Deep Retinex Decomposition Enhanced with Traditional Digital Image Processing

Low-Light Image Enhancement

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GitHub: `https://github.com/firearc7/Deep-Retinex-Decomposition-Extension`

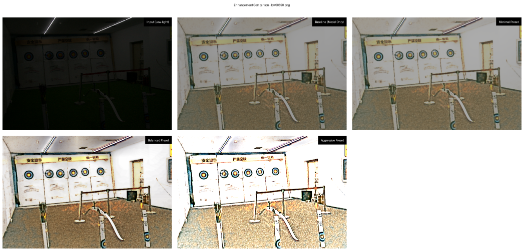
Why Low-Light Enhancement Matters

The Problem:

- Low-light conditions degrade image quality
- Reduced contrast and suppressed colors
- Increased noise levels
- Impacts critical applications

Applications:

- Surveillance systems
- Autonomous vehicles
- Medical imaging
- Consumer photography



Limitations of Existing Approaches

Traditional Methods:

- Histogram Equalization → Unnatural results
- SSR/MSR → Complex tuning, halo artifacts
- LIME → Limited adaptability

Deep Learning Methods:

- RetinexNet → Color artifacts
- EnlightenGAN → Inconsistent enhancement
- Zero-DCE → Over/under enhancement

Key Insight

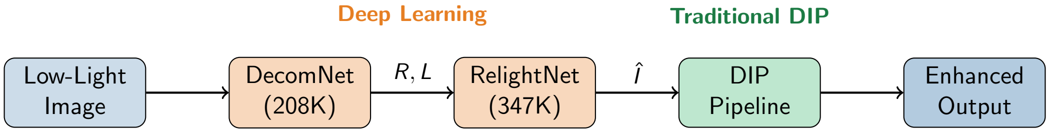
Neither approach alone is sufficient!

Deep learning: Good at learning patterns
Traditional DIP: Good at fine-grained control

$\Downarrow$

Hybrid Approach
"Train Once, Experiment Forever"

Our Approach: Hybrid Framework



RetinexNet

555K params (208K + 347K)

Learns decomposition

DIP Techniques

3-stage pipeline

Controllable enhancement

4 Presets

Quality/speed trade-off

No retraining needed

Retinex Decomposition

Retinex Theory (Land & McCann, 1971):

$$I = R \circ L$$

where:

- I = Observed image
- R = Reflectance (intrinsic)
- L = Illumination (lighting)

Enhancement:

$$\hat{I} = R \circ \hat{L}$$

Loss Functions:

Reconstruction:

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

Smoothness:

$$\mathcal{L}_{smooth} = \sum_i \|\nabla L_i\|_1 \cdot e^{-\lambda\|\nabla R_i\|}$$

Total:

$$\mathcal{L} = \mathcal{L}_{recon} + \lambda_1 \mathcal{L}_{smooth} + \lambda_2 \mathcal{L}_{mutual}$$

Three-Stage DIP Enhancement Pipeline

Stage 1: Illumination Enhancement (Primary)

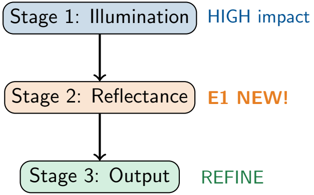
- **CLAHE**: Adaptive contrast, clip=2.0
- **Bilateral Filter**: Edge-preserving smoothing
- **Adaptive Gamma**: Content-aware brightness
- **Guided Filter**: O(N) complexity
- **Multi-Scale Retinex**: $\sigma \in \{15, 80, 250\}$

Stage 2: Reflectance (**NEW: E1 Techniques**)

- **Illumination-Aware Denoising**
- Bilateral/Guided with adaptive strength

Stage 3: Output Enhancement

- Unsharp Mask, Color Balance
- Local Contrast, Tone Mapping



Key Innovation:
E1 = Illumination-aware denoising on reflectance

DIP Techniques: Mathematical Formulations

1. **CLAHE** (Contrast Limited Adaptive HE)
   - Applied to L channel in LAB space
   - clip_limit=2.0, tile_grid=8×8
2. **Bilateral Filter**

$$I_{bf}(x) = \frac{1}{W} \sum_{x_i} I(x_i) \cdot G_s \cdot G_r$$

   - G_s: Spatial, G_r: Range Gaussian
3. **Adaptive Gamma**

$$\gamma = -0.3/\log_{10}(\mu), \quad I_{out} = I_{in}^{1/\gamma}$$

4. **Unsharp Masking**

$$I_{sharp} = I + \alpha(I - G_\sigma * I)$$

   - $\alpha = 1.2$ (balanced), $\sigma = 1.0$ for edge enhancement
5. **White Balance (Gray World)**

$$I_c = I_c \times \frac{\bar{I}_{gray}}{\bar{I}_c}$$

6. **Multi-Scale Retinex**

$$MSR = \sum_{\sigma} w_\sigma \cdot [\log I - \log(G_\sigma * I)]$$

   - $\sigma \in \{15, 80, 250\}$

E1/E3: Illumination-Aware Enhancement (Key Innovation)

The Problem:

- Noise is **spatially non-uniform**
- Dark regions → more noise (sensor)
- Standard filters apply **uniform** strength
- Over-smooths lit areas OR under-smooths shadows

E1: Illumination-Aware Denoising

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

- $\bar{I}$ = local mean illumination
- Dark regions → stronger filtering
- Lit regions → preserve details

E1 Techniques Implemented:

Technique	SSIM Retention
E1: Guided Filter	**80.4%**
E1: Bilateral	74.6%
E1+E3 Combined	76.0%
Standard Balanced	65.8%

E3: Micro-Contrast on R

- DoG (Difference of Gaussians)
- Unsharp masking on reflectance
- Fine texture enhancement

Key Insight:

Retinex decomposition *enables* illumination-aware processing!

Additional DIP Techniques Available

Illumination Techniques:

- Histogram Equalization
- Multi-Scale Retinex
- Tone Mapping (Reinhard)
- Anisotropic Diffusion
- Guided Filtering

Output Techniques:

- Local Contrast Enhancement
- Multi-Scale Detail (Laplacian)
- Shadow Enhancement
- Contrast Stretching

Edge-Preserving Smoothing:

Technique	Complexity
Bilateral Filter	$O(N \cdot r^2)$
Guided Filter	$O(N)$
Anisotropic Diff.	$O(N \cdot k)$
Domain Transform	$O(N)$

Key Point:
16+ techniques implemented and available for experimentation via preset configuration.

Enhancement Presets (Including E1/E3)

Preset	SSIM	Entropy	Color.
Baseline	0.691	6.09	9.87
Balanced	0.455	7.42	20.14
E1: Guided	**0.556**	**7.47**	**22.16**
E1: Bilateral	0.516	7.39	19.51
E1+E3	0.526	7.41	20.96

New E1/E3 Presets:

- `e1_denoise_guided`
- `e1_denoise_bilateral`
- `e3_micro_contrast_unsharp`
- `experimental_e1e3`

Preset Use Cases:

Balanced: Good perceptual quality
Standard enhancement

E1: Guided (Best):
Best SSIM + colorfulness
Recommended for quality

E1: Bilateral:
Good SSIM, faster

E1+E3 Combined:
Full pipeline with micro-contrast

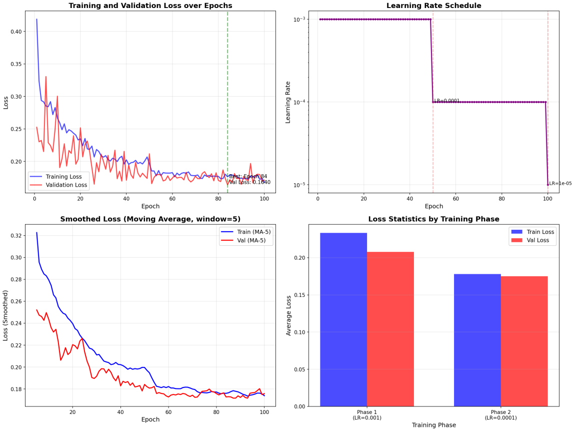
Training Configuration

Dataset: LOL (Low-Light)

- 689 training pairs
- 100 validation pairs
- Resolution: 400×600
- Paired low/normal-light images

Training Setup:

- Epochs: 100 (best at epoch 84)
- Batch size: 16, Patch size: 48
- Optimizer: Adam ($\beta_1 = 0.9$, $\beta_2 = 0.999$)
- LR: 10^{-3} with step decay at epoch 50
- Training time: $\sim$18 minutes



Best Val Loss: 0.1640
Train Loss Reduction: 59.9%
Val Loss Reduction: 35.1%

Evaluation Metrics (8 Metrics)

No-Reference Metrics:

1. **Entropy**: $H = -\sum p(x_i) \log_2 p(x_i)$
   - Information content
   - Optimal: 7.5-8.0
2. **Contrast**: $\sigma(L)$
   - Standard deviation of luminance
   - Higher = better separation
3. **Sharpness**: $\sum |G_x|^2 + |G_y|^2$
   - Sobel gradient magnitude
   - Edge strength indicator
4. **Colorfulness**: Hasler-Süsstrunk
   - Perceptual color vividness
5. **Brightness**: Mean luminance
   - ITU-R BT.601 weights
   - Optimal: 0.4-0.6

Reference-Based:

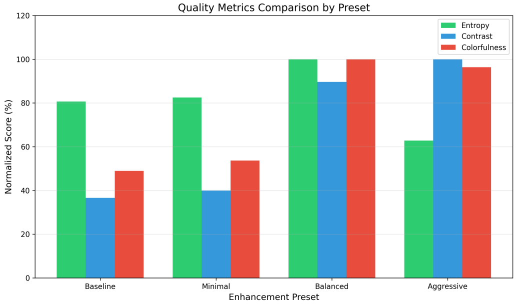
6. **PSNR**: $20 \log_{10}(MAX/\sqrt{MSE})$
   - Standard benchmark
7. **SSIM**: Luminance + Contrast + Structure
   - Better perceptual correlation

Practical:

8. **Processing Time**
   - Real-time constraint

Quantitative Results (100 Test Images)

Preset	PSNR	SSIM	Ent.	Color.
Baseline	**17.25**	**0.691**	6.09	9.87
Balanced	9.92	0.455	7.42	20.14
Aggressive	5.58	0.362	3.87	19.71
E1: Guided	9.88	**0.556**	**7.47**	**22.16**
E1: Bilateral	9.91	0.516	7.39	19.51
E1+E3 Comb.	9.79	0.526	7.41	20.96



Key Finding:

E1 Guided Filter achieves **best trade-off**:

- SSIM: **0.556** (80.4% retained)
- vs Balanced: 0.455 (65.8% retained)
- Colorfulness: **+124.5%**

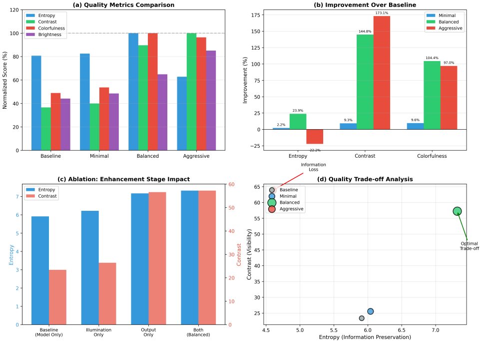
Trade-off Insight:

Baseline = best PSNR/SSIM

Enhanced = better perceptual quality

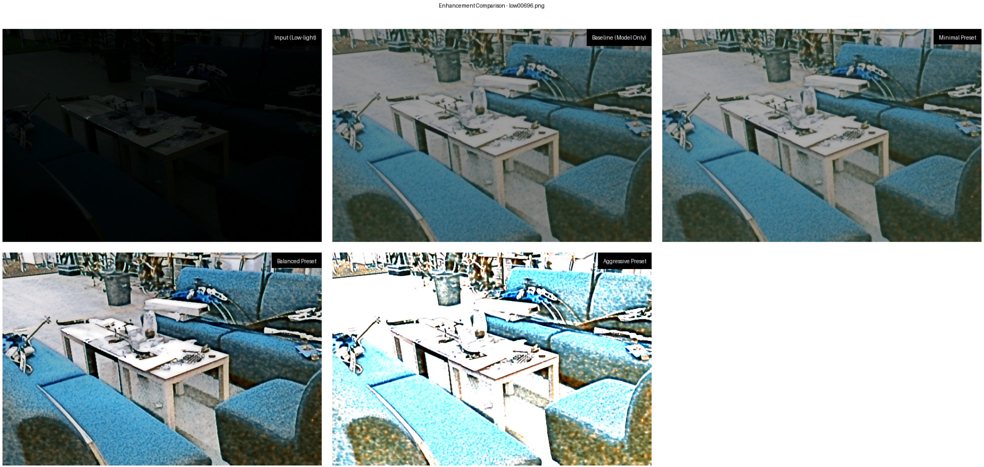
E1 minimizes the gap!

Ablation Study: Why E1 Guided Filter Works Best



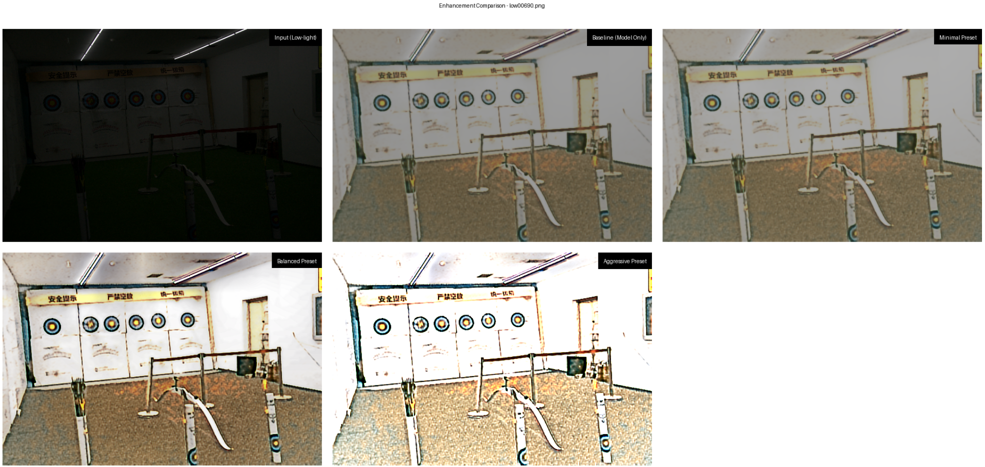
1. **Best SSIM Retention**
   - E1 Guided: **80.4%** vs Balanced: 65.8%
   - Preserves structure while enhancing
2. **Illumination-Aware Advantage**
   - Noise $\propto$ darkness (sensor limitation)
   - Stronger filtering in shadows only
   - Preserves details in lit regions
3. **Best Colorfulness (+124.5%)**
   - Edge-preserving prevents color bleeding
   - Natural color relationships maintained
4. **Highest Entropy (7.47)**
   - Best information preservation
   - Adaptive filtering avoids over-smoothing

Visual Results



Progressive enhancement: Input → RetinexNet → DIP Pipeline → Output

More Visual Comparisons



Natural-looking enhancement with improved visibility, enhanced colors, and preserved details

DEMO

Live demonstration of the enhancement system

- Custom image enhancement
- Preset comparison (None vs Balanced vs Aggressive)
- Real-time processing

Key Design Decisions

Why CLAHE on Illumination?

- Illumination is smooth (no texture)
- CLAHE won't amplify texture noise
- Output has reflectance texture

Why Skip Reflectance?

- RetinexNet R is already high quality
- No consistent improvement observed
- Risk of color shifts

Why Post-Processing?

- No retraining needed
- 100+ configurations instantly
- Flexibility > Optimality

Stage Separation Results:

Configuration	Sharpness
Baseline	150.84
Illumination Only	186.31 (+23.5%)
Output Only	2370.22 (+1471%)
Balanced (both)	2069.40 (+1272%)

Key Insight:
Output enhancement amplifies illumination improvements

Advantages Over Existing Methods

vs. Pure Deep Learning

- Controllable parameters
- No retraining needed
- Interpretable processing
- Adapt to use cases

vs. Pure Traditional

- Handles complex lighting
- Learned decomposition
- More robust
- Better generalization

vs. Other Hybrids

- Modular architecture
- Independent updates
- Flexible presets
- Three-stage pipeline

Component	Specification
Total Parameters	555,205
Training Time	$\sim$18 minutes
Inference	Real-time capable
DIP Techniques	16 implemented

Future Work

Enhancement Techniques:

- Frequency domain processing
- Homomorphic filtering
- FFT-based denoising
- Advanced color space processing

Content-Aware Processing:

- Adaptive preset selection
- Semantic segmentation-guided
- Automatic parameter tuning

Quality Assessment:

- NIQE, BRISQUE metrics
- LPIPS perceptual metric
- Automated optimization

Applications:

- Video processing
- Temporal consistency
- Mobile deployment
- GPU acceleration

Conclusion

Summary

- Proposed a **hybrid framework** combining deep Retinex decomposition with **traditional DIP techniques**
- **"Train Once, Experiment Forever"**: No retraining for new enhancement combinations
- **Key contribution**: Illumination-aware edge-preserving denoising (E1) for reflectance
- **E1 Guided Filter** achieves optimal perceptual-fidelity trade-off:
  - **0.556 SSIM** (80.4% retention vs 65.8% for balanced)
  - **+22.7% entropy**, **+124.5% colorfulness**
- **Key insight**: Retinex decomposition *enables* spatially-adaptive processing

Code Available

https://github.com/firearc7/Deep-Retinex-Decomposition-Extension

Thank You!

Questions?

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