-to-Noise Ratio (SNR), Peak Signal-to-Noise Ratio (PSNR), and Structural Index (SI). The bar chart would visually represent how each technique performs based on these metrics. The x-axis represents the different contrast enhancement techniques applied to the handicraft bell metal image. The y-axis shows the corresponding numerical values of the performance metrics used to evaluate the effectiveness of each method.

In the chart, each metric would have its own set of bars, color-coded for clarity. For MSE, which measures the difference between the original and enhanced images (lower is better), UM and TFM-CLAHE would have shorter bars compared to HE, AHE, and UM. This indicates that UM and TFM-CLAHE produce images closer to the original, with fewer errors. For SNR and PSNR (higher is better), UM and TFM-

CLAHE [10] would have taller bars than the other techniques. This shows that these methods enhance the image quality by improving the signal relative to noise, making the images clearer and more detailed. For SI (higher is better, indicating better structural preservation), UM and TFM-CLAHE would again outperform the others, with taller bars. This means they preserve the structural details of the image more effectively.

Overall, the bar chart would clearly show that UM and TFM-CLAHE is superior to HE, AHE, and CLAHE. They achieve lower MSE, higher SNR, higher PSNR, and better SI, making them the preferred techniques for image enhancement. The visual comparison in the bar chart would make it easy to understand why UM and TFM-CLAHE is considered better, as their bars consistently outperform the others across all metrics.

6. Conclusion and future work

Bell metal handicrafts are highly valued in Assamese culture, where they are made using traditional methods handed down through generations. Although they hold cultural and artistic value, applying computer vision techniques to analyze these items proves difficult because of their detailed textures, inconsistent lighting, and complicated photographic environments. These factors frequently degrade image clarity and impact the precision of automated classification.This research utilized five contrast enhancement methods HE, AHE, UM, CLAHE and TFM-CLAHE on images of handicraft bell metal items. The results showed that UM and TFM-CLAHE consistently surpassed the others. Both methods successfully improved fine details while preserving clarity and preventing over-enhancement. Their dominance was validated by numerical metrics, attaining reduced MSE and SI figures, SNR and PSNR values. These findings emphasize their appropriateness as preliminary steps for classifying and evaluating the quality of handicraft images.

Future studies might concentrate on merging the suitable contrast enhancement techniques with image processing and deep learning models to enhance image recognition precision even more. Furthermore, expanding the dataset with a wider range of bell metal images will enhance machine learning model generalization.

Overall, the findings contribute to digital preservation, objective quality assessment, and global promotion of Assamese handicraft bell metal artistry, showcasing the practical impact and effectiveness of the proposed methodology.

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