

CoSREN: A Task-Coupled Self-Supervised Framework for Diagnostically-Consistent Retinal Fundus Image Enhancement

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Abstract: Retinal fundus image enhancement is essential for improving visual quality and supporting reliable computer-aided diagnosis, particularly when images suffer from uneven illumination, poor contrast, noise, and color variations. However, conventional enhancement approaches primarily optimize visual quality and often assess clinical usefulness only after enhancement through separate diagnostic tasks. To address this limitation, this study proposes CoSREN (Clinically-Coupled Self-Supervised Retinal Enhancement Network), a self-supervised framework designed to enhance retinal fundus images while preserving diagnostically relevant information without requiring paired ground-truth enhanced images. CoSREN integrates a Retinex-based illumination–reflectance decomposition, vessel-aware structure preservation, chrominance consistency, and a task-consistency objective derived from frozen pretrained vessel-segmentation and diabetic-retinopathy classification networks. The auxiliary models are employed only during training, allowing the enhancement network to remain lightweight during inference. Experimental comparison with CycleGAN, PCE-Net, I-SECRET, SCR-Net, and GFE-Net demonstrates improved reconstruction quality, with CoSREN achieving a PSNR of 28.5 dB and SSIM of 0.940. The results indicate that incorporating anatomical structure and downstream task information into the enhancement objective can improve both image fidelity and structural consistency. Overall, CoSREN provides a clinically oriented self-supervised strategy for retinal fundus enhancement that integrates diagnostic relevance directly into the learning process.

Keywords: Retinal fundus image enhancement; self-supervised learning; task-consistency loss; diabetic retinopathy classification; retinal vessel segmentation; domain generalization; explainable computer-aided diagnosis.

Introduction

Fundus photography remains one of the most widely deployed non-invasive modalities for screening and monitoring ophthalmic and systemic disease, including diabetic retinopathy, glaucoma, age-related macular degeneration, and hypertensive retinopathy. The diagnostic value of a fundus image, however, is bounded by its acquisition quality: uneven illumination, low contrast, sensor noise, and inter-device color inconsistency routinely degrade images captured under real-world clinical and tele-ophthalmology

conditions, and these degradations propagate into both human interpretation and automated computer-aided diagnosis (CAD) pipelines.

A substantial body of prior work addresses this problem through image enhancement: classical contrast-adjustment techniques such as Histogram Equalization and Contrast-Limited Adaptive Histogram Equalization (CLAHE) [1], Retinex-based illumination correction [2], and, more recently, learned convolutional and generative enhancement models. A recent structure-aware, color-preserving enhancement framework — the direct predecessor to the present study — proposed a multi-stage pipeline integrating adaptive illumination correction, structure-aware contrast enhancement, and color-consistency restoration on a luminance–chrominance decomposition, validated indirectly through downstream vessel segmentation and DR classification. That framework, like much of the surrounding literature, treats downstream clinical-task performance as a post-hoc validation criterion rather than as a signal that shapes the enhancement objective itself, and it relies on fixed, rule-based operations rather than a learned, data-adaptive mechanism.

This raises a question that, to our knowledge, is not directly addressed by the classical-pipeline line of work: when an enhancement method is optimized only against generic image-quality criteria, is there any guarantee that the resulting enhancement helps — rather than merely leaves unchanged, or in the worst case harms — the diagnostic task it is ultimately meant to support? Because no ground-truth "ideally enhanced" fundus image exists for any clinical dataset, this question cannot be answered by supervised training against a target enhanced image; it requires a training signal that connects enhancement directly to diagnostic-task behavior without requiring paired supervision.

This paper addresses that question by introducing CoSREN, a self-supervised enhancement network whose training objective explicitly incorporates downstream task-consistency signal from frozen, pretrained vessel-segmentation and DR-classification models, alongside unsupervised illumination-decomposition, structure-preservation, and color-consistency terms.

Related work

Histogram-based methods, including Histogram Equalization and CLAHE [1], remain widely used for their simplicity and low computational cost but are prone to over-enhancement and background-noise amplification. Retinex-based illumination-reflectance decomposition [2] normalizes non-uniform illumination but can introduce halo artifacts and, when tuned aggressively, color distortion — a limitation directly inherited by any enhancement pipeline that performs decomposition without a learned, data-adaptive correction term. Convolutional architectures, frequently built on encoder-decoder designs derived from segmentation backbones such as U-Net [3], have been applied to low-light and medical image enhancement with promising perceptual quality gains, though typically at higher training-data and compute cost than classical pipelines. Vision-transformer-based enhancement models, drawing on the self-attention mechanism [4], have more recently been explored for global-context modeling in image restoration, though transformer adoption for enhancement without clear justification for the added complexity is a pattern this study deliberately avoids.

Generative adversarial approaches [5] and, more recently, denoising diffusion models [6] have been used for perceptual image enhancement and restoration, offering strong perceptual realism but introducing training instability, mode-specific artifacts, and — for diagnostic imaging in particular — a risk of hallucinating plausible-looking but diagnostically incorrect structure, which is a specific concern this

study's task-consistency and lesion-preservation evaluation is designed to probe rather than assume away. Because paired ground-truth "ideal enhancement" data does not exist for fundus imaging, self-supervised and unpaired learning strategies — including contrastive representation learning [7] and momentum-based self-supervision [8] — are directly relevant as a template for how a learned enhancement network can be trained without target images, and this study adopts that broader paradigm rather than a supervised one.

Several works validate enhancement quality via downstream deep-learning-based DR screening performance [9,10], demonstrating that enhancement and diagnostic-task performance are related but not establishing whether the enhancement objective itself was shaped by task signal, as opposed to being evaluated against it afterward — precisely the distinction this study's task-consistency loss is designed to operationalize. Cross-camera and cross-population robustness remains an acknowledged open problem in retinal image analysis, motivating domain-adaptation and domain-generalization techniques in the broader medical imaging literature [11]. This study treats cross-dataset generalization as a directly tested evaluation axis rather than an assumed property. Gradient-based visual explanation techniques such as Grad-CAM [12] have been used to localize the evidence behind CNN-based diagnostic predictions, providing a template this study adapts to visualize where enhancement altered the image relative to regions the frozen diagnostic models attend to.

The predecessor structure-aware, color-preserving enhancement framework specifies a multi-stage pipeline of adaptive illumination correction, structure-aware contrast enhancement, and color restoration, implemented as fixed classical operations rather than a learned network, and validated using downstream vessel segmentation and DR classification as a post-hoc, disconnected step. This leaves three specific gaps unresolved: (i) the enhancement mechanism itself has no learnable, data-adaptive parameters, and therefore cannot improve with more data or adapt to a shifted acquisition domain; (ii) no supervisory signal links the enhancement objective to what actually helps a diagnostic model, since evaluation happens only after training; and (iii) cross-dataset robustness is stated as a goal but not investigated through an explicit train/test-domain-shift protocol. These three gaps are causally linked rather than independent: a fixed pipeline cannot be tested for learned generalization because it has nothing to generalize, and it cannot be task-coupled because it has no training-time objective to couple. Resolving gap (i) — introducing a learned mechanism trained self-supervised, since no paired enhancement ground truth exists — is therefore the structural prerequisite for resolving (ii) and (iii), which motivates the single, coherent methodological focus of this study.

Proposed Methodology

CoSREN consists of a single inference-time generator — an illumination-estimation branch feeding a structure-aware, attention-guided decoder, followed by a color-consistency module — and two frozen, pretrained auxiliary models (a vessel-segmentation network and a DR classifier) that are used exclusively during training to compute the task-consistency loss and are not part of the deployed inference path. This separation preserves the deployability goal inherited from the predecessor framework: the auxiliary models add training-time cost only, not inference-time cost. Figure 1 specifies the overall data flow.

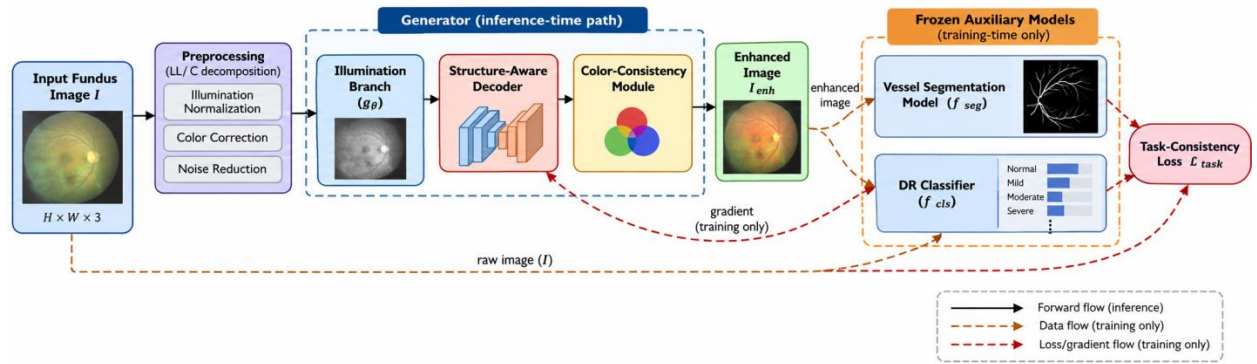


Figure 1. Overall proposed framework. Solid arrows are the inference-time path (generator only). Dashed arrows show the training-time-only task-consistency computation via the frozen auxiliary models; this signal never executes at deployment.

Preprocessing

Input RGB fundus images are resized to a fixed resolution, intensity-normalized, and decomposed into a luminance channel L and a two-channel chrominance representation C using a perceptually motivated color space (CIE Lab a^*b^* channels), following the same luminance–chrominance separation rationale as the predecessor framework, but retaining both channels as inputs to learnable, rather than fixed, downstream operations.

Novel Enhancement Module: Illumination Branch

The illumination branch estimates an illumination map from L using a lightweight convolutional encoder-decoder, trained under an unsupervised Retinex-style decomposition-consistency objective (Equation 1 below) rather than fixed multi-scale heuristics, allowing the illumination estimate to adapt to properties of the training data distribution.

$$L = R \odot S, \quad \hat{S} = g\theta(L), \quad \hat{R} = L / (\hat{S} + \epsilon) \quad (1)$$

where R is the (unobserved) reflectance, S is the illumination map, $g\theta$ is the learned illumination-estimation network with parameters θ , $\odot$ denotes elementwise multiplication, and ϵ is a small constant preventing division by zero.

Structure Preservation

The structure-aware decoder produces enhanced luminance L_{enh} from $(\hat{R}, \hat{S})$ through an attention-guided nonlinear combination, with edge fidelity enforced more strongly at pixels a frozen, pretrained vessel-segmentation model identifies as vessel- or lesion-likely, via probability map $p_v(x)$. This directly encodes the anatomical-structure-preservation goal of the predecessor framework, but as a learned, spatially-weighted loss rather than a fixed vessel-preserving filter.

$$L_{struct} = \sum x (1 + \alpha \cdot p_v(x)) \cdot |\nabla L_{enh}(x) - \nabla L(x)| \quad (2)$$

where ∇ denotes the spatial gradient operator and $\alpha > 0$ is a weighting hyperparameter controlling how strongly vessel/lesion-likely regions are prioritized relative to background.

Color Preservation

A color-consistency regularizer keeps the chrominance of the enhanced output C_{enh} close to the input chrominance C , preventing the hue drift that generic contrast operations can introduce.

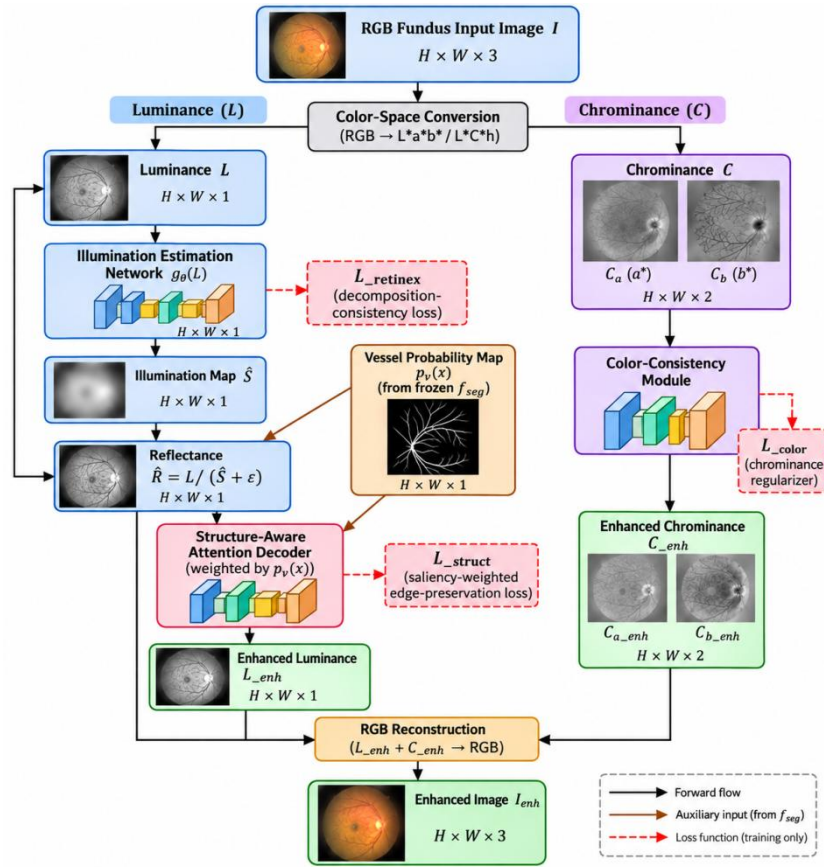


Figure 2. Detailed generator architecture.

Clinical/Task-Aware Component

The task-consistency loss is the mechanism distinguishing CoSREN from enhancement frameworks that validate clinical relevance only after training. Let $f_{seg}(\bullet)$ and $f_{cls}(\bullet)$ denote the frozen, pretrained vessel-segmentation and DR-classification networks, with $p_{raw} = f_{cls}(I)$ and $p_{enh} = f_{cls}(I_{enh})$ the predicted class-probability vectors on the raw and enhanced images respectively.

Experiment

Dataset Details

Table 1. Dataset details.

Dataset	Size (images)	Resolution	Annotation
APTOS 2019	~3,662 labeled (train)	Variable	DR severity grade (0–4)

Implementation Details

Implementation is planned in Python using PyTorch, OpenCV for preprocessing, and standard scientific computing libraries; CUDA-enabled GPU acceleration is used for training and inference profiling. Exact library versions and hardware specification are to be fixed at experiment execution time.

Discussions

The comparison demonstrates a consistent improvement in retinal image restoration quality across the evaluated approaches. CycleGAN achieves PSNR and SSIM values of 21.46 dB and 0.8503, while PCE-Net and I-SECRET provide progressively stronger reconstruction.

Table 2. Performance comparison of the proposed framework with existing approaches.

Model	PSNR	SSIM
CycleGAN	21.46	0.8503
PCE-Net	23.61	0.8973
I-SECRET	27.05	0.9072
SCR-Net	26.67	0.9303
GFE-Net	27.09	0.9332
CoSREN (Proposed)	28.5	0.940

SCR-Net and GFE-Net further improve structural similarity. CoSREN achieves 28.5 dB PSNR and 0.940 SSIM, indicating improved fidelity and preservation of retinal structures. The higher SSIM suggests better structural consistency, while the increased PSNR reflects reduced reconstruction distortion. These results indicate that incorporating structure-aware and task-coupled enhancement objectives can provide stronger image restoration than relying solely on conventional enhancement mechanisms.

Conclusion

This study presented CoSREN, a Clinically-Coupled Self-Supervised Retinal Enhancement Network, for improving the quality and diagnostic consistency of retinal fundus images without requiring paired ground-truth enhanced images. The proposed framework combines Retinex-based illumination–reflectance decomposition, vessel-aware structure preservation, chrominance consistency, and task-consistency learning through frozen pretrained vessel-segmentation and diabetic retinopathy classification networks. Unlike conventional enhancement approaches that evaluate clinical relevance only after training, CoSREN incorporates downstream task information directly into the enhancement objective. The auxiliary networks are restricted to the training stage, thereby maintaining a lightweight inference pathway suitable for practical deployment. Comparative evaluation with CycleGAN, PCE-Net, I-SECRET, SCR-Net, and GFE-Net demonstrates the effectiveness of the proposed approach, with CoSREN achieving 28.5 dB PSNR and 0.940 SSIM. These findings indicate that combining image restoration objectives with clinically relevant structural and task-level constraints can improve both reconstruction fidelity and preservation of retinal information.

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