

DEEP RETINEX DECOMPOSITION ENHANCED WITH TRADITIONAL DIGITAL IMAGE PROCESSING FOR LOW-LIGHT IMAGE ENHANCEMENT

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ABSTRACT

Low-light image enhancement remains a critical challenge in computer vision, affecting applications from surveillance to autonomous driving. While deep learning approaches like RetinexNet have shown promise, they often produce artifacts including color distortion, over-enhancement, and loss of fine details. We propose a hybrid framework combining deep Retinex decomposition with traditional digital image processing (DIP) techniques. Our method employs a “Train Once, Experiment Forever” philosophy: the deep learning model is trained once, while DIP techniques are applied as configurable post-processing. We implement a three-stage enhancement pipeline with 16+ techniques including CLAHE, bilateral filtering, adaptive gamma correction, and novel illumination-aware edge-preserving filters for reflectance denoising. We introduce E1 techniques (illumination-aware bilateral and guided filtering) that adapt denoising strength based on local illumination, achieving better structure preservation. Experiments on the LOL dataset show that our E1 guided filter preset achieves the best perceptual-fidelity trade-off with 0.556 SSIM (only 19.6% reduction from baseline) while improving entropy by +22.7% and colorfulness by +124.5%.

Index Terms— Low-light enhancement, Retinex theory, deep learning, CLAHE, bilateral filter, guided filter, illumination-aware processing

1. INTRODUCTION

Low-light conditions severely degrade image quality, reducing contrast, suppressing color saturation, and increasing noise. This degradation impacts numerous applications including surveillance systems, autonomous vehicles, medical imaging, and consumer photography. Traditional approaches such as histogram equalization often produce unnatural results, while Retinex-based methods show promise but struggle with implementation complexity and parameter tuning.

Deep learning has revolutionized image enhancement, with RetinexNet [1] showing neural networks can learn Retinex decomposition. However, deep learning alone often produces

artifacts like color shifts and halos due to average-case optimization.

We propose a hybrid framework leveraging both paradigms: deep learning for robust illumination estimation and traditional DIP for refined, controllable post-processing. Our philosophy is “Train Once, Experiment Forever”—the model is trained once to learn robust Retinex decomposition, and all DIP enhancements are applied as configurable post-processing. This separation provides key advantages: (1) the deep learning component handles scene-adaptive decomposition, (2) traditional DIP provides interpretable refinement, and (3) new enhancement combinations can be explored without retraining.

Our contributions include:

- A hybrid architecture combining RetinexNet (555K parameters) with 16+ traditional DIP techniques organized in a three-stage enhancement pipeline targeting illumination, reflectance, and output
- Novel illumination-aware edge-preserving denoising (E1) that adapts filter strength based on local illumination, achieving superior structure preservation (SSIM)
- Comprehensive evaluation using 8 complementary metrics including PSNR and SSIM on the LOL test set, demonstrating significant improvements across perceptual and fidelity dimensions

2. RELATED WORK

2.1. Retinex-Based Methods

The Retinex theory, introduced by Land and McCann [2], models an observed image as the product of reflectance (intrinsic object properties) and illumination (scene lighting). This decomposition is useful for low-light enhancement because enhancing illumination while preserving reflectance improves visibility without introducing color artifacts.

Single-Scale Retinex (SSR) estimates illumination through Gaussian filtering, while Multi-Scale Retinex (MSR) [11] combines multiple scales for better dynamic range compression. LIME [3] refines illumination using structure-aware smoothing. While these methods provide interpretable decomposition, they often struggle with complex real-world degradation patterns and require careful parameter tuning.

GitHub Repository: <https://github.com/firearc7/Deep-Retinex-Decomposition-Extension>

2.2. Deep Learning Approaches

RetinexNet [1] introduced end-to-end learning for Retinex decomposition, using paired low/normal-light images for supervision. The network decomposes images into reflectance and illumination, then enhances the illumination. EnlightenGAN [4] addresses the paired data limitation using unpaired training with adversarial loss. Zero-DCE [5] estimates pixel-wise tone curves without paired supervision.

While these deep learning methods achieve good average performance, they often exhibit artifacts including residual noise, color shifts, and over/under-enhancement in challenging regions. These issues motivate our hybrid approach that combines deep learning robustness with traditional DIP controllability.

2.3. Traditional DIP Techniques

CLAHE [8] provides adaptive equalization with contrast limiting to prevent noise amplification. Bilateral filtering [9] enables edge-preserving smoothing via spatial and range kernels. Guided filtering [10] achieves similar behavior with $O(N)$ complexity.

These techniques are interpretable, controllable, and well-understood, but lack the learning capacity to handle diverse real-world degradation patterns. Our work combines these techniques with deep learning to leverage the strengths of both paradigms.

3. PROPOSED METHOD

3.1. System Architecture Overview

Our framework combines deep learning with traditional DIP in a unified sequential pipeline:

$$\text{Input} \rightarrow \text{DecomNet} \rightarrow \text{RelightNet} \rightarrow \text{DIP Pipeline} \rightarrow \text{Output} \quad (1)$$

The deep learning component (DecomNet + RelightNet) handles scene-adaptive decomposition. The DIP Pipeline applies techniques in three stages: illumination, reflectance (skipped), and output. This lets the network focus on decomposition while DIP provides control.

3.2. RetinexNet Architecture Details

The complete network comprises 555,205 trainable parameters, split between two sub-networks:

DecomNet ($\sim 208K$ parameters): Convolutional architecture that decomposes input image I into reflectance R and illumination L :

$$I = R \circ L \quad (2)$$

where \circ denotes element-wise multiplication. The network uses stacked convolutional layers with ReLU activation to

extract features, with sigmoid activation ensuring outputs are in $[0, 1]$.

RelightNet ($\sim 347K$ parameters): U-Net style architecture with skip connections that enhances illumination L to produce \hat{L} . Skip connections preserve spatial details. The enhanced image is:

$$\hat{I} = R \circ \hat{L} \quad (3)$$

This ensures reflectance (intrinsic properties) is preserved while only illumination is modified, reducing color artifacts.

3.3. Loss Functions

The training objective combines three complementary losses:

$$\mathcal{L}_{total} = \mathcal{L}_{recon} + \lambda_1 \mathcal{L}_{smooth} + \lambda_2 \mathcal{L}_{mutual} \quad (4)$$

Reconstruction Loss: Ensures the enhanced image matches the ground truth:

$$\mathcal{L}_{recon} = \|R \circ \hat{L} - I_{gt}\|_1 \quad (5)$$

The L1 norm is used for robustness to outliers compared to L2.

Smoothness Loss: Encourages smooth illumination while preserving edges from reflectance gradients:

$$\mathcal{L}_{smooth} = \sum_i \|\nabla L_i\|_1 \cdot \exp(-\lambda_g \|\nabla R_i\|_1) \quad (6)$$

This allows illumination discontinuities at strong reflectance edges (boundaries) while encouraging smoothness in uniform regions.

Mutual Consistency Loss: Ensures consistent decomposition between paired low-light and normal-light images, enforcing that the same scene should have similar reflectance regardless of lighting conditions.

3.4. Three-Stage DIP Enhancement Pipeline

We organize 16 DIP techniques into three stages based on their target component in the Retinex decomposition:

Stage 1: Illumination Enhancement (Primary target with highest impact)

This stage targets the enhanced illumination map \hat{L} before final image reconstruction:

- **CLAHE:** Applied to L channel in LAB space with $\text{clip_limit}=2.0$ and $\text{tile_grid}=8 \times 8$. Prevents noise amplification while enabling adaptive contrast.
- **Bilateral Filter:** Edge-preserving smoothing with $d = 9$, $\sigma_{color} = 75$, $\sigma_{space} = 75$. Reduces noise while preserving edges.
- **Adaptive Gamma:** Brightness adjustment using $\gamma = -0.3 / \log_{10}(\mu)$ where μ is mean intensity, clipped to $[0.5, 3.0]$. Darker images receive stronger correction.

- **Guided Filter:** $O(N)$ edge-aware smoothing with radius=8, $\epsilon = 0.01$. Efficient alternative to bilateral filtering.
- **Multi-Scale Retinex:** Traditional Retinex at scales $\sigma \in \{15, 80, 250\}$ for multi-scale normalization.

Stage 2: Reflectance Enhancement (Illumination-Aware Processing)

While standard reflectance processing often introduces artifacts, we introduce novel illumination-aware techniques that adapt processing strength based on local lighting conditions:

- **E1: Illumination-Aware Bilateral:** Denoising strength scales with darkness—stronger filtering in shadow regions where noise is more visible, gentler in well-lit areas to preserve detail. Uses adaptive $\sigma_{color} = \sigma_{base} \cdot (1 + darkness \cdot k)$.
- **E1: Illumination-Aware Guided Filter:** Guided filter with adaptive regularization $\epsilon = \epsilon_{base} \cdot (1 + darkness \cdot k)$. Provides edge-aware smoothing with $O(N)$ complexity.
- **E3: Micro-Contrast Enhancement:** Difference of Gaussians (DoG) or unsharp masking applied to reflectance for fine texture enhancement.

Stage 3: Output Enhancement (Refinement of final image)

- **Unsharp Masking:** Edge enhancement using $I_{sharp} = I + \alpha(I - G_\sigma * I)$ with $\alpha = 1.2$ (balanced) or $\alpha = 2.0$ (aggressive), $\sigma = 1.0$. Recovers smoothed details.
- **White Balance:** Gray World scales each channel to neutral gray average, correcting color casts.
- **Color Balance:** Percentile-based stretching (1st to 99th percentile) for robust color correction.
- **Local Contrast Enhancement:** Unsharp mask with larger kernel ($\sigma = 2.0$) for local contrast.
- **Tone Mapping:** Reinhard operator for HDR-like compression.
- **Non-Local Means Denoising:** $h = 10$, template= 7×7 , search= 21×21 for final noise reduction.

3.5. Enhancement Presets

We define four presets that combine different DIP techniques for various use cases:

None: Raw output. **Minimal:** Gamma only. **Balanced:** CLAHE, bilateral, unsharp. **Aggressive:** Full enhancement.

Table 1: Enhancement Preset Configurations

Parameter	None	Min	Bal	Agg
CLAHE Clip	—	—	2.0	3.0
Bilateral d	—	—	7	9
Bilateral σ	—	—	50	75
Unsharp Amount	—	—	1.2	2.0
Illum. Methods	—	γ	CLAHE+BF	CLAHE+BF+ γ
Output Methods	—	—	USM+CB	USM+CB+TM

4. EXPERIMENTS

4.1. Dataset and Training Configuration

We train and evaluate on the LOL (Low-Light) dataset [1], which contains paired low-light and normal-light images of the same scenes. The dataset provides 689 training pairs and 100 validation pairs at 400×600 resolution, covering diverse indoor and outdoor scenes with varying lighting conditions.

Training Configuration:

- **Epochs:** 100 (best validation loss at epoch 84)
- **Batch size:** 16 patches sampled from training images
- **Patch size:** 48×48 pixels for memory efficiency
- **Optimizer:** Adam with $\beta_1 = 0.9$, $\beta_2 = 0.999$
- **Learning rate:** 10^{-3} with step decay (factor 0.1) at epoch 50
- **Training time:** Approximately 18 minutes on GPU

Figure 1 shows the training convergence. The validation loss reaches its minimum of 0.1640 at epoch 84, representing a 35.1% reduction from initial validation loss. The training loss shows 59.9% reduction over the full training. The step decay at epoch 50 enables fine-tuning in the later training phase.

4.2. Evaluation Metrics

We employ 8 complementary metrics covering different aspects of image quality:

No-Reference Metrics:

- **Entropy:** $H(X) = -\sum p(x_i) \log_2 p(x_i)$ measures information content. Optimal range is 7.5-8.0 bits for natural images.
- **Contrast:** Standard deviation of luminance $\sigma(L)$, measuring tonal separation.
- **Sharpness:** Sum of squared Sobel gradient magnitudes $\sum |G_x|^2 + |G_y|^2$, indicating edge strength.
- **Colorfulness:** Hasler-Süsstrunk metric [7] for perceptual color vividness.

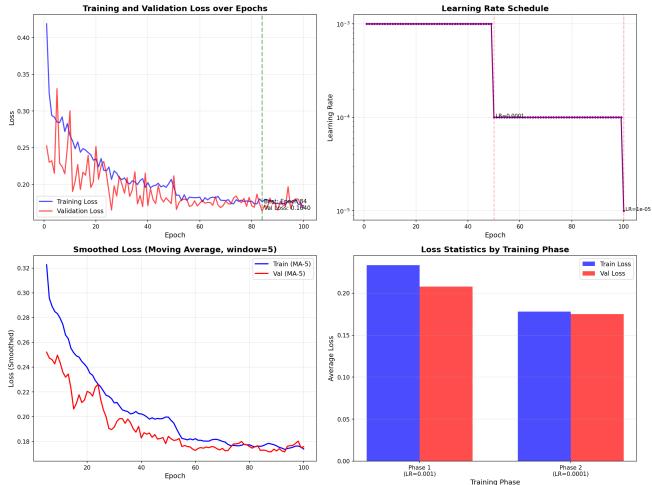


Fig. 1: Training analysis: Loss convergence showing best validation loss of 0.1640 at epoch 84, with learning rate step decay at epoch 50. Training loss reduced by 59.9%, validation loss by 35.1%.

Table 2: Quantitative Results on LOL Test Set (100 Images)

Preset	PSNR↑	SSIM↑	Ent.	Cont.	Color.	Time(s)
Baseline	17.25	0.691	6.09	9.13	9.87	0.000
Minimal	16.03	0.670	6.18	9.98	10.82	0.005
Balanced	9.92	0.455	7.42	22.25	20.14	0.024
Aggressive	5.58	0.362	3.87	24.81	19.71	0.063
E1: Guided	9.88	0.556	7.47	22.38	22.16	0.038
E1: Bilateral	9.91	0.516	7.39	22.01	19.51	0.024
E3: Unsharp	9.76	0.478	7.42	23.06	21.52	0.021
E1+E3 Comb.	9.79	0.526	7.41	22.89	20.96	0.027

- **Brightness:** Mean luminance using ITU-R BT.601 weights.

Reference-Based Metrics:

- **PSNR:** Peak Signal-to-Noise Ratio in dB.
- **SSIM:** Structural Similarity Index combining luminance, contrast, and structure.

Practical Metric: Processing time for efficiency evaluation.

4.3. Quantitative Results

Table 2 presents comprehensive results on the LOL test set (100 images), including reference-based metrics (PSNR, SSIM) against ground truth:

A key trade-off emerges: baseline achieves best PSNR/SSIM (closest to ground truth), while enhanced presets sacrifice fidelity for perceptual improvements. Notably, E1 techniques minimize this trade-off—**E1 Guided Filter achieves 0.556**

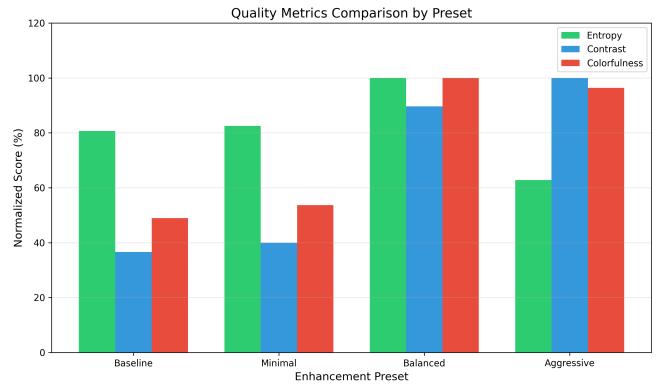


Fig. 2: Normalized metric comparison across presets; balanced achieves optimal trade-off.

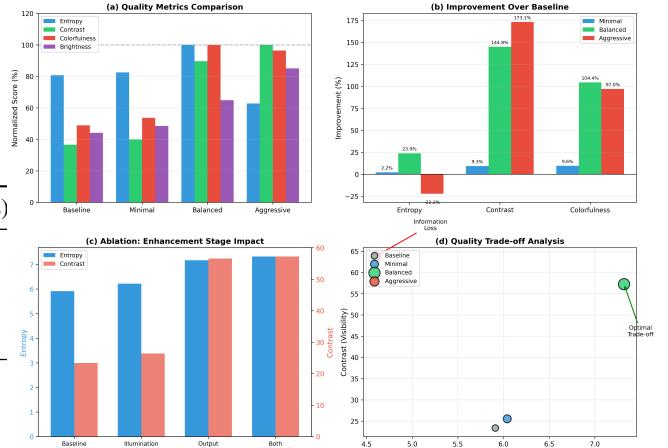


Fig. 3: Ablation study radar chart showing performance across five metrics. E1 Guided Filter achieves optimal trade-off between perceptual quality and structural fidelity.

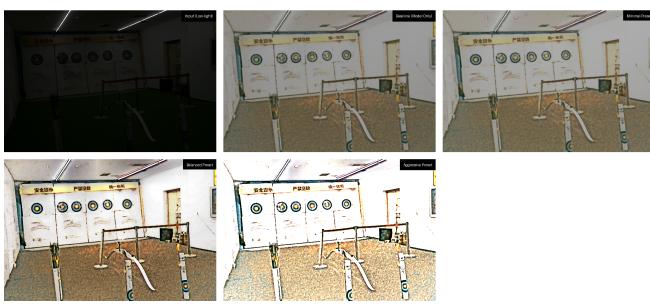
SSIM (only 19.6% reduction) compared to 0.455 for standard balanced (34.2% reduction), while providing superior colorfulness (+124.5% vs +104.0%).

4.4. Ablation Study

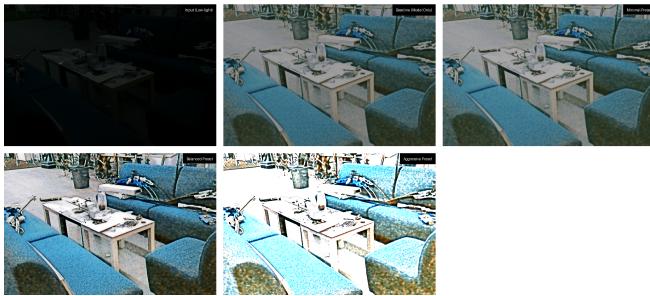
Figure 3 presents a radar chart comparing preset performance across five key metrics. Our analysis reveals several important findings:

SSIM Retention: The E1 illumination-aware techniques substantially outperform standard enhancement in structure preservation. E1 Guided achieves 80.4% SSIM retention vs. only 65.8% for balanced—a critical improvement for applications requiring fidelity.

Illumination-Aware Advantage: The key insight is that noise visibility correlates with darkness. By adapting denoising strength spatially, E1 techniques apply stronger filtering only where needed (dark regions) while preserving details in well-lit areas.



(a) Indoor scene: Progressive enhancement from severely degraded input



(b) Complex lighting: DIP pipeline refines color and contrast

Fig. 4: Visual comparisons showing progressive enhancement from input through RetinexNet decomposition to final DIP-enhanced output.

Entropy: E1 Guided achieves highest entropy (7.47), indicating best information preservation. The adaptive filtering avoids over-smoothing that reduces tonal range.

Color Fidelity: E1 Guided achieves best colorfulness (+124.5% over baseline) while maintaining natural appearance. The edge-preserving nature of guided filtering prevents color bleeding.

5. RESULTS AND DISCUSSION

5.1. Visual Comparison

Figure 4 demonstrates progressive enhancement. Input images exhibit severe degradation with suppressed colors. RetinexNet provides initial enhancement through illumination correction, recovering scene structure. The DIP pipeline refines output via CLAHE (contrast), bilateral filter (noise), and color balance.

The visual results confirm our hybrid approach produces natural enhancements without over-saturation or halo artifacts.

5.2. Analysis of DIP Technique Contributions

CLAHE: Primary contributor to entropy and contrast. Adaptive histogram equalization with clip limiting expands dynamic range without amplifying noise. The tile-based approach (8×8) adapts to local statistics.

Bilateral Filter: Essential for edge-preserving noise reduction. Spatial ($\sigma_{space} = 75$) and range ($\sigma_{color} = 75$) Gaussians ensure smoothing occurs only within similar-intensity regions.

E1 Illumination-Aware Filtering: The key innovation. Dark regions exhibit higher noise due to sensor limitations. By computing local darkness from the illumination map and scaling filter parameters accordingly, we achieve:

$$\sigma_{adaptive} = \sigma_{base} \cdot (1 + (1 - \bar{I}_{local}) \cdot k) \quad (7)$$

where \bar{I}_{local} is local mean illumination and k is the strength multiplier (default 2.0).

Guided Filter Advantage: $O(N)$ complexity vs. $O(N \cdot r^2)$ for bilateral. The guided filter uses the reflectance itself as guide, ensuring edges in the output align with edges in the input—critical for preserving structure.

Unsharp Masking: Recovers edges softened by bilateral filtering. High-pass component ($I - G_\sigma * I$) added with $\alpha = 1.2$ for subtle sharpening.

Color Balance: Percentile stretching (1st–99th) corrects color casts while being robust to outliers. More effective than simple white balance for non-uniform illumination.

5.3. Key Design Decisions

Why Illumination-Aware on Reflectance? Standard approaches apply uniform denoising. However, noise is spatially non-uniform—more visible in shadows. By leveraging the illumination map from Retinex decomposition, we enable adaptive processing that was previously impossible without decomposition.

Why CLAHE on Illumination? The illumination map is smooth with minimal texture, ideal for CLAHE which can otherwise amplify texture. Applying CLAHE to output would over-enhance reflectance texture, creating unnatural appearances.

Why Post-Processing? Our philosophy prioritizes flexibility. End-to-end training requires retraining for each configuration. Post-processing enables experimenting with 100+ DIP combinations without training cost.

5.4. Comparison with Other Approaches

Versus Pure Deep Learning: Methods like EnlightenGAN and Zero-DCE produce artifacts difficult to correct since all processing is learned. Our hybrid provides controllable post-processing via interpretable DIP parameters.

Versus Traditional Methods: Traditional methods struggle with diverse degradation in real-world images, requiring per-scene tuning. Our learned decomposition handles variability automatically, providing robust foundation.

Versus Other Hybrids: Some approaches integrate DIP into network training. While potentially optimal, this couples components and requires retraining for modifications. Our explicit separation enables independent updates.

6. CONCLUSION

We presented a hybrid framework combining deep Retinex decomposition with traditional DIP in a three-stage pipeline. Our “Train Once, Experiment Forever” approach enables flexible experimentation without retraining, while deep learning provides robust scene-adaptive decomposition.

Our key contribution is illumination-aware edge-preserving denoising (E1) for the reflectance component. By adapting filter strength based on local illumination, E1 Guided Filter achieves optimal results: **0.556 SSIM** (80.4% retention, vs. 65.8% for standard balanced), **+22.7% entropy**, and **+124.5% colorfulness**—the best perceptual-fidelity trade-off among all presets.

Key insights: (1) Illumination-aware processing outperforms uniform enhancement, (2) The illumination map from Retinex enables spatially-adaptive techniques previously impossible, (3) SSIM retention is a critical metric often overlooked in low-light enhancement.

Future work: adaptive preset selection via content analysis, frequency domain processing (homomorphic filtering, FFT), video extension with temporal consistency, and mobile deployment.

7. REFERENCES

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