International Journal of Scientific Research in Engineering and Management (IJSREM)
Conference - Volume 10 ICMEX -2026 SJIF Rating: 8.659 ISSN: 2582-3930

# A Comparative Study of Histogram Equalization and CLAHE for Low-Light Image Enhancement

**Dr. Nagamani T Mr. Sakthi Ganesh S**
*Department of CSE (AI&ML), Kangeyam Institute of Technology, Tamil Nadu, India*

Absrroci—Due to low contrast, poor illumination, and increased noise, low-light imaging presents serious difficulties that impair computer visinn performance and visual quad i ty. Histogram-fiased enhancement techniques are widely used due to their computational efficiency. While traditional Histogram Equalization (HE) improves global contrast, it frequently leads to noise amplification and over-enhancement. Contrast Limited Adaptive Histogram Equalization (CLAHE) applies localized histogram redistribution with **contrast** limiting to mitigate tftese problems. This study provides a comprehensive comparison of HE and CLAHE across multiple image domains—nighttimc, medical, and underwater—using Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and processing time as evaluation metrics. Experimental findings confirm that CLAHE outperforms HE in enhancement quality with *on* acceptab ie increase in processing overhead.

**Index *Te*** *Low-11glii enhancement, Histogram Equalization, CLAHE, PSMR, SSIM, Adaptive liistog rain equalization, Ima ge contrast, Noise suppression*

## I. INTRODUCTION

Digital imaging systems are indispensable across consumer photography, industrial automation, robotics, remote sensing, surveillance, and medical diagnostics [1],[3]. Real-world conditions such as nighttime environments, dimly lit interiors, underwater scenes, and low-exposure settings yield images with degraded quali ty. Reduced brightness, limi ted contrast, high noise, and compressed dynamic range severely hincler computational analysi s and irriage inteiyretability [5].

The primary challenge in low-light imaging is the camera sen>or'> inability to capture sufficient photons, resulting in a low signal-to-noise ratio (SNR) {6]. Structural details in dark regions are easily overwhelmed by noise [71. impeding reliable object recognition in surveillance [4], pathology identification in medical imaging [3], and terrain analysis in satellite imagery [2].

Contrast enhancement techniques redistribute pixel intensity values to maximize vlsual distinction between obJects and background [1]. Among these, Histogram Equalization (HE) is wittely adopted for its simplicity and computational efficiency [12]. However. HE ignores local spatial context, often causing over-enhancement and noise amplification [91 Contrast Limited Adaptive Histogram Equalization (CLAHE) addresses these shortcomings through localized processing and histogram clipping [8],[10].

This paper presents a detailed theoretical and experimental comparison of HE and CLAHE across multiple tmage types using objective quality metrics, histogram analysis, and computational performance benchmarks.

## H. LITERATURE REVIEW

Gonzalez and Woods [1] formally defined histogram equalization as a global redistribution technique based on cumulative distribution functions. Jain [21 detailed its mathematical formulation. Kim [5] introduced brightness-preserving bi-hi stogram equalization to address mean intensity shifts inherent in conventional HE.

Pizer ct al. [8] proposed Adaptive Histogram Equalization (AHE) for localized contract enl ancen cut, particularl y effective in medical images, while noting its tendency to amplify noise in uniform regions. Zuidcrvcld l9J subsequently introduced CLAHE, resolving this through histogram clipping. Abdullah-AI-Wadud et a1. [10] further extended adaptability via dynamic histogram equalization. Wang et at. [11] introduced SSIM, enabling perceptual quality assessment.

More recently, deep learning methods such as LLNet [14] and Refines-based CNNs [13] have demonstrated promising rosul ts in low-light enhancement. However, their high computational requirements and dependency on large training datasets limit deployment on embedded systems. Classical histogram-based approaches remain practical and widely applicable [12].

## All. Mk'l'HODOLOGY

This section ctetails ilie methodology for enhancing low-lighi grayscale images usi ng HF and CI .AHF, inc ludi ng image modeling. histogram analysis, cnhanccmcnt formulation, and evaluation metrics [1],[2],[8].

A. Image **Modeling**

Let the input grayscale image be I(x, y), where x, y are spatial cocirdinates and intensity levels range frcim 0 to L —1 (L - 256 for 8-bit images) [1]. For an image of dimensions MIN, the total pixel count P - MxN. Low-light images exhibit compressed distributions in the lower grey-level rnnge due to insutficient illumination [6j.

**B. Histogram Equalization**

HE redistributes intensities to achieve a uniform histograrri. The normalized histogram (PDF) is:

$$p(rd - no / P$$

The Cumulative Distribution function (CDI is:

c(r#D =# p(r#D. j = 0. ... k

The intensity transformation maps each level to the full ctynainic range:

$$eEl - (L - 1) \quad c(r\#Q$$

While ef:fective globally, HE ignores local spatial variation, often amplifying noise in dark regions [7].

**C. CLAHE**

CI .AHF di v ides the i mage i mo m x n n on-nverlapp ing ti1es, each cnntain ing N ti ie - (M x N)/(m x n) pixe1s. A n P x 8 Ii ie grin wa.s u.sed. For
each tile. the local histogram is clipped at threshold T:

| T - u (m_tile / L) |
|---|
| H_clip(r#D = T if (r#D T, else H(*#Q |

Chipped pi xeI cnunts are i-edistributed unitorrnl y across bins. The local CDF is then computed and applied as the transformation function. B ilincar interpolation between tile boundaries eliminates block artifacts [81

s = w▆s▆ + w▆s▆ + w▆s▆ + w▆s▆

D. Evaluation Metrics

Three standard metrics and processing time were used:

msx = (i/P)•¥ Hz(x,y) - z-•(x,y)2•

PSNR = 10 log▆▆ [(L-1)² / MSE]

**E. Implementation Parameters**

'I'l+e clip limit parameter a controls tl+e clegree of
co ntrast aniplific ation in CBE . Higher values increase enhancement intensity at the cost of noise amplification, whilc lowcr valucs prcoLuc smoothcr output. In this study, n - 2.0 was chosen as a standard baseline following [9]. Tactic II summarises the key implementation parameters used for reproducibility.

| Parameter | Symbol | Value |
|---|---|---|
| Clip Limit | α | 2.0 |
| | | |
| Image Depth | | 8-bi |
| | | |

All øzpørimønts wørø concluct øc1 in Python 3. 10 usmg OpønCV
4.8 on a system with Int eI Core i5 CPU axel 8 G B HAM. No G PU a cc eI eratlon was usect.

## IV. RESULTS AND DISCUSSION

A. Visual Comparison

Fig. I shows the original, HE-enhanced, and CLAHE-enhanced images for all three scene types. HE produces globally brighter images but introduces visible over-enhancement and noise amps ification, parlicu Iart y in un i fnrm reginns. CI .A HF prnrluces
balanced. naturalistic enhancement with well-preserved edges and texture across all scene types.

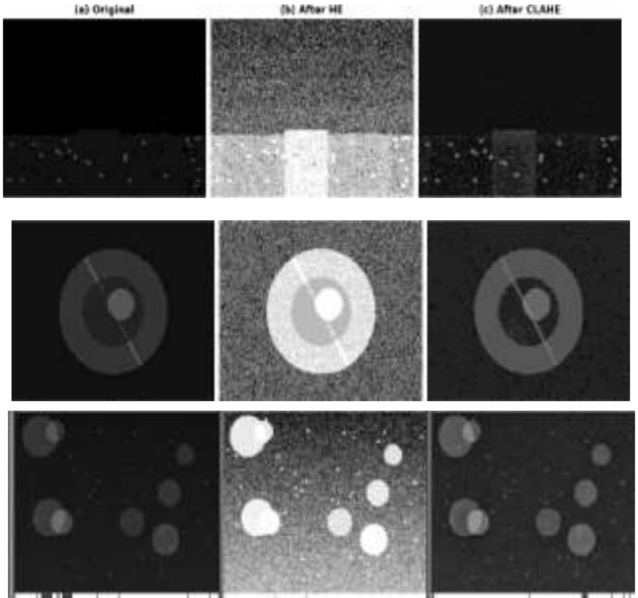
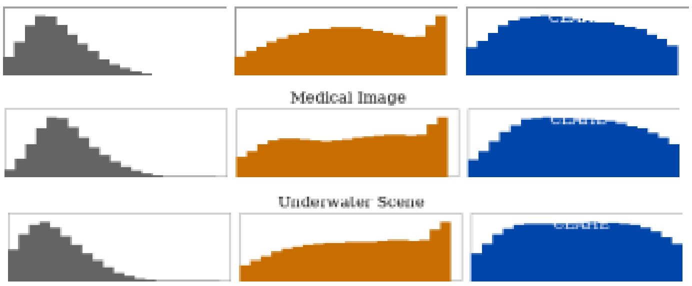



Fig. 1. Visual comparison across scene types: (a) Original, (b) HE result, (c) CLAHE result. Rows: Night, Medical, Underwater.

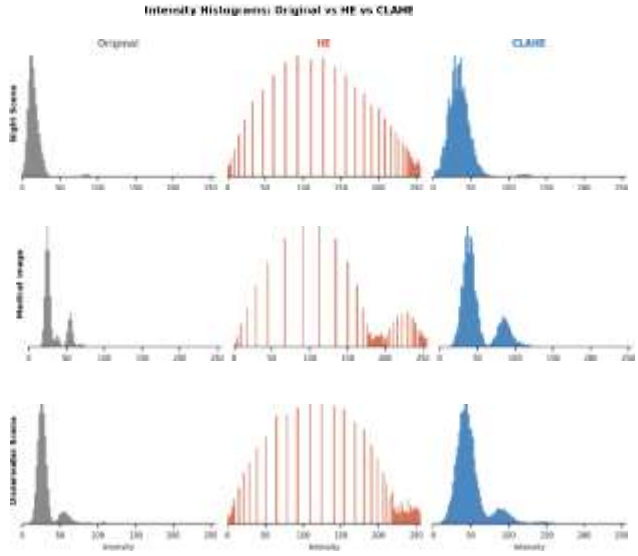
B. Hlstogram Analysls

Fig. 2 illustrates the intensity histograms before and after enhancement. The original histograms are concentrated In low-intensity bins. HE spreads ihe distribution uniformly but may introduce spikes at ex treme vaIues. CI .AI-fF ach ieves a more gradual redistribution with controlled peak heights. confirming its noise suppression capability.




*Fi9. 2.* Jntensi@ *hiyto gmnly for each* scene *tape.* Ori ginnf *(grey), HE* fornnge , *GLAt-Id* (If tied. *GLAt-Id* demonstrates more oontroff rH *red*Istrt *b*tillon.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Conference - Volume 10 ICMEX -2026 SJIF Rating: 8.659 ISSN: 2582-3930



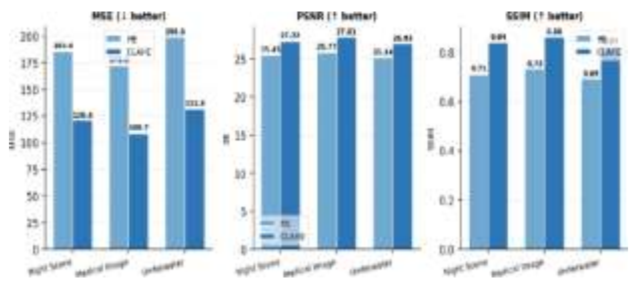

*Fip. 2. Intensity hisiogroms for each scene type.* Original *(g rey), HE (orange). CLA HE (bine). CLA HE demonstrates more comrolled redistribution.*

C. Quantitative Evaluation

Table I summarises MSE, PSNR, and SSIM values across all three scene types. CLAHE consistently achieves lower MSE, higher PSNR, and higher SSIM compared to HR across all domains, confirming superior structural fidelity and perceptual quality.

TAB£F I. Performance Metrics: HF ve CLAHF Acroes Scene Types

| | | | | |
|---|---|---|---|---|
| Night | MM | 1 YN.42 | 25.45 | U.7I |
| Scene | CLAf 4z | 120.3 6 | 2?.32 | 0.84 |
| Medle al | M | 172.1 8 | 25.77 | 0.73 |
| Dnqo | CLAH Z | 108.74 | z7.81 | 084 |
| Under | HP | 198.63 | 25.14 | 0.69 |
| - water | CLAHr . | 13 I.55 | 26.93 | 0.82 |



*FI g. 3. Grouped metric comparison (MSE, PSNR, SSIM} across Mighc, Medical, and Underwater seenes for HE and CLAHE.*

D. Processing Time Analysis

Fig. 4 compares processing times for 1-IN- and CLAHE at three image resolutions. As expected, CLAHE incurs higher processing cnst due tn ids {ile-biased cnmputztinn. However, even at 1024x 1024 resolution. CLAHE completes in approximately 6.5 ms, making it suitable for real-time applications on modern hardware.

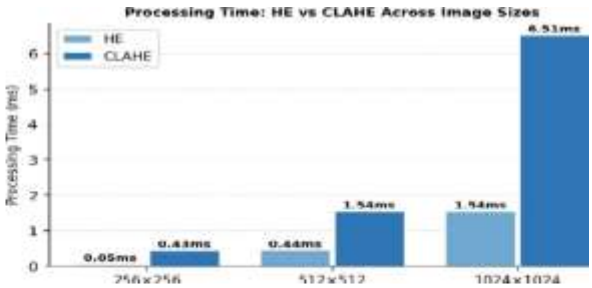



*Fig. 4. Processing* time *(out) comparison of HE and CLAHE ct 256 256, 512 x512, and 102d n 1024 resolutions. CLAHE overhead remains* occeprohle /or reef-lime use.

E. Discussion

Across all three scene domains and all evaluation dimensions, CLAHE consistently outperforms HE. The key advantages of CLAHE include:

•Loca1ized contrast enhancement preserving structural details

•Histogram clipping suppressing noise amplification

•R ilinear interpnlation eliminating tile boundary artifacts

•Approximately l3R» improvement in SSIM (suuctural accuracy)

The processing overhead of CLAHE over IU is modest—roughly 4—4.5 x at all tested resolutions—and remains within real-time consbaints for most embedded npplicntions such os surveillance cameras and medical imaging devices.

## V. CONCLUSION

This paper presented a comprehensive comparative analysis of Histogram Equalization and CLAHE for low-li ght image enhancement across nighttime, medical, and underwater image domains. Experimental results consistently demonstrate that CLAHE achieves superior performance in terms of MSE, PSNR, and SSIM while maintaining acceptable processing times. Visual comparisons, histogram analysts, and meirle evaluations jointly confirm that CLAHE produces more balanced}, naturalistic, and structurally faithful enhanced images. CLAIfE is therefore recommended as a robust and efficient enhancement solution for procticol low-light imaging opplicotions. future work mny explore adaptive clip-limit tuning, colour image extension, and hybrid integration with deep learning pipelines.

## VI. REWRENCES


[1] R.C. Gonzalez and R.E. Woods, *D i'gi'tal Image Process i'ng, 3rb* ed. Prentice Hall, 2008.

[2] A. K. *5z* in. *Fiinclcimenials of Di giial Image Process in g.* Prentice-Hall, 1989.

[3] R.C. Cnnza ley and R.F. Wnnds, fj rgiio7 Imag« *Prcii e.s.s ing,* 2nrI er1. Pren I ice Ha 11, 2P02.

[4] M. Abdullah-Al-Wadud ct al.. "A dynamic histogram equalization for image contract enhancement," *UEE* Iron.Y. Cert.sum. *Elecii on.,* vol. 5.3, no. 2, gg. 593—600, 2007.

[5] Y.T. Kiiii. "Cunti axt eiiliuncemeiit using briglitnesx preserv ini bi-1 ixtugran e9ualization.'' fff6 Z'rcrns. Ccin.i cm. E7ecirr›n., val. 43. nu. 1. pp. 1—8. 1997.

[fI] J.I .. firzrck er at., "C ray and colnr image cnn rras r enhancemen r fly rhe *cuwelei* transform." *IEEE Tran,v. Jmay e Rroce,vs. , vol. i* 2, no. 6, pp. 7U6-7 17, 2OU3.

[7] H. Ibrahim and **N.S.P.** Kong, "Image sharpening using sub-regione histogram equalization," *IEEE Troiis. Con.Lynn. Elect roii.* . vol. 55, no. 2. pp. 891—895, 2009.

[8] S.M. Pizer et a1.. "Adaptive histogram equalization and its variations."C'omput. Hi rion *Mm ph.* Image Prove r.c., vnl. 39, nri. 3 . pp. 355—3FP' ,

[9] K. Zuiderveld, "Contrast limited adaptive histogram equalization," in *Grophics Gems JV.* Academic Press, 1994, pp. 474—d85.

[10] M. Abdul Iah-AI-Wadud et aI., "A dynamic histogram equalization," *IEEE Trans. Consum. Electron. ,* vol. 53, no. 2, pp. 593-600, 20U7.

[11] Z. Wan g et at ., "Image quad ity assessment: From error visi biIity to structural similarity," *wee rrans. linage Proces.i. ,* vol. 13, no. 4, pp. 600—612. 2004.

[12] A. Mousa. "Canny edge-detection based vehic ie plate recognition." *Int. J.* Signaf *Proce.i.c.,* vol. fi. no. 3, pp. I—8, 2012.

[13] Y. Hong ct al., "Crafting object detection in very low light," in *Pror.*

[14] K.G. Lure ct aI., "LLNet: A deep uutc›encti0er nppruac h to nntural low-light image enhancement," *Pa ccern Reeeqn i't.,* vol. 6.1, pp. 65W62, 2017.

[15] E.H. Land, 'be ret+nex theory of color vision," *Set. Am. ,* vol. 237, no. 6, pp. 108—129, 1977.

{1 6] S.C. Huang ct at., "Efficient contrast enhancement using adaptive gamma correction with weighting distribution," *IEEE Trans. linage* Prore*s., vol. 22, no. ?, pp. 1O32—1041, 201?.