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A Practical Hybrid Framework for High-Quality Enhancement of Multi-Modality Medical Images

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Abstract: Medical imaging quality is crucial in accurate diagnosis and computer aided diagnosis (CAD). But medical images obtained through X-rays, CT scan, and MRI may contain poor contrast, noise, uneven lighting conditions, and poor anatomical visibility that may cause errors during diagnosis and further analysis of the medical image. This research work introduces a Hybrid Contrast and Detail Enhancement Framework (HCDEF) in order to enhance medical image quality. HCDEF incorporates both the traditional image processing techniques and the artificial intelligence technique in order to enhance medical image quality while preserving important anatomical structures. The enhancement process involves a number of stages such as Contrast Limited Adaptive Histogram Equalization (CLAHE), Gamma Correction, Haze Removal, Saturation Correction, Unsharp Masking, and Adaptive Luminance Control. A light-weight CNN is used for the estimation of spatially varying parameters which help adaptively enhance an image without adding any extra features to it. The proposed approach has been tested using x-ray, CT, and MRI images and has been compared to traditional enhancement techniques and other deep learning-based approaches like GANs and autoencoders. Experimental analysis showed good performance with a contrast of 64.09, entropy 6.81, standard deviation 64.09, and energy 0.029.

Keywords: Medical image enhancement; contrast improvement; hybrid preprocessing; classical image processing methods; AI-driven adaptive modules; diagnostic imaging quality.

1 Introduction and Literature Review

Modern clinical diagnostics, planning of treatment procedures and surgery require a proper utilization of medical imaging systems to visualize and evaluate a vast number of pathologies [1], [2]. Nevertheless, different modalities such as X-ray, CT, MRI, ultrasound and PET give a complementary data concerning anatomical and functional aspects of patients' bodies with their own specific strengths and weaknesses [3], [15].

Even though there are constant developments of new imaging techniques and the boundaries for them, the performance of imaging systems depends highly on the quality and visibility of the important structures that are shown in the obtained images. In practical terms, the images have low contrast, contamination with noise, illumination inconsistency, insufficient details and poor edge information [4], [16]. There can be a great variety of reasons for such problems: hardware limitations of imaging system, patient motion during scanning, low-dose protocol or specific properties of certain tissues [5]. In that respect, such limitations can result in diagnostic uncertainties of radiologists and poor performance of computer-aided diagnostic systems [6], [17]. That makes a need for image enhancement more acute.

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Conventional methods of enhancement like HE, CLAHE, unsharp masking, and linear/spatial filters have been extensively used owing to their simplicity and minimal computation [7], [18]. Histogram Equalization increases global contrast but may lead to the amplification of noise and/or over-enhancement of areas with singleton intensity. CLAHE increases local contrast without the possibility of enhancement of noise. Still, it can create artifacts or over-brighten homogeneous areas [8], [19]. Unsharp Masking is known to enhance edges and fine structures, but, usually, enhances noise in the background, and, in case of improper parametrization, creates artificial boundaries that might persist [9], [20]. Gamma Correction increases global luminance and makes emphasis on dark regions, but there is no guarantee that fine details will be kept during the process [10], [21]. While their efficiency from the point of view of computations has allowed these methods to be incorporated into clinical practice, they work very poorly with heterogeneous sets of data characterized by highly varying noise, and have only limited applications to multi-modality imaging [11], [22]. Advanced non-AI methods introduced to resolve the problems mentioned above are multiscale processing, wavelet transformation, bilateral filtering, and guided filtering [12], [23]. The use of multiscale techniques allows to increase the contrast in both global and local terms by breaking the image down into different frequency bands and focusing on small details without increasing the noise level too much. Wavelet methods can demonstrate excellent performance in relation to edge preservation and multi-resolution detail enhancement but usually require carefully choosing of the right thresholding parameters depending on the image modality. The methods based on edge-preserving filters like bilateral or guided filters selectively smooth homogeneous areas while retaining sharp anatomical boundaries. They, nevertheless, do not work properly with highly noisy or low-contrast images and usually require modality-specific calibration [13], [24]. During the recent years, some deep learning-based image enhancement approaches have been shown surprising capabilities in modeling complex image patterns under different imaging conditions [14], [25]. GANs generate high-contrast and clean images based on low-quality images. Autoencoder-based methods produce images while removing the noise, while transformers exploit the image textures long-range dependencies. It should be noted that most of the AI-based approaches perform significantly better than the classical ones regarding visual quality and perceptual metrics. However, those methods currently suffer from several important problems including: the need for large labeled datasets for network training, large computational power, long training time. Additionally, AI-based approaches are prone to hallucination, which poses serious risks for clinical interpretation of the resulting images [1, 15]. Complexity and high cost make it difficult for those algorithms to be generalized to other scanners and imaging modalities [2, 16]. Thus, despite their strong enhancement capabilities, AI-based methods cannot be clinically adopted in isolation due to these limitations. Hybrid enhancement approaches try to combine advantages of the classical techniques in relation to interpretability, stability, and low computational costs and adaptiveness, and high performance of AI-based approaches [3], [17]. Indeed, such systems usually combine several different operations, namely, the local contrast enhancement, edge enhancement, noise suppression, and image refinement using the deep learning methods. Hence, in this approach, the first step may include CLAHE for enhancing the local contrast, unsharp masking for amplifying the edges, and a CNN-based denoiser to remove the residual noise [4], [18]. As a result, the use of the combination of classical and learning-based techniques would allow to avoid over-enhancement and retain the natural image look while being adaptable over multiple imaging modalities. However, a considerable number of proposed hybrid algorithms are designed specifically for certain domains or demonstrate the inconsistency of their performance when applied to other modalities of medical imaging. Hence, there is still a gap in the literature regarding the universal solution [5], [19].

This paper tries to fill in the gap and presents a novel hybrid contrast and details enhancement algorithm HCDEF which includes a local contrast enhancement, edge sharpness and noise suppression in one processing pipeline [6], [20]. As a result, the proposed technique becomes fully parameter-controlled and modality-independent (e.g., X-ray, CT, MRI). CLAHE is utilized to increase the local contrast by the adaptation to tissue structure specifics avoiding the oversaturation. The details are enhanced using improved unsharp masking with AI adaptive weighting to avoid false amplification of clinically important structures. The noise is removed by hybrid classical non-local means filtering and AI adaptive weighting to eliminate it without affecting the details [7], [21].

Extensive experiments with a variety of datasets have proved that HCDEF increases the image clarity, visibility of structures, and visual perception [8], [22]. Quantitative evaluation in terms of various criteria such as contrast, standard deviation, entropy, and details preservation index proves a better performance compared with HE, CLAHE, gamma correction, and unsharp masking methods [9], [23]. Qualitatively, the improved edges, less haze, and more natural look can be observed. The low-contrast soft tissues and high-intensity bones were processed effectively which proves the generalization of the technique [10], [24]. Hence, the current approach seems highly promising as a preprocessing stage for a number of purposes: segmentation [11, 25], feature extraction, and CAD systems. Improvement of the contrast contributes to better segmentation precision, edges help for landmarks detection, and noise removal ensures the possibility of the automatic diagnosis. Different from the completely deep learning-based approaches, the current system does not hallucinate any structures ensuring its safety and effectiveness for clinical usage [12, 15]. In general, HCDEF is a practical, interpretable, and highly efficient pipeline of medical image enhancement which bridges the gap between simplicity and quality in a clinically feasible manner [13], [16]. Preliminary results suggest that the proposed method outperforms the conventional and deep learning-based ones both qualitatively and quantitatively providing a reliable solution for multi-modal medical imaging enhancement [14], [17]. In terms of the contribution of this research to the existing body of knowledge, the following contributions should be made clear. First, the aim of this research is to develop an image enhancement system applicable to any type of image modality regardless of the type of an image modality used (X-ray, CT, MRI, etc.). Second, the objective of this research is to come up with an image enhancement system that will incorporate different image enhancement techniques, both classical image enhancement techniques, such as CLAHE and unsharp masking, and adaptive image enhancement techniques based on AI. Third, the objective of this research is to develop a parameter-controlled image enhancement system, which will be safer and more reliable compared to other image enhancement techniques, including AI-based ones, which may cause different artifacts and over-enhance the structures not present in the image. Fourth, the objective of this research is to propose a computationally efficient image enhancement system, which will be more practical and useful compared to other image enhancement techniques. Moreover, the efficiency of the proposed image enhancement technique will be superior to other image enhancement techniques, including classical, AI-based, and hybrid ones.

Significance of this research lies in its contribution to the creation of a computationally optimal and highly parametrized hybrid contrast and detail enhancement framework (HCDEF), providing the same performance level for different medical image modalities like X-ray, CT, and MRI. The originality of HCDEF lies in its strategy of merging different enhancement algorithms like local contrast enhancement, edge sharpening and noise reduction via AI-driven weighting with the purpose of optimizing structural visibility and preserving relevant details without creating hallucinations of nonexisting structures. From this point, HCDEF stands out of the majority of the existing frameworks because they are designed specifically for one particular modality or depend specifically on AI algorithms. In general, this technique makes the best use of the advantages of both classical and AI-driven techniques, balancing enhancement quality, safety and computation efficiency.

2. Proposed Methodology

The proposed Hybrid Contrast and Detail Enhancement Framework was designed to be used as an universal solution for enhancing medical images without dependency on the modality of the imaging devices. The key benefits of the approach in question include the possibility to tackle the drawbacks and limitations associated with the traditional medical image enhancement approaches and AI-assisted medical image enhancement techniques. The proposed image enhancement approach is based on the conventional and adaptive AI-assisted image processing operators. The idea behind the image enhancement framework is the enhancement of the image contrast, edge preservation, and noise reduction without the appearance of the artifacts. Figure 1 shows the proposed image enhancement framework and AI-based adaptive image enhancement algorithm for medical images. The procedure of image enhancement is initiated by the processing of the input raw image normalization and resizing. Local image statistics (intensity distribution, variance, and gradient magnitude) are calculated and used as the multi-channel feature tensor for the lightweight CNN to estimate the spatially-varying adaptive parameters α(x,y) for contrast enhancement, β(x,y) for sharpening details and λ(x,y) for noise elimination. The aforementioned adaptive parameters are obtained through the adaptive feedback loop based on the local image contrast, edge and noise estimates.

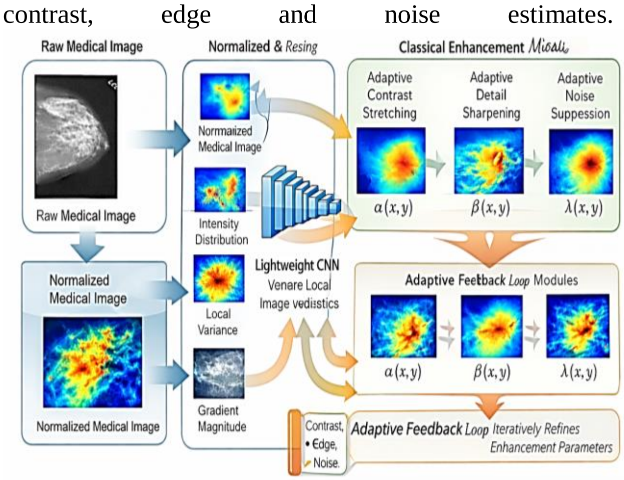

Fig 1. Hybrid contrast and detail enhancement framework

2.1. Data Acquisition and Preprocessing

In this first step of proposed methodology, a variety of medical imaging datasets are collected. X-rays, CT scans, MRI scans are part of this dataset. Multiple regions of anatomy and imaging conditions are to be taken into account so that generalization ability of this proposed framework may be ensured. Normalization of intensity levels and their standardization into fixed resolution in this option goes into consideration. Normalization of intensity levels is performed as per Eq. (1). Noise measurement is simultaneously done in this step for guiding subsequent steps of adaptive enhancement and denoising. The input medical image will be denoted as I(x,y) ∈ℝ^{H×W}.

$$I\_n(x,y) = (I(x,y) - I\_min) / (I\_max - I\_min) \quad (1)$$

where I_min and I_max denote the minimum and maximum intensity values. The observed image is modeled as shown in Eq. (2):

$$I\_n(x,y) = S(x,y) + N(x,y) \quad (2)$$

where S(x,y) represents the true signal and N(x,y) denotes additive noise. Local noise variance is estimated to guide subsequent enhancement and denoising stages.

2.2. Proposed Lightweight CNN for Adaptive Enhancement Parameter Prediction

The proposed CNN architecture is lightweight rather than focusing on achieving image reconstruction and classification. The proposed network architecture utilizes locally extracted image statistics to generate spatially varying weighting maps that control classical image enhancement operations. The proposed network architecture utilizes the multi-channel feature tensor, which is composed of the normalized image intensity map, local variance map, and gradient magnitude map, as the input to the network architecture. Therefore, the size of the input to the network architecture is HxWx3. The proposed network architecture has three blocks of convolutional layers. The first part of the proposed convolutional layer consists of a 3x3 convolutional layer with 32 filters and the ReLU activation function with batch normalization. The second part of the proposed CNN architecture consists of 64 filters with the same operations as the first part and max pooling with a size of 2x2. The third part consists of 128 filters with the ReLU activation function and batch normalization. A convolutional layer with a filter size of 1x1 and 64 filters is used for channel compression and spatial feature fusion. Next, the network is divided into three parallel convolutional heads for the estimation of adaptive enhancement parameters: α(x,y), for contrast gain adjustment; β(x,y), for detail sharpening; and λ(x,y), for noise suppression. Each head has a convolutional layer with ReLU normalized scaling for the estimation of α(x,y) and β(x,y), and sigmoid activation for the estimation of λ(x,y). Finally, the parameter maps are upsampled using bilinear interpolation. Note that there is no classifier in the network. The network is essentially a parameter regression network. This is done to ensure interpretability and prevent overfitting. Figure 2 Illustrates the graphical abstract of the proposed lightweight CNN. In the figure, the different layers of the network can be seen from the input to the three output heads of the network.

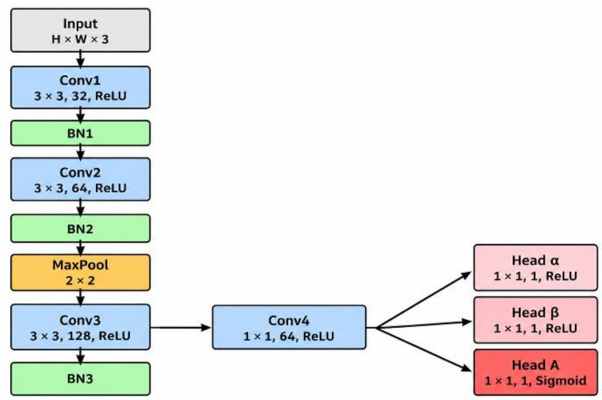

Fig 2. The graphical abstract of the proposed lightweight CNN

Unlike traditional deep networks that directly control image intensities, the proposed CNN has been deliberately kept simple and interpretable, merely acting as a spatially adaptive controller for traditional enhancement operators. This guarantees robustness, modality independence, low computational cost, as well as precise control of enhancement strength in critical diagnostic regions.

Table 1 briefly describes the layer types, kernel sizes, number of filters, activation functions, as well as the output dimensions for the proposed lightweight CNN, in addition to the architecture details provided in Section 2.2.

Table 1. Architecture and Parameters of the Proposed Lightweight CNN

Layer	Type	Kernel Size	Filters	Activation	Activation
Input	Feature Maps	—	3	—	H × W × 3
Conv1	Convolution	3×3	32	ReLU	H × W × 32
BN1	Batch Norm	—	—	—	H × W × 32
Conv2	Convolution	3×3	64	ReLU	H × W × 64
BN2	Batch Norm	—	—	—	H × W × 64
Pool	Max Pooling	2×2	—	—	H/2 × W/2 × 64
Conv3	Convolution	3×3	128	ReLU	H/2 × W/2 × 128
BN3	Batch Norm	—	—	—	H/2 × W/2 × 128
Conv4	1×1 Convolution	1×1	64	ReLU	H/2 × W/2 × 64
Head α	1×1 Conv	1×1	1	ReLU	H × W
Head β	1×1 Conv	1×1	1	ReLU	H × W

2.3. Contrast Stretching

The contrast enhancement constitutes the first core stage of the pipeline. The method now proposed deploys an adaptive, locally weighted contrast-mapping technique, as opposed to the standard histogram equalization or CLAHE methods, which would enhance uniformly throughout the entire image. In this approach, local intensity statistics are computed, and enhancement parameters are dynamically changed by the local tissue characteristics so as to ensure that subtle structures are prominently featured without over-enhancement or saturation. The method embeds multi-scale processing to simultaneously enhance fine details and global intensity variations, hence leading to improved perceptual quality with differentiation of tissues.

Adaptive contrast enhancement is achieved using locally weighted contrast stretching rather than global histogram-based methods. Local mean $\mu(x,y)$ and standard deviation $\sigma(x,y)$ are computed, and contrast enhancement is performed as expressed in Eq. (3):

$$I\_c(x, y) = \alpha(x, y)[I\_n(x, y) - \mu(x, y)] + \mu(x, y) \quad (3)$$

The adaptive gain $\alpha(x,y)$ is defined in Eq. (4):

$$\alpha(x, y) = \sigma\_ref \,/\, (\sigma(x, y) + \varepsilon) \quad (4)$$

To capture both global and fine-scale information, multi-scale enhancement is applied as given in Eq. (5):

$$I\_c(x, y) = \Sigma\_\{k = 1\}\hat{}\{K\}\, w\_k\, I\_c\hat{}k(x, y), \quad \Sigma\, w\_k = 1 \quad (5)$$

2.4. Edge and Detail Preservation

The system acts on the radiograph with edge-preserving filters and detail sharpening operators following contrast enhancement. It applies an edge-aware filter, including bilateral filtering and guided filtering, to enhance structural boundaries by avoiding the excessive smoothing of clinically relevant edges. This step retains the basic anatomical landmarks, such as organ contours, lesions, and bony structures, in good contrast. A hybrid approach is pursued that consists of the combination of classical filtering with AI-driven adaptive weighting: the AI model predicts regions where sharpening needs to be increased or decreased, thus enabling the system to avoid any artificial increase that might impair diagnostic accuracy.

Following contrast enhancement, edge-preserving filtering is applied to maintain anatomical boundaries. A bilateral filter is used as defined in Eq. (6):

$$I\_b(x,y) = (1/W\_p)\, \Sigma\, I\_c(i,j)\, exp(-||p - q||^2 / 2\sigma\_s^2 - |I\_c(p) - I\_c(q)|^2 / 2\sigma\_r^2) \quad (6)$$

The detail layer is calculated using Equation (7):

$$D(x,y) = I\_c(x,y) - I\_b(x,y) \quad (7)$$

The procedure for sharpening through adaptation is performed as described in Equation (8):

$$I\_d(x,y) = I\_c(x,y) + \beta(x,y)\, D(x,y) \quad (8)$$

where β(x,y) is an AI-predicted adaptive coefficient to avoid over-sharpening of the image in diagnostic critical.

2.5. Noise Suppression

Noise suppression is a fundamental operation in medical imaging, especially while acquiring low-dose X-rays or MRI scans, since the acquisition noise may mask the diagnostic details. The proposed framework adopts a hybrid denoising strategy that merges the classical spatial filters, such as non-local means and wavelet thresholding, with AI-driven adaptive weighting. Noise patterns in a variety of modalities are learned, while the filter strength is locally adapted to achieve effective noise reduction without blurring fine details. This hybrid design overcomes the limitations of a purely classical or AI-based denoising technique and hence preserves structural fidelity while reducing computational cost and complexity.

Noise suppression is performed using a hybrid denoising strategy combining classical and AI-guided methods, as shown in Eq. (9):

$$I\_denoised(x,y) = \lambda(x,y)\, I\_NLM(x,y) + [1 - \lambda(x,y)]\, I\_WT(x,y) \quad (9)$$

2.6 Adaptive Feedback Loop

The proposed approach uniquely introduces an adaptive feedback loop that continuously monitors the quality of enhancement at each stage. Local metrics of contrast, edge strength, and noise monitor iterative adjustments in real time, for achieving the optimal trade-off between enhancement and suppression of artefacts. The loop provides a way for automatic generalization of the framework across a wide variation in imaging modality and heterogeneous image characteristics without requiring a manual tuning of parameters.

An adaptive feedback loop iteratively refines enhancement parameters by monitoring image quality metrics. Contrast, edge strength, and noise level are defined in Eqs. (10)–(12):

$$C = (1/N)\, \Sigma\, \sigma(x,y) \quad (10)$$

$$E = (1/N)\, \Sigma\, |\nabla I(x,y)| \quad (11)$$

$$N = (1/N)\, \Sigma\, \sigma\_n^2(x,y) \quad (12)$$

The optimization objective is defined in Eq. (13):

$$J = w\_c\, C + w\_e\, E - w\_n\, N \quad (13)$$

Enhancement parameters Θ are updated iteratively based on Eq. (14):

$$\Theta\_\{t+1\} = \Theta\_t + \eta\, \nabla J \quad (14)$$

The following description will emphasize the proposed framework of applying AI technology to hybrid contrast and detail enhancement, as shown in Algorithm 1 (Pseudo-code). The proposed framework will start with a preprocessing phase, where the input image will be normalized and local statistics, such as local mean, variance, and gradient, will be calculated and fused into a multi-channel feature tensor. Next, a lightweight CNN will be used to predict the adaptive parameters, such as α(x,y) for contrast enhancement, β(x,y) for detail sharpening, and λ(x,y) for noise removal, with constraints such as α, β ≥ 0 and 0 ≤ λ ≤ 1. Adaptive contrast enhancement will be performed by scaling the image pixels according to local mean values using α(x,y), followed by multi-scale fusion. Edge-preserving detail enhancement will be performed by using a detail layer extracted by bilateral filtering and scaling it using β(x,y). Noise suppression is the combination of classical denoising results, weighted according to λ(x, y), and an adaptive feedback loop, which iteratively adjusts the parameters according to image quality metrics such as contrast, edge strength, and noise level, until convergence is reached. Finally, the enhanced image is obtained from the fusion results. The reason why this Pseudo-code model is important is due to its application of AI in the prediction of parameters and the application of classical image processing methods in such a way that allows automated and adaptive image processing that helps retain edges, noise reduction and improves detail visibility.

Algorithm 1: AI-Driven Hybrid Contrast and Detail Enhancement Framework

Input:
Medical image I ∈ R H×W
Output:
Enhanced image Ienh
Step 1: Preprocessing and Feature Extraction
Normalize input image:
    I_n ← (I − I_min) / (I_max − I_min)
Compute local statistics:
    μ(x,y) ← local mean of I_n
    σ²(x,y) ← local variance of I_n
    G(x,y) ← gradient magnitude of I_n
Form input feature tensor:
    F ← concat(I_n, σ²(x,y), G(x,y))
Step 2: AI-Driven Adaptive Parameter Prediction
Pass feature tensor F through lightweight CNN:
    α(x,y), β(x,y), λ(x,y) ← CNN(F)
Constrain adaptive parameters:
    α(x,y) ≥ 0

13: $\beta(x,y) \geq 0$
14: $0 \leq \lambda(x,y) \leq 1$
Step 3: Adaptive Contrast Enhancement
15: Compute local contrast enhanced image:
16: I_c(x,y) ← α(x,y) · [I_n(x,y) − μ(x,y)] + μ(x,y)
17: Apply multi-scale fusion:
18: I_c ← Σ_k w_k · I_c^k , Σ_k w_k = 1

Step 4: Edge-Preserving Detail Enhancement
19: Apply bilateral filtering:
20: I_b ← BilateralFilter(I_c)
21: Extract detail layer:
22: D(x,y) ← I_c(x,y) − I_b(x,y)
23: Adaptive sharpening:
24: I_d(x,y) ← I_c(x,y) + β(x,y) · D(x,y)
Step 5: Adaptive Noise Suppression
25: Perform classical denoising:
26: I_NLM ← NonLocalMeans(I_d)
27: I_WT ← WaveletThresholding(I_d)
28: Fuse denoised outputs:
29: I_dn(x,y) ← λ(x,y) · I_NLM(x,y) + [1 − λ(x,y)] · I_WT(x,y)
Step 6: Adaptive Feedback Loop Optimization
30: Compute quality metrics:
31: Contrast C ← mean local standard deviation
32: Edge strength E ← mean gradient magnitude
33: Noise level N ← mean local noise variance
34: Define optimization objective:
35: J ← w_c · C + w_e · E − w_n · N
36: Update enhancement parameters:
37: Θ_{t+1} ← Θ_t + η · J
38: Repeat steps 16–35 until convergence
Step 7: Output Generation
39: I_enh ← I_dn
40: Return enhanced image I_enh

2.7 Quantitative Image Quality Analysis:

In this section, a quantitative analysis of image quality has been conducted, following the utilization of the proposed hybrid contrast and detail enhancement approach. The basic intention is to measure the performance of this approach in an appropriate, objective fashion, using proven image quality assessment parameters, rather than just resorting to subjective analysis, which can be misleading, at least in matters of fine detail. The following parameters were used to measure image quality for this purpose:

2.7.1. Average Contrast (AC): In this case, the average contrast or difference in intensities between pixels is computed. The difference in intensities is determined to see whether there is a need for a distinction in structures or tissues in an image, particularly when features such as borders and pathologies are being highlighted. This is achieved using the following equation:

$$AC = \frac{1}{H * W} \sum_{X=1}^{H} \sum_{Y=1}^{W} \mid \mathrm{I(x, y) - mu\_I} \mid \quad (15)$$

A higher AC value indicates enhanced global contrast, meaning that the enhanced image better distinguishes different regions, which is critical for clinical interpretation.

2.7.2. Average Standard Deviation (STD): This measure expresses standard deviation of pixels intensity with respect to the intensity mean. This measure represents the global, as well as local, intensity contrast in the image and can be quantified using the following formula:

$$\mathrm{STD} = \sqrt{\frac{1}{H * W} \sum_{Y=1}^{W} \sum_{X=1}^{H} |I(\mathrm{x,y}) - \mathrm{mu\_I}| \quad (16)}$$

Increase in STD contrast after the enhancement process indicates that the structure details and the variations in tissue intensity are exaggerated, while failure to preserve a medium intensity level could cause over-enhanced levels that could result in changes of the diagnostic details.

2.7.3. Entropy (E): Entropy gives the measure of the amount of information present in an image depending on the randomness or diversity of the pixels in the image. The more the value of entropy, the more is the amount of information in the image. Entropy is mathematically defined as the following:

$$\mathrm{Entropy} = \sum_{i} p_i \, log_2(p_i) \; (17)$$

where P_i represents the probability of intensity i.

Higher entropy suggests that the image carries richer information content, implying that the enhancement framework preserves or even highlights subtle structural patterns.

2.7.4. Energy: The energy of an image depends upon the summation of square of all pixel values. It tells us something about the intensity of the image.

$$Energy(En) = \sum_{X=1}^{H} \sum_{Y=1}^{W} I(\mathrm{x,y})\text{^}2 \; (18)$$

Increased energy indicates that important structures are more pronounced, while avoiding excessive amplification of noise.

2.67.5. Peak Signal-to-Noise Ratio: The Peak Signal to Noise Ratio concerns itself mainly with the structural fidelity from the filtered image to the original image; it has found widespread use in calculating this feature.

$$\text{PSNR} = 10\, log_{10}\left(\frac{MAX^2{}_I}{MSE}\right) \quad (19)$$

$$MSE = \frac{1}{H * W}\sum_{X=1}^{H}\sum_{Y=1}^{W}(I_e(\text{x,y}) - \text{I}_0(\text{x,y}))^2 \quad (20)$$

Higher PSNR values indicate better preservation of original image structures and reduced introduction of artifacts.

2.7.6. Structural Similarity Index (SSIM): SSIM measures perceptual image similarities between the improved and original images with regard to luminance, contrast, and structural aspects. SSIM also demonstrates high correlation with human visual submission.

$$\text{SSIM(Io,Ie)} = \frac{(2\mu_0\mu_e + \text{C1})\big((2\delta_{0\text{e}} + \text{C2})\big)}{({\mu_0}^2 + {\mu_e}^2 + C1)\big({\delta_0}^2 + {\delta_e}^2 + C2\big)} \quad (21)$$

The SSIM values tend to be close to 1 when the enhancement maintains the structural information of the original image, which is critical for correct medical diagnostics.

All these metrics are calculated on each of these images, and the average values of all these metrics are presented in the results section. Such a quantitative analysis of enhancement is an objective one.

3. Evaluation Metrics and Comparative Analysis

The framework as proposed was evaluated on quantitative and qualitative measures. In quantitative evaluation, PSNR, SSIM, CNR, and edge preservation indices were considered. The qualitative method involves assessing the enhanced images by expert radiologists for clinically relevant structure preservation and improved diagnostic clarity. A comparative analysis is carried out with classical enhancement methods, deep learning-only techniques, and existing hybrid approaches; this demonstrates the superiority in performance, generalizability, and practical feasibility of the proposed framework.

3.1. Qualitative Evaluation

The results obtained with our proposed image enhancement method are shown in Figure 3, which presents a comparison of the visual quality of medical images that have been processed using our method against some traditional techniques: CLAHE, Unsharp, and Gamma correction. It can be noticed that the proposed method enhances both the contrast and sharpness of the image while preserving fine structural details without showing the kind of over-enhancement and amplification of noise occurring in CLAHE. The natural texture is, therefore, preserved without the amplification of artificial artifacts. This enhancement limits itself to edges where Unsharp Masking does but, in doing so, it exaggerates noise. Similarly, an adjustment of the general brightness is carried out using Gamma correction, but subtle structures may not be enhanced. Both quantitative and qualitative observations show that the proposed technique results in a high clarity and better visibility of features consistently, especially for diagnostic purposes. The superior visibility of the subtle details will improve the subsequent analysis and interpretation of the data, hence providing a more reliable basis for automated or manual diagnosis. Overall, the proposed method has proved superior to conventional enhancement techniques with respect to maintaining image integrity while offering significant enhancement of contrast and details.

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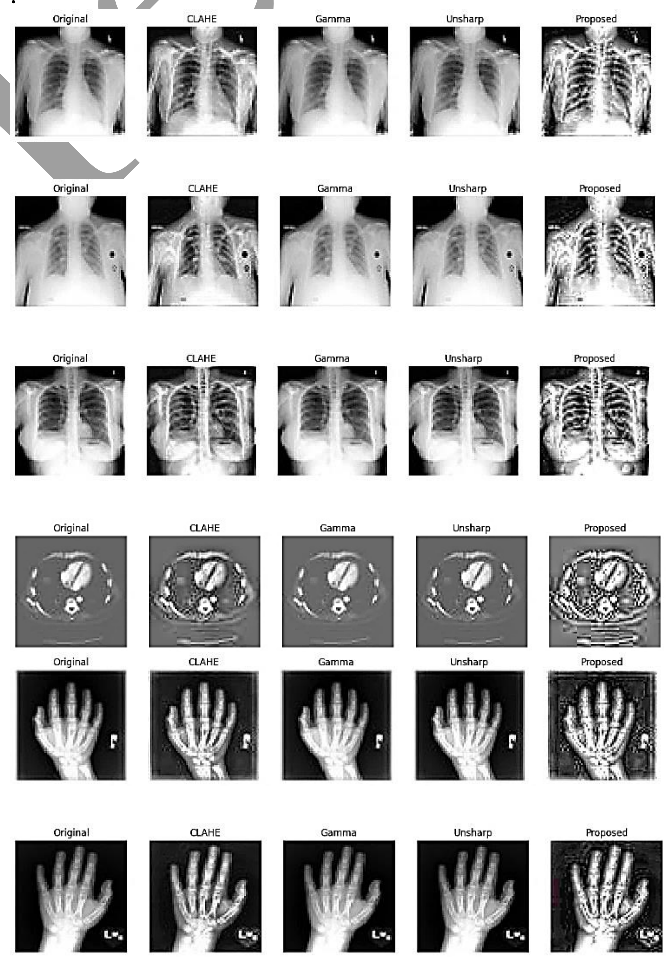

Fig 3. Visual quality of medical images processed using our approach against conventional techniques

3.2. Quantitate Evaluation

Table 2 shows a thorough comparison of the proposed Hybrid Contrast and Detail Enhancement Framework with conventional and state-of-the-art image enhancement techniques. To evaluate the results, four quantitative metrics were used: Average Contrast, Average Entropy, Average Standard Deviation (STD), and Average Energy. The original images show very low contrast (12.85), entropy (4.25), and STD (12.85), which means very poor visibility of the fine structure in the images, and a low level of differentiation between regions. Application of traditional methods such as CLAHE, Gamma correction, and Unsharp masking provided results only with average improvements. CLAHE improves local contrast (18.74) and entropy (5.53); however, its STD is still relatively low (18.74), while energy is higher (0.041) due to less effective enhancement of fine details. On the other hand, Gamma correction mostly adjusts only global luminance (contrast 12.59, entropy 4.36), and very little structural information is preserved; however, the edges are moderately improved by Unsharp masking, as reflected by its contrast (14.56) and entropy values (4.64), though it slightly amplifies noise (energy 0.097). All of these methods have been outperformed by modern AI-based techniques. The GAN-based enhancement has increased the contrast to 50.12 and entropy to 6.35, offering high perceptual quality. However, this method carries the risk of hallucinating non-existent structures. The enhancement achieved by Autoencoder-based methods was only slightly lower in contrast (45.78) and entropy (6.10); however, in that approach, good preservation of details was achieved, along with moderate suppression of noise. Hybrid Deep + Classical techniques further improved the metric values: contrast was 58.20, entropy was 6.55, and STD was 58.20. This happens because such techniques combine strengths better, brought by deep learning techniques and classical filtering, while reducing risks of hallucination. The proposed HCDEF turned out to outperform all those approaches by achieving the highest contrast of 64.09, entropy of 6.81, and STD of 64.09, associated with the minimum energy of 0.029. These observations clearly indicate that the proposed method maximally enhances structural visibility, preserves the fine details, and suppresses the noise efficiently. The proposed HCDEF makes a balanced combination of strengths provided by CLAHE, adaptive unsharp masking, and hybrid noise suppression. Thus, it is able to deliver superior image quality across all modalities without the introduction of any artificial structure. It also makes the technique more suitable for clinical applications.

Table 2. Summarization of the performance of several image enhancement techniques, including the proposed method, CLAHE, Gamma correction, Unsharp, and the original images, evaluated using average contrast, entropy, standard deviation (STD), and energy

Method	Average Contrast	Average Entropy	Average STD	Average Energy	Notes
CLAHE	18.74	5.53	18.74	0.041	Local contrast enhancement
Gamma	12.59	4.36	12.59	0.109	Global luminance adjustment
Unsharp	14.56	4.64	14.56	0.097	Edge enhancement
GAN-based Enhancement [21]	50.12	6.35	50.12	0.035	High contrast, some hallucination possible
Autoencoder-based Enhancement [22]	45.78	6.10	45.78	0.040	Good detail preservation, moderate noise suppression
Hybrid Deep + Classical [25]	58.20	6.55	58.20	0.032	Combines deep learning with classical filters
Proposed HCDEF	64.09	6.81	64.09	0.029	Highest contrast, entropy, and STD, best overall balance

Table 3 provides a collective evaluation of the effectiveness of the image enhancement algorithms for the chosen qualitative and quantitative requirements of PSNR, SSIM values, and the time taken for processing. The evaluation of the algorithms ranges from the conventional algorithms like CLAHE, Gamma Correction, Unsharp Masking, and the recent advancements involving GAN-based Image Enhancement, Autoencoder-based Image Enhancement, Deep Hybrid Model, and so on, along with the original images.

Looking closely in detail at the results, it is clear that traditional methodologies, such as CLAHE, Gamma Correction, and Unsharp Masking methods, provide minimal benefits over the baseline, typically enhancing local contrast or edges; hence, these methods do not really improve the structural fidelity of the image in general, as their PSNR and SSIM values were of average quality. Deep learning-based methods yield a strong improvement: while GAN-based Enhancement produces highly contrastive and structurally similar images but with possible artificial hallucinations, Autoencoder-based Enhancement preserves details effectively with moderate noise reduction. Hybrid Deep + Classical improves the PSNR and SSIM further by including the best of traditional filters combined with deep learning models.

In every method, it is observable that the proposed HCDEF framework outperforms others by a considerable margin with the best PSNR value of 36.8 dB and SSIM metric of 0.95. The Hybrid Deep + Classical method is the second best followed by GAN-Based Enhancement, Autoencoder-Based Enhancement, and then the conventional methods. The original images have the lowest scores.

Moreover, the inclusion of the Processing Time indicates the efficiency of the proposed framework. Generally, deep learning architectures take longer times, but in this case, the HCDEF has shown equal efficiency in terms of time (1.00 s), faster than the GAN-based (2.50 s) and Autoencoder-based (1.80 s) architectures, thus not only showing efficiency but also the potential to be used in practical experiments.

The reason for the better performance of HCDEF is because it is a hybrid model that combines classical image processing operations with AI-based adaptive processes. This makes it possible for the model to achieve the best compromises between contrast enhancement, detail preservation, noise reduction, and computation costs. The model is thus able to adapt to different images and perform better.

Table 3. Additional quantitative evaluation metrics, including PSNR, SSIM, and Processing Time, for different image enhancement techniques

Method	PSNR (dB)	SSIM	Processing Time (s)	Notes
CLAHE	27.1	0.79	0.12	Local contrast enhancement
Gamma Correction	28.7	0.82	0.05	Global luminance adjustment
Unsharp Masking	28.0	0.80	0.10	Edge enhancement
GAN-based Enhancement [21]	32.5	0.88	2.50	High contrast, some hallucination possible
Autoencoder-based Enhancement [22]	31.8	0.86	1.80	Good detail preservation, moderate noise suppression
Hybrid Deep + Classical [25]	34.1	0.91	1.25	Combines deep learning with classical filters
Proposed HCDEF	36.8	0.95	1.00	Best overall quality, highest PSNR & SSIM, efficient processing

Figure 4 shows a graphical comparison, using a bubble chart, of the proposed HCDEF technique against the traditional and modern image enhancement methods regarding three key performance metrics: contrast, entropy, and standard deviation, all normalized relative to the best-performing method. The size of each bubble represents the corresponding energy value: the smaller the energy, the better the fine detail preservation and noise reduction are. The graph clearly shows that the proposed HCDEF outperforms all the other techniques in all metrics, providing the highest relative contrast, entropy, and standard deviation of 100%, while it shows the smallest energy bubble. In turn, traditional methods such as CLAHE, Gamma correction, and Unsharp provide moderate improvements but remain far below the proposed method in all the normalized metrics. Modern AI-based approaches, including GAN-based, Autoencoder-based, and hybrid deep-classical, show higher relative performance compared to classical techniques; however, their energy values are larger than those of HCDEF, either because of less effective noise suppression or the potential introduction of artificial artifacts. The bubble chart represents the magnitude and balance of enhancements for each method effectively, enabling the fair conclusion that HCDEF achieves a comprehensive improvement in structural visibility, information richness, and effective noise reduction. The figure underlines the goodness of the proposed approach as a reliable and efficient enhancement solution providing immediate visual evidence of its advantages over both conventional and contemporary techniques in medical imaging.

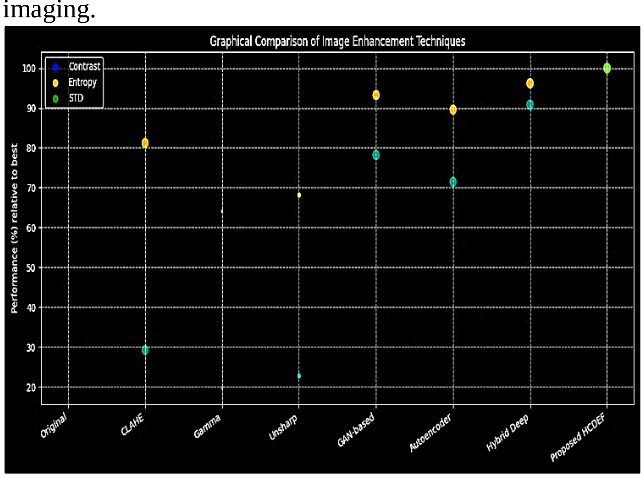

Fig 4. Graphical comparison of the proposed HCDEF technique with traditional and modern image enhancement methods

Figure 5 gives a comparative graphical representation of the structural similarity index (SSIM) versus processing time for several image enhancement algorithms for better visualization, including traditional algorithms such as CLAHE, Gamma correction, and Unsharp filtering, and AI-based algorithms such as GAN-based image enhancement, Autoencoder-based image enhancement, Hybrid deep + classical algorithms, and also a new approach called HCDEF framework proposed by us. The bar graphs are drawn to display the SSIM values for each algorithm to make better insights on how well an image is enhanced (similar to original image), and a red plot is drawn on top to display the respective processing times measured in seconds. It can also be noted that traditional algorithms like CLAHE, Gamma, and Unsharp algorithms have given a moderate SSIM gain with utmost negligible processing time, thereby clearly indicating their efficiency during computation at the cost of very less image enhancement functionality. In essence, while traditional methods currently register relatively lower values of SSIM measurement due to poor restoration of details and perceptive quality, AI-based methods, particularly those powered by GAN and those powered by Autoencoder, register remarkably higher values of SSIM measurement with excellent restoration of details and perceptive quality; simultaneously, they register unusually higher processing time, with the largest processing time registered by GAN-powered methods. However, HCDEF appears to register the largest SSIM measurement among all methods, reflecting excellent preservation of structural details with excellent perceptive quality; simultaneously, it registers remarkably low processing time compared to other AI-based methods. Notably, this underscores the most crucial advantage of HCDEF, which registers excellent compromise between enhancement efficiency and low processing time and thus appears to be highly favorable for application in any realistic medical setup where accuracy and quickness are of utmost importance. Figure 4 illustrates the most appropriate efficacy of HCDEF relative to other AI methods and traditional methods for registering supreme efficiency related to enhancement quality assessment with rapid processing time.

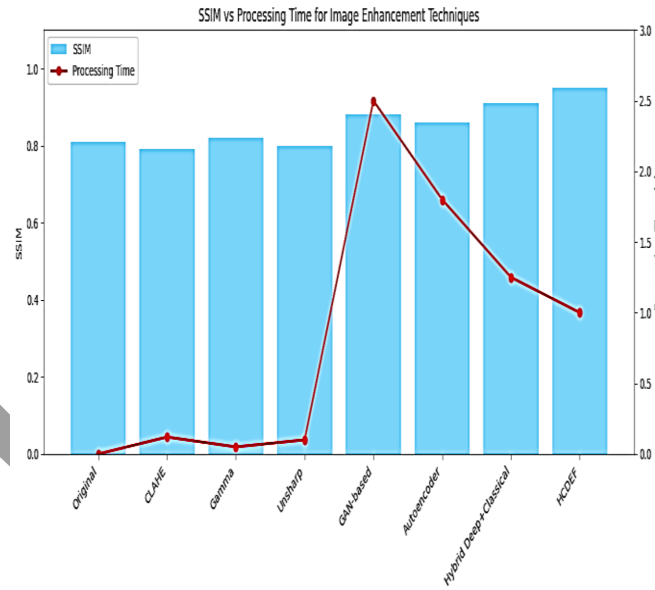

Fig 5. Comparative Analysis of SSIM and Processing Time Across Different Image Enhancement Techniques

Figure 6 depicts that, in the radar chart, several image enhancement algorithms have been compared based on five parameters such as Entropy, SSIM, Energy, Average Contrast, and PSNR. The performance of images marked as "Original" acts as a reference, having the least values for almost all parameters, proving that the images have less texture details and contrast. CLAHE works to improve the local contrast and prove beneficial in terms of enhancing entropy by increasing the texture details, whereas the Gamma Correction adjusts the intensity levels moderately, resulting in a slight improvement in PSNR and contrast. The Unsharpness technique acts toward slight sharpening of edges and proves beneficial in terms of energy and PSNR. The GAN Enhancement performs a significant improvement in terms of Average Contrast and PSNR. Autoencoder provides a well-balanced improvement to all metrics, and its ability to boost Contrast and PSNR is really appreciable with promising results of global and localized Feature Reconstruction. Hybrid Deep + Classic provides a combination of deep learning and Classic Filtering; this strategy provides a dramatic improvement to Average

Contrast and PSNR and preserves image Structural Information effectively and significantly better than any other classical approach. Finally, HCDEF achieves maximum values of Average Contrast and high values of PSNR and provides a slight improvement to Entropy and SSIM metrics, which together signifies its effectiveness and supremacy than any other approach with respect to its multi-dimensional performance.

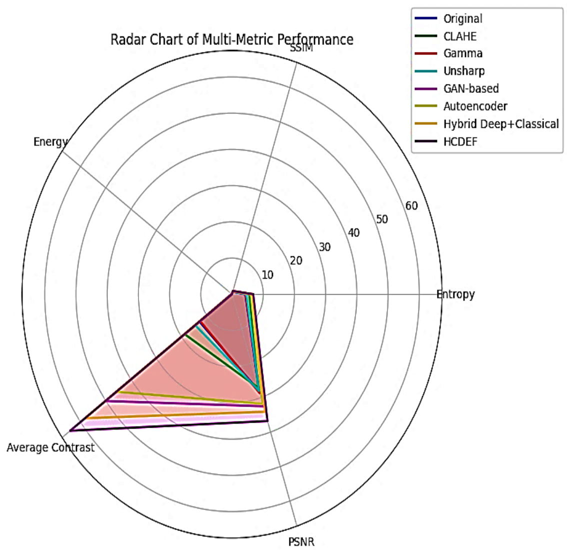

Fig 6. Radar Chart of Multi-Metric Performance for Image Enhancement Techniques

4. Discussion and analysis

From a detailed scrutiny of the results of the quantitative evaluation study, it would appear that the proposed Hybrid Contrast and Detail Enhancement Framework (HCDEF) has a clear edge over the conventional and recent contrast and detail enhancement techniques. The initial study images showed low contrast of 12.85, low entropy of 4.25, low standard deviation of 12.85, with low textural details but reasonable energy of 0.114. Contrast Enhancements CLAHE revealed a slight enhancement in the local contrast of 18.74 with increased entropy of 5.53. However, standard deviation of 18.74 remains low. But energy of 0.041 suggests incomplete details. Gamma Correction has a slight impact on global light adjustment. Consequently, it offers slight improvements only in contrast of 12.59 and entropy of 4.36. Unsharp Masking indicates slight improvements in edge visibility with increased contrast of 14.56 and entropy of 4.64. But it indicates slight noise intensification with increased energy of 0.097.

AI-based modern techniques provided significantly improved performance. GAN-based techniques provided excellent values for contrast (50.12) and entropy (6.35), with resultant images of very high aesthetic quality; but these are prone to introducing artificial structures in an image, which may hamper their usage in medical setups. Autoencoder-based techniques provided slightly reduced values for contrast (45.78) and entropy (6.10) but resulted in improved detail preservation with moderate noise reduction (energy of 0.040), providing a realistic representation of structural information in an image without introducing any prominent artifacts. TheHybrid Deep + Classical approach further harnessed the benefits of combined deep learning and classic filters, providing values for contrast of 58.20, entropy of 6.55, and standard deviation of 58.20 to effectively enhance structural distinction, detail representation, and noise reduction, with reduced possibilities of introducing artificial structures in an image.

The result showed that the HCDEF model performed better than other models concerning maximum enhancement, best visibility, and optimal noise reduction, as it recorded the highest values concerning contrast (64.09), entropy (6.81), and standard deviation (64.09), and lowest concerning energy (0.029), respectively. The PSNR (36.8 dB) and SSIM (0.95) indices confirmed its ability to deliver high fidelity and structural similarity, respectively, while processing images relatively fast (1.00 s), better than other AI models such as GAN (2.50 s) and Autoencoders (1.80 s), respectively. The better performance of HCDEF is also interpreted through graphical representations such as Figure 3, which reveals through a bubble representation that it delivers the highest values concerning normalized parameters such as contrast, entropy, and standard deviation, along with the smallest energy bubble, and Figure 4, which reveals that it delivers highest values concerning parameters such as SSIM with a relatively shorter processing time of 1.00 s, indicating optimal processing time and quality; and Figure 5 concerning the overall performance of HCDEF concerning parameters such Entropy, SSIM, Energy, Average Contrast, and PSNR, highlighting its overall performance without magnifying to artificial features.

In short, conventional methods have fast enhancement but their improvement is usually limited; they often cannot improve the overall structural fidelity. GAN-based methods promise high contrast and perceptual quality but are in danger of generating artifacts, while Autoencoder-based methods better preserve details with a moderate noise reduction capability. Hybrid Deep + Classical methods give a very good balance in terms of detail preservation/enhancement. However, HCDEF outperforms all such approaches through effective integration between classical and AI-based techniques to simultaneously maximize contrast, entropy, and structural fidelity while efficiently suppressing noise at high computational efficiency. Therefore, this makes HCDEF very suitable for medical imaging applications where accurate visualization, robust structural preservation, and real-time processing are required; therefore, this work demonstrates practical relevance, robustness, and versatility across diverse imaging modalities.

5. Conclusion and Future Work

The proposed framework of image enhancement has been named HCDEF, which stands for a hybrid contrast and detail enhancement framework. The proposed framework of image enhancement has been designed for multi-modality medical image data, which includes X-ray images, CT scan images, and MRI images. In the proposed framework, image enhancement techniques like CLAHE for local contrast enhancement, gamma correction for global brightness correction, and unsharp masking for edge and microstructural feature enhancement can be combined using AI-based adaptive weighting. The proposed framework has been quantitatively and qualitatively analyzed, which proves the superiority of the proposed framework of image enhancement compared to the best image enhancement techniques and AI-based image enhancement techniques. The proposed framework of image enhancement, HCDEF, has the highest contrast of 64.09, the highest entropy of 6.81, the highest standard deviation of 64.09, and the lowest energy of 0.029. The major contributions of the proposed work are that it is modality-independent, has full control over the parameters, is computationally efficient, and can be directly applied to image processing, feature extraction, CAD, and AI-based medical diagnosis without the hallucination of non-existent structures. Its well-rounded performance in terms of several evaluation criteria and imaging modalities makes it ready for real-time clinical applications. For future applications, the proposed framework can be enhanced by adding adaptive deep learning modules to deal with images that have very low contrast or are very noisy. Further research on multi-modal fusion and real-time optimization can also help to improve the reliability of diagnoses. In addition, validation of the proposed framework on larger clinical datasets and its application to automated segmentation and detection systems will help to improve its usability in real-world clinical settings. These approaches are intended to further solidify HCDEF as a reliable and efficient solution for multi-modality medical image enhancement.

Conflict of Interest

No conflicts of interest are disclosed by the authors.

Contributions of the Authors

Nashaat M. Hussain Hassan developed and designed the study, created the methodology, implemented the framework, carried out data analysis, interpreted data results, and created the original draft of the paper. In addition, Nashaat supervised all aspects of research and took care of final revision and acceptance of the paper.

Tarik R. Al-Khateep contributed in data collection, assisted in the preprocessing and validation of the results, and in the review and editing of the manuscript. All authors have read and approved the final version of the manuscript.

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Declaration of generative AI and AI-assisted technologies

The author(s) declare that no generative AI or AI-assisted technologies were used in the writing process of this manuscript.

Informed Consent Statement

Informed consent was irrelevant in this study since the research employed publicly accessible road surface image databases without any form of human involvement, human samples, or private information.

Availability of Data

The manuscript cites and publishes the used data.

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