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Enhancement of Retinal Fundus Images Using Hybrid Fusion enhancement

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ABSTRACT: Retinal fundus images with poor quality can make it difficult for doctors and computer-based tools to give accurate results. While deep learning models like CoFeNet are useful, they often need powerful hardware and a large amount of labeled data. To overcome these issues, to implement a new method called Hybrid Image Fusion Enhancement. This technique uses a mix of basic image processing steps to improve the quality of fundus images—without the need for deep learning. The steps include contrast enhancement using CLAHE, adding Gaussian noise for regularization, applying Retinal Structure Attention (RSA), using non-local means for noise reduction, and combining the results through hybrid fusion and sharpening. This method helps to clearly show important eye structures like blood vessels and the optic disc. Since it is lightweight and doesn't rely on large datasets, it can be easily used in day-to-day medical imaging.
Index Terms: Fundus image enhancement, CLAHE, RSA, Non-local means, Hybrid fusion, Image clarity, Medical imaging.

I . INTRODUCTION

Retinal fundus imaging plays a key role in diagnosing eye diseases such as diabetic retinopathy, glaucoma, and age-related macular degeneration. The quality of these images is crucial for both doctors and automated systems to detect and analyze important features like blood vessels and the optic disc. However, due to poor lighting, patient movement, and other imaging limitations, fundus images often suffer from low contrast, noise, and uneven brightness. These problems make it harder to clearly view important retinal structures, which can affect the accuracy of diagnosis.

To improve image quality, many enhancement methods have been developed. Traditional techniques like histogram equalization can boost contrast but may also cause unwanted artifacts. Deep learning methods such as CoFeNet have shown good results, but they need large labeled datasets, high computational power, and often produce images with lower quality compared to Implemented Hybrid Image Fusion Enhancement method. In this work, new image enhancement approach is used that combines traditional processing steps. This method improves image clarity while preserving fine details and does not require any deep learning or large-scale training. It offers a practical solution for improving fundus image quality in clinical and research settings. Quantitative results using metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) demonstrate that the Implemented method outperforms existing approaches, making it a practical choice for improving fundus images in medical imaging applications.

II. EXISTING METHOD

The current state-of-the-art method for retinal fundus image enhancement is the CoFeNet model, a deep learning framework designed to improve the quality of fundus images by selectively enhancing degraded regions and important retinal structures. CoFeNet employs three main components:

- **Low Quality Attention (LQA):** This module detects and focuses on degraded areas of the image affected by poor illumination, noise, or blur, enabling targeted enhancement of these low-quality regions.
- **Retinal Structure Attention (RSA):** This module emphasizes critical anatomical features such as blood vessels and the optic disc, ensuring that important retinal structures are preserved and highlighted during enhancement.
- **Image Correction Module:** This component performs global and local adjustments to correct color distortion, uneven illumination, and contrast imbalance, restoring the natural appearance of the fundus images.

This integrated architecture allows CoFeNet to produce enhanced images with improved Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM), outperforming conventional enhancement techniques on benchmark datasets such as DRIVE and Kaggle RFMiD2.0.

Despite its promising performance, CoFeNet has several limitations. It requires extensive training on large annotated datasets and significant computational resources for both training and inference, which can limit its practical application. Additionally, the model may introduce over-enhancement or artifacts in certain regions, potentially reducing clinical reliability. The deep learning model's black-box nature also limits interpretability and fine control over the enhancement process.

To address these challenges, this paper proposes a Hybrid Fusion Enhancement method that combines classical image processing techniques—such as Contrast Limited Adaptive Histogram Equalization (CLAHE), noise simulation, bilateral filtering, non-local means denoising, adaptive fusion, and sharpening—to improve fundus image quality. Unlike CoFeNet, the proposed approach does not require training data or deep networks, offering greater interpretability and computational efficiency. This hybrid pipeline aims to overcome CoFeNet's limitations by providing a robust, data-independent method that achieves competitive or superior image enhancement results while avoiding common issues such as over-enhancement and artifacts.

III. IMPLEMENTED METHOD

The Methodology for Hybrid Fusion Enhancement describes as follows and which is shown in Figure1.

This method combines traditional image processing techniques to improve retinal fundus images without relying on deep learning. It starts with CLAHE for local contrast enhancement, followed by simulated Gaussian noise addition to prepare the image for denoising. Retinal structures are preserved using bilateral filtering (RSA), and further noise reduction is achieved through Non-Local Means denoising. Finally, the method fuses the denoised and contrast-enhanced images and applies sharpening to enhance fine details and clarity. These steps are explained below.

Step 1: Contrast Enhancement using CLAHE

The original retinal fundus image undergoes contrast enhancement using Contrast Limited Adaptive Histogram Equalization (CLAHE) applied to the luminance channel in LAB color space with a clip limit of 3.0 and tile grid size of 8×8.

Step 2: Gaussian Noise Addition

Artificial Gaussian noise with a small variance of 0.0005 is added to simulate real-world imaging noise and prepare the image for robust noise reduction.

Step 3: Retinal Structure Attention (RSA) via Bilateral Filtering

The image is processed with a bilateral filter that performs edge-preserving smoothing. This filter reduces noise while maintaining sharpness of crucial retinal structures such as blood vessel edges. Using a kernel size of 9 and sigma values of 120 for both color and spatial components, the bilateral filter ensures noise is minimized without blurring important anatomical details, effectively preserving retinal structure attention.

Step 4: Non-Local Means (NLM) Denoising

NLM denoising is applied with patch size 7 and patch distance 11, adapting filtering strength based on estimated noise levels to effectively suppress noise while retaining texture and details.

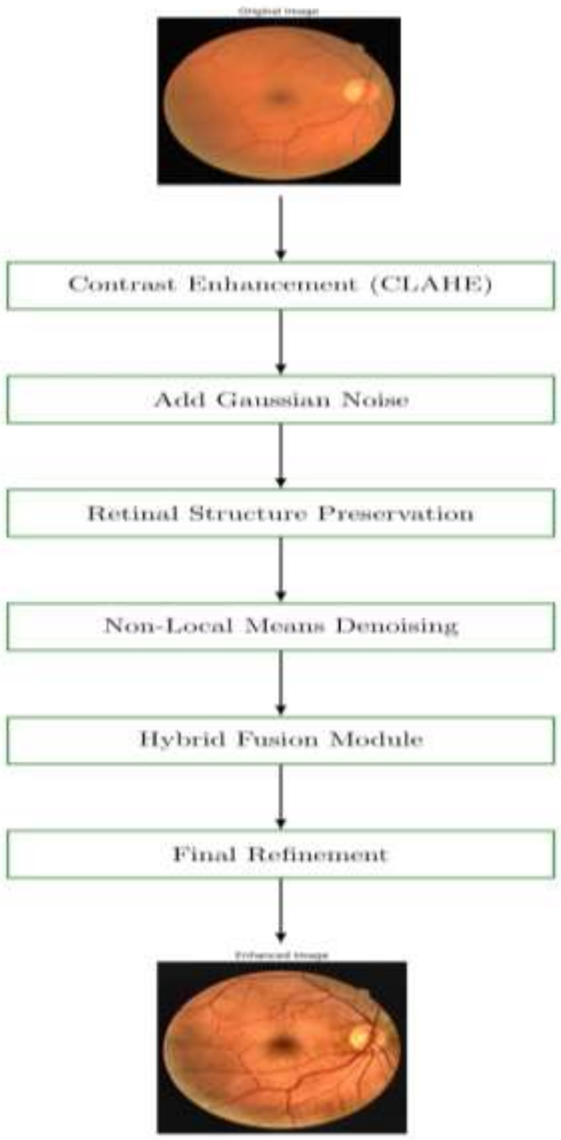
Step 5: Weighted Hybrid Fusion of Enhanced and Denoised Images

The denoised image and the CLAHE-enhanced image are fused through weighted averaging with weights of 0.3 and 0.7, respectively, balancing noise reduction and contrast preservation.

Step 6: Final Image Sharpening via Unsharp Masking

The fused image undergoes sharpening by unsharp masking, where a Gaussian blur with sigma 2 is subtracted from the original image using weights 1.5 (original) and -0.5 (blurred), enhancing fine details and edges.

Input Image



Enhanced Image

Figure 1: Flow chart of the Hybrid Image Fusion Enhancement System

IV. PERFORMANCE METRICS

Different Performance Metrics used to check the performance of implemented system is explained herewith:

4.1 Peak Signal-to-Noise Ratio (PSNR)

PSNR is used to measure the quality of reconstruction of lossy compression or enhancement. PSNR is expressed in **decibels (dB)** and is calculated based on the **Mean Squared Error (MSE)** between the original and processed images. Higher PSNR values typically indicate **lower error** and **better image quality**.

$$\text{PSNR} = 10\log_{10}(\frac{R^2}{MSE}) \quad (1)$$

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)^2 \quad (2)$$

Where:

- R: maximum possible pixel value (255 for 8-bit images)
- A **higher PSNR** value means better image quality.

4.2 Structural Similarity Index Measure(SSIM)

SSIM evaluates the **structural similarity** between two images. It considers **luminance (mean)**, **contrast (variance)**, and **structure (covariance)**. SSIM values range from **0 to 1**, where 1 means **perfect similarity**.

$$\text{SSIM}=\frac{(2\mu_x\mu_y+C1)(2\sigma_{xy}+C_2)}{(\mu_x^2+\mu_y^2+C_1)(\sigma_x^2+\sigma_y^2+C_2)} \quad (3)$$

Mean

The **mean** of an image represents the **average intensity** of the pixels. It indicates the overall **brightness level** of the image.

$$\mu_x = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (4)$$

$$\mu_y = \frac{1}{N}\sum_{i=1}^{N} y_i \quad (5)$$

Variance

The variance measures how much pixel intensities **deviate from the mean**, indicating **image contrast** or spread of intensity values**.**

$$\sigma_x^2 = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu_x)^2 \quad (6)$$

$$\sigma_y^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left(y_i - \mu_y\right)^2 \quad (7)$$

Covariance

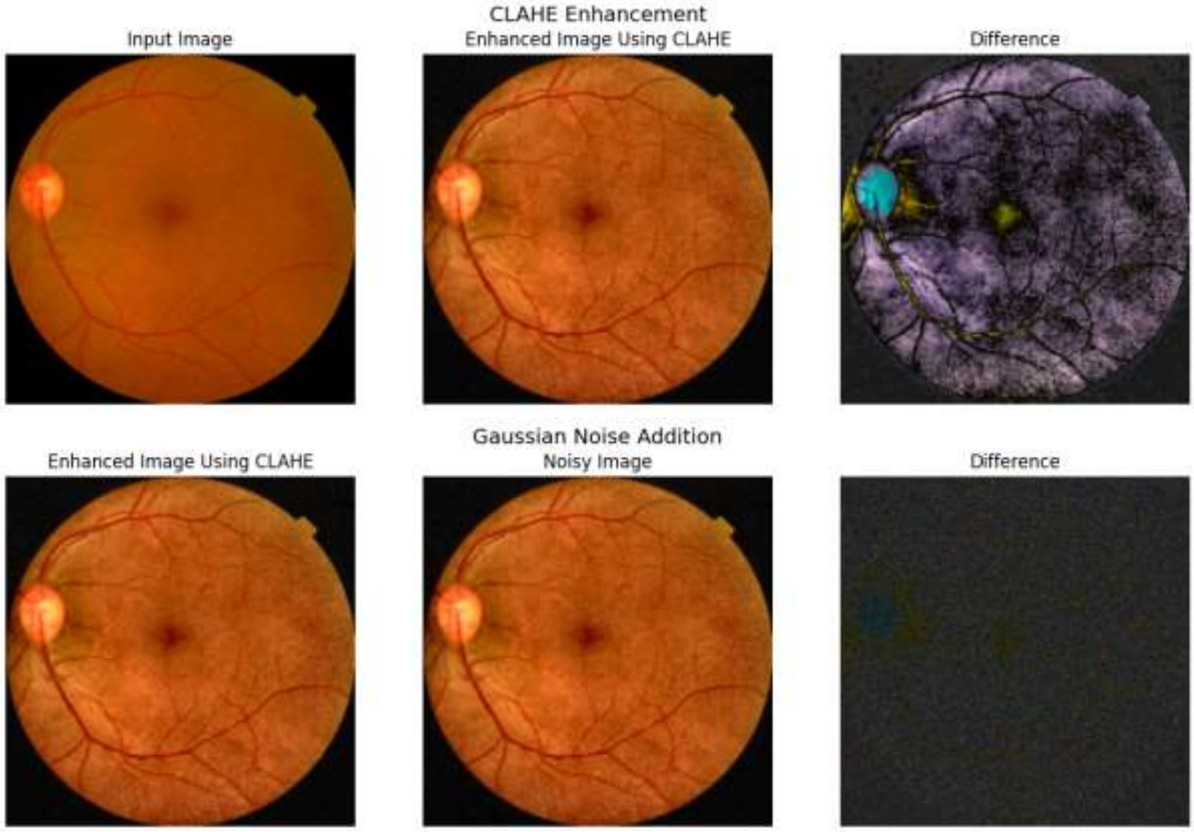
Covariance shows the **joint variability** between two images (original and enhanced). It tells us how changes in one image reflect changes in another.

$$\sigma_{xy} = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu_x)\left(y_i - \mu_y\right) \quad (8)$$

V. SIMULATION RESULTS

Low-quality retinal image is first enhanced using CLAHE to improve contrast. Gaussian noise is added to simulate real-world conditions. RSA filtering is applied next to reduce noise while preserving important edges. Denoising step is used to clean remaining noise and improve clarity. Hybrid fusion of denoised and CLAHE images gives a balanced enhancement result. Final image is sharpened to highlight fine details, this process shown in Figure 1 and its Results Shown in Figure 2. This process is repeated for each input image.

IMAGE-1



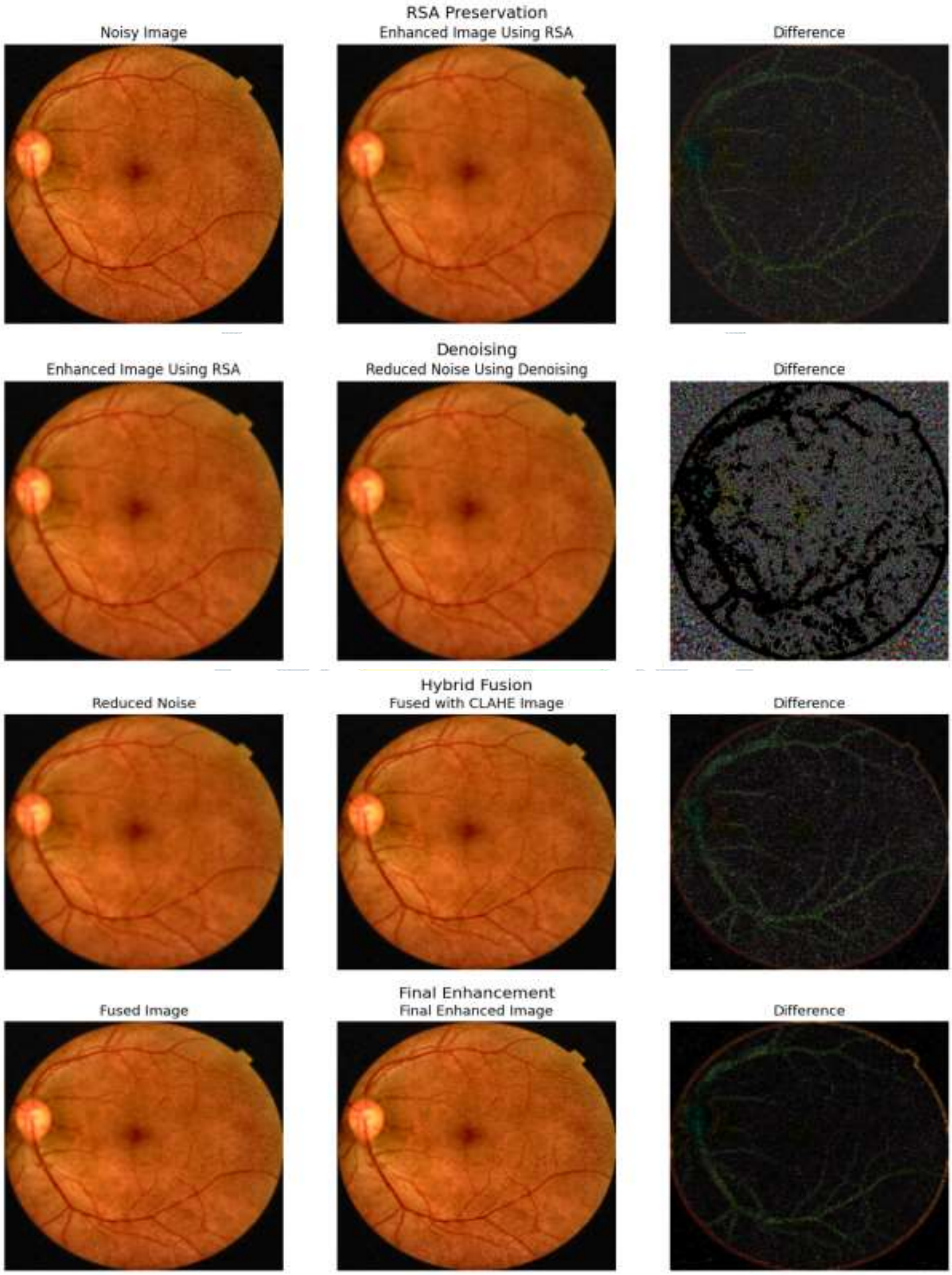


Figure 2: Step-by-Step Enhancement Results for Image-1 from CLAHE to Final Output

Using Equations 1 and 2, PSNR is calculated for each enhanced image to assess the quality after enhancement Shown in Table 1. Using Equations 3, 4, 5, 6,7 and 8 are used to compute SSIM based on the enhanced image's structure, contrast, and brightness consistency Shown in Table 2. This evaluation process is repeated for every enhanced image.

Table 1: Peak Signal-to-Noise Ratio (PSNR) results for the 5 images.

Image	MSE	PSNR (dB)
1	99.358	28.16
2	84.158	28.88
3	101.7965	28.05
4	92.434	28.47
5	96.732	28.28

Table 2: Structural Similarity Index (SSIM) components and values for the 5 images

Image	μ_x	μ_y	σ_x^2	σ_y^2	σ_{xy}	SSIM
1	77.129	86.216	3888.4	4084.51	3874.604	0.9861
2	94.706	97.419	7492.4	6794.97	7034.129	0.9844
3	58.642	73.610	3035.6	3719.37	3289.175	0.9481
4	79.957	85.147	5251.5	5182.47	5058.278	0.9725
5	74.041	83.222	5067.2	5206.33	5055.310	0.9776

VI. CONCLUSION

This work presents a Hybrid Image Fusion Enhancement method aimed at improving the visual quality of retinal fundus images through a structured sequence of image processing techniques. The enhancement pipeline includes contrast improvement using CLAHE, noise simulation, edge-preserving smoothing via bilateral filtering, denoising through Non-Local Means, adaptive fusion, and sharpening. These steps work together to enhance image clarity while preserving important anatomical details such as blood vessels and the optic disc.

The results demonstrate notable improvements in both visual quality and quantitative image quality metrics. Enhanced images show better contrast, reduced noise, and improved structural visibility, supporting more reliable clinical interpretation and further image analysis. The method is simple and efficient to implement and can be effectively applied in practical medical imaging applications.

VII. REFERENCES

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