Deep Retinex Decomposition Enhanced with Traditional Digital Image Processing

Low-Light Image Enhancement

Archit Choudhary Yajat Lakhanpal

International Institute of Information Technology, Hyderabad

December 2025

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

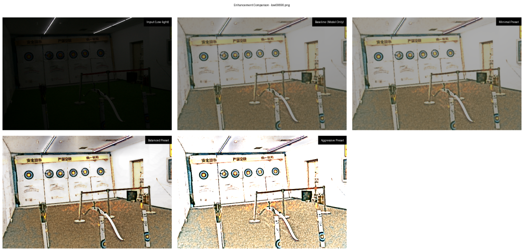
Why Low-Light Enhancement Matters

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

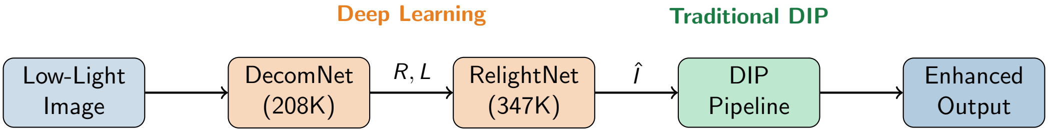
Neither approach alone is sufficient!

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

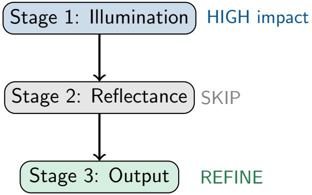
Stage 1: Illumination Enhancement (Primary)

- **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 (Skip—already good)

Stage 3: Output Enhancement

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



Key Design Decision:
Illumination > Reflectance
(RetinexNet R is already good)

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**

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

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

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:
All techniques implemented and available for experimentation via preset configuration.

Enhancement Presets

Parameter	None	Min	**Bal**	Agg
CLAHE Clip	–	–	**2.0**	3.0
Bilateral d	–	–	**7**	9
Bilateral σ	–	–	**50**	75
Unsharp Amt	–	–	**1.2**	2.0
Time (s)	0.005	0.011	**0.089**	0.134

Preset Use Cases:

None: Raw model output
Benchmark comparison

Minimal: Subtle improvement
Real-time video, mobile

Balanced (Best): Best quality/speed
Production default

Aggressive: Maximum enhancement
Extremely poor inputs

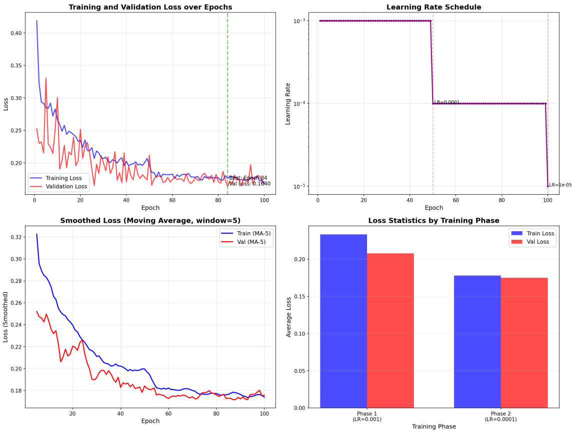
Training Configuration

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:

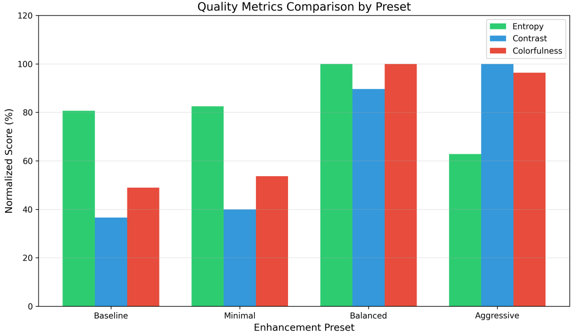
6. **PSNR**: $20 \log_{10}(MAX/\sqrt{MSE})$
   - Standard benchmark
7. **SSIM**: Luminance + Contrast + Structure
   - Better perceptual correlation

Practical:

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

Quantitative Results (100 Test Images)

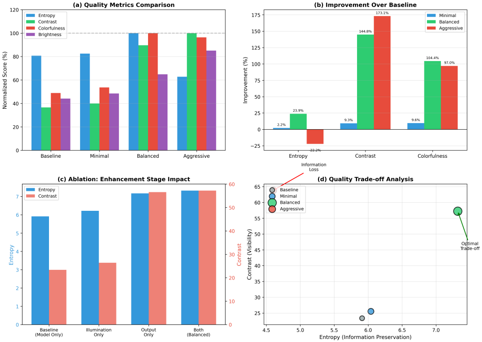
Preset	Ent.	Cont.	Color.	Time
Baseline	5.91	23.37	25.05	0.005
Minimal	6.04	25.53	27.47	0.011
Balanced	**7.32**	**57.22**	**51.20**	0.089
Aggressive	4.60	63.82	49.36	0.134
Illum Only	6.22	26.40	28.16	0.043
Output Only	7.17	56.57	50.49	0.071



Balanced Improvements:

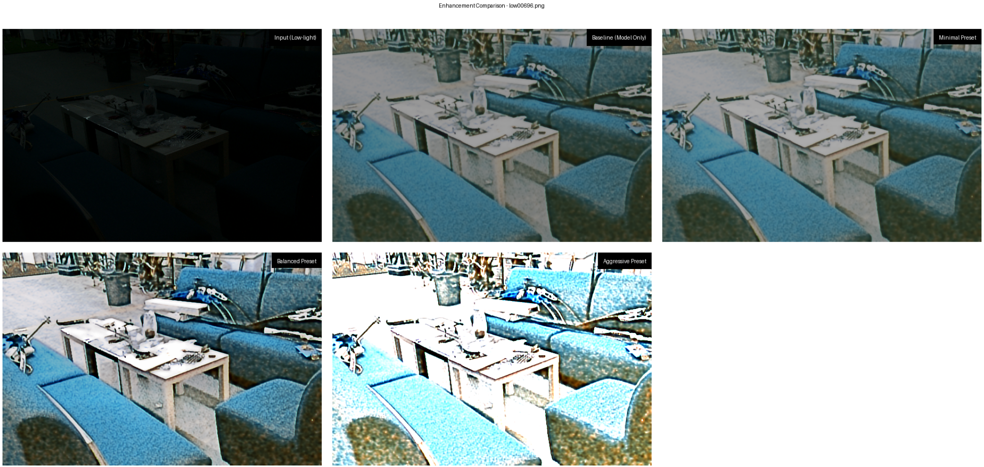
- Entropy: **+23.9%**
- Contrast: **+144.8%**
- Colorfulness: **+104.4%**
- Sharpness: **+1272%**

Ablation Study: Why Balanced Works Best



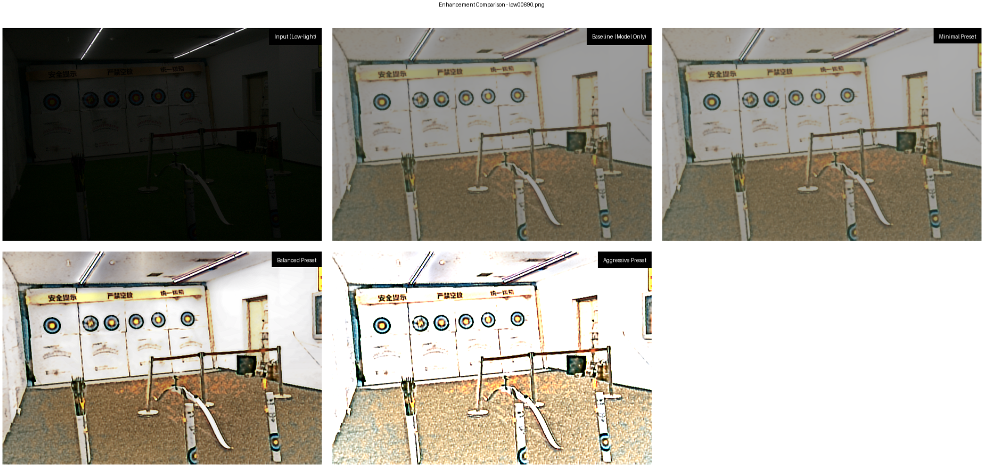
1. **Information Preservation**
   - Highest entropy (7.32); Aggressive destroys tonal info (4.60)
2. **Optimal Contrast (+144.8%)**
   - CLAHE + Bilateral synergy without saturation artifacts
3. **Natural Sharpness**
   - No halo artifacts; Aggressive causes edge overshoot
4. **Color Fidelity (+104.4%)**
   - Highest colorfulness (51.20) with natural relationships
5. **Appropriate Brightness**
   - Preserves highlight headroom

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
- **Three-stage pipeline**: Illumination, Reflectance (skip), Output enhancement
- **Balanced preset** achieves optimal results:
  - +23.9% entropy, +144.8% contrast, +1272% sharpness, +104.4% colorfulness
- **Key insight**: Illumination enhancement > Reflectance enhancement

Code Available

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

Thank You!

Questions?

Archit Choudhary & Yajat Lakhanpal
International Institute of Information Technology, Hyderabad

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