

# Lightweight Additive Blend Maps for Texture-Preserving Face Retouching: A Neural Approach to Traditional Photographic Techniques

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## Abstract

Professional photography face retouching requires achieving a balance between texture preservation and quality increase, a problem that conventional automated methods find difficult to effectively handle. We provide a new lightweight neural architecture that converts conventional dodge-and-burn photography methods into predictions for learnable additive blend maps. Instead of rebuilding whole images, our method uses a small U-Net that predicts pixel-level changes, allowing for exact brightness adjustments while maintaining the original skin texture. With a 6MB model that operates effectively on common hardware, the technique produces high-quality results while preserving texture fidelity, which is crucial for professional applications. Experimental validation offers significant computing advantages while demonstrating competitive performance with current methods.

## Introduction

Face retouching has become an indispensable component of modern digital photography workflows, driven by unprecedented demand from professional studios, social media platforms, and consumer applications. The photography industry processes millions of portraits daily, yet current automated solutions struggle with a fundamental trade-off: achieving high-quality imperfection removal while preserving the natural skin texture that defines professional photography standards.

Traditional face retouching approaches relied heavily on nonlinear digital filters and manual editing techniques (Arakawa 2004; Batool and Chellappa 2014). These methods consistently produced over-smoothed, artificial results that failed professional requirements because they couldn't distinguish between imperfections requiring removal and natural skin characteristics requiring preservation. The fundamental issue was treating all skin variations uniformly rather than selectively addressing problematic areas.

Deep learning revolutionized this field significantly. AutoRetouch (Shafaei, Little, and Schmidt 2021a) demonstrated that generative adversarial networks could learn to differentiate between blemishes and natural skin features while maintaining texture quality. Building on this foundation, BPFRe (Xie et al. 2023) introduced attention mech-

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Figure 1: Wrinkle removal using additive mask prediction. The model outputs the additive mask which is then added to the source image to get the desired retouched image.

anisms for progressive blemish removal, ABPN (Lei et al. 2022) achieved real-time processing through hierarchical refinement, and transformer-based approaches like RetouchFormer (Wen et al. 2024) and RetouchGPT (Xue et al. 2025) explored soft inpainting and language-guided editing.

However, these state-of-the-art methods share a critical limitation: they rely on complex generative architectures that reconstruct entire images, creating computational bottlenecks unsuitable for real-time professional workflows. More problematically, these reconstruction-based approaches often struggle with texture preservation, producing the same over-smoothed results that plague traditional methods - compromising the natural appearance essential for professional photography.

**Key Insight:** Professional face retouching fundamentally requires selective modification of specific facial features while preserving original image content, particularly the subtle texture information that defines natural skin appear-

ance. This observation suggests that reconstruction-based approaches may be inherently misaligned with task requirements.

We present a novel lightweight U-Net architecture that employs additive blend map prediction for efficient face retouching. Drawing direct inspiration from traditional darkroom dodge-and-burn techniques, our approach predicts additive masks that encode selective brightness adjustments. These masks are applied to original images through mathematical operations that mirror traditional darkroom techniques, dramatically reducing computational overhead while maintaining perfect texture preservation.

Our contributions include:

- A lightweight U-Net architecture (6MB) that maintains texture preservation while enabling fast inference (sub-100ms)
- An additive processing pipeline that mathematically mirrors traditional dodge-and-burn techniques
- Comprehensive analysis demonstrating practical viability for professional photography workflows at scale

## Related Work

### Traditional Methods

Early face retouching approaches relied on image processing techniques targeting specific imperfections. Arakawa (Arakawa 2004) introduced nonlinear digital filters for facial beautification, establishing early foundations but producing unnatural results. Batool and Chellappa (Batool and Chellappa 2014) developed texture orientation methods for wrinkle removal, while specialized techniques emerged for different imperfection types: Lipowezky and Cahen (Lipowezky and Cahen 2008) addressed freckle detection, Leyvand et al. (Leyvand et al. 2006) focused on attractiveness enhancement through geometric warping, and Velusamy et al. (Velusamy et al. 2020) proposed wavelet-based texture restoration.

These methods remained fundamentally limited—they addressed only specific imperfection types, required extensive manual parameter tuning, and consistently failed to preserve natural skin texture. Most critically, they lacked the semantic understanding necessary to distinguish between natural skin variations and actual imperfections.

### Deep Learning Breakthroughs

AutoRetouch (Shafaei, Little, and Schmidt 2021a) pioneered GAN-based professional face retouching, demonstrating that neural networks could learn to differentiate between blemishes and natural skin features while preserving texture quality. This work established the feasibility of automated professional retouching but required substantial computational resources.

BPFRe (Xie et al. 2023) addressed training data limitations through progressive frameworks with blemish-aware attention mechanisms, while ABPN (Lei et al. 2022) introduced adaptive blend pyramid networks achieving real-time processing on ultra high-resolution images through hierarchical feature refinement.

**Critical Limitation of Current Approaches:** Many deep learning methods rely on inpainting methodologies like AOTGan (Zeng et al. 2021) and LaMa (Suvorov et al. 2021) that use binary masks separating regions into “preserve” or “reconstruct” categories. When binary masks are provided, models lose original texture context within masked regions, forcing generative reconstruction that inevitably results in texture inconsistencies and over-smoothing—particularly problematic for professional applications requiring natural skin appearance.

### Transformer Methods and Computational Challenges

Recent work explored transformer architectures for enhanced quality. RetouchFormer (Wen et al. 2024) formulated retouching as “soft inpainting” using selective self-attention mechanisms, while RetouchGPT (Xue et al. 2025) introduced interactive retouching through Large Language Models. Despite impressive visual results, these methods require substantial computational resources due to attention complexity and large model sizes (often > 100MB), severely limiting practical deployment scenarios.

### The Deployment Gap

Current methods create a significant gap between research quality and deployment reality. Professional workflows require efficient high-resolution processing (4K+) while maintaining strict quality standards. Existing approaches either sacrifice quality for speed or require expensive GPU infrastructure incompatible with typical photography businesses.

Traditional dodge-and-burn approaches offer a compelling alternative: they perform selective brightness adjustments on existing pixels rather than generating new content, providing theoretical foundations for lightweight models that can meet real-world deployment constraints.

## Application Description

### Target Environment and Real-World Context

Our face retouching system is designed for integration into Aftershoot, a professional photo editing application serving over 50,000 photographers and content creators worldwide. The system must handle the demanding requirements of professional photography workflows while operating efficiently on standard hardware configurations typical in photography businesses.

**Professional Use Case:** A wedding photographer captures 2,000+ images during an event and needs to deliver 200-300 edited photos within 48 hours. Current manual retouching workflows create bottlenecks—each image requires 2-3 minutes of detailed attention, making large-scale processing economically unfeasible. Existing automated tools either produce unacceptable quality or require expensive cloud processing that violates client privacy expectations.

## AI Technology and Technical Innovation

### Architectural Innovation: From Reconstruction to Transformation

While standard U-Net (Ronneberger, Fischer, and Brox 2015) architectures employ skip connections to merge high-level semantic features with low-level details for image reconstruction, directly applying U-Net to face retouching creates unnecessary computational overhead and texture preservation challenges. Our innovation lies in reformulating the problem entirely.

**Core Innovation:** Instead of reconstructing images, we predict transformation instructions. This enables perfect texture preservation because we never generate new pixel content: we only modify existing pixels based on learned brightening and darkening patterns.

### Detailed Architecture Design

**Encoder Architecture:** We employ a carefully designed encoder with progressive spatial downsampling and strategic channel expansion through four stages:  $64 \rightarrow 128 \rightarrow 256 \rightarrow 512$  channels. Input images are processed at  $512 \times 512$  resolution—a deliberate balance between computational efficiency and feature preservation that maintains essential facial details while enabling real-time processing.

Each downsampling stage uses MaxPool2d followed by double convolution blocks featuring two sequential  $3 \times 3$  convolutions, batch normalization, and ReLU activation. This design captures multi-scale facial features essential for understanding both local imperfections and global facial context.

**Decoder Architecture:** The decoder reconstructs spatial resolution using bilinear upsampling operations and carefully designed skip connections from corresponding encoder levels. These skip connections are crucial—they preserve fine-grained spatial information needed for accurate blend map prediction at pixel level. Channel dimensions reduce progressively:  $512 \rightarrow 256 \rightarrow 128 \rightarrow 64$ .

The final output layer includes a specialized upsampling module with  $2 \times$  bilinear upsampling followed by  $3 \times 3$  convolution refinement, generating high-resolution blend maps that maintain spatial precision necessary for professional quality results.

### Blend Map Prediction: The Mathematical Foundation

**Mathematical Formulation:** Our approach reformulates face retouching as pixel-wise transformation through blend map prediction. The network predicts 3-channel blend maps  $B \in \mathbb{R}^{H \times W \times 3}$  encoding modification instructions for each RGB channel. Blend maps contain values in range  $[0,1]$ , where:

- 0.5 represents no modification
- Values below 0.5 darken the region (burn)
- Values above 0.5 brighten the region (dodge)

**Professional Integration:** The mathematical relationship  $R = I + 2(B - 0.5)$  directly implements Photoshop's Linear

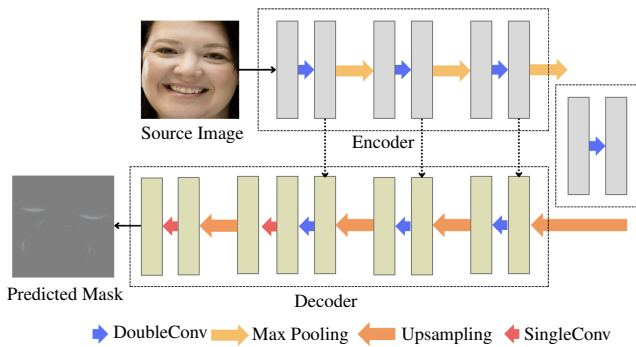


Figure 2: U-Net-based face retouching model that predicts blend maps. The encoder (top) progressively downsamples the input face image through four stages with double convolutions (blue arrows) and max pooling (orange arrows), expanding channels from 64 to 512. The decoder (bottom) reconstructs spatial resolution using upsampling (orange arrows) and single convolutions (red arrows), with skip connections (dotted arrows) preserving fine details. The network outputs a predicted mask containing pixel-level modification instructions that are mathematically blended with the original image to produce the final retouched result.

### Integration Specifications

- Local processing capability to maintain client privacy and data security
- Sub-100ms processing time per image for real-time preview capabilities
- Consistent quality across diverse lighting conditions and skin tones
- Seamless integration with existing RAW processing pipelines

### Engineering Challenges and Solutions

**Challenge 1: Texture Preservation vs. Imperfection Removal** Traditional approaches fail because they treat these as competing objectives. Our additive blend approach treats them as complementary—we modify pixel intensities while preserving the underlying texture structure that defines natural skin appearance.

**Challenge 2: Edge Device Deployment** Professional photographers often work on laptops with limited GPU capabilities. Our 6MB model size and efficient architecture enable deployment on standard hardware without sacrificing quality, addressing a critical barrier to adoption in professional workflows.

**Challenge 3: Scalability Across Diverse Conditions** Professional photography encompasses extreme diversity—from studio portraits with controlled lighting to outdoor wedding photography with challenging conditions. Our training strategy incorporates this diversity while maintaining robust performance across scenarios.

Method	PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$
Pix2PixHD	29.38	0.9181	0.0766
AutoRetouch	44.18	0.9804	0.0133
ABPN	44.41	0.9918	0.0169
BPFRe	45.29	0.9935	0.0092
RetouchFormer	45.72	0.9936	0.0078
<b>Ours</b>	<b>45.33</b>	<b>0.9934</b>	<b>0.0124</b>

Table 1: Quantitative comparison with competing methods on FFHQR ( $\downarrow$  lower is better;  $\uparrow$  higher is better). \*Metrics are reported from original publications on the FFHQR dataset.

Light blend mode, ensuring seamless compatibility with existing professional workflows, where R is the final retouched image, I is the original input image, and B is the predicted blend map. We chose this formulation to enable photographers to understand and trust the system’s operations.

**Ground Truth Generation:** To train our model, we generate ground truth blend maps using the inverse mathematical relationship:  $B = 0.5 + (R - I)/2$ , where we compute the blend map by passing the original image I and the manually retouched image R through this inverse equation. This approach allows us to extract the exact enhancement operations performed by professional photographers and translate them into learnable blend map targets.

**Texture Preservation Mechanism:** Unlike inpainting methods using binary masks that force complete pixel reconstruction, our approach embeds intensity modification instructions directly in the blend map. This preserves original texture characteristics including pores, fine lines, and natural skin variations that define professional-quality results. The original image provides the texture foundation, while our predictions provide the enhancement instructions.

## Training Strategy and Loss Design

**Multi-Component Loss Function:** We train using three carefully balanced loss components:

$$L_{joint} = \lambda_1 L_{blend} + \lambda_2 L_{perc} + \lambda_3 L_{tv} \quad (1)$$

- $L_{blend}$ : Direct supervision(MSE Loss) on predicted blend maps ensures accurate transformation predictions

$$MSE = \frac{1}{n} \sum_{i=1}^n \|R_{gt,i} - R_i\|^2$$

- $L_{perc}$ : Perceptual loss (Johnson, Alahi, and Fei-Fei 2016) on final retouched outputs maintains visual quality standards
- $L_{tv}$ : Total variation regularization (Rudin, Osher, and Fatemi 1992)encourages spatial smoothness, preventing artifacts

We use weighting parameters  $\lambda_1 = 1.0$ ,  $\lambda_2 = 0.25$ , and  $\lambda_3 = 0.1$ , determined through ablation studies that balance blend map accuracy, perceptual quality, and spatial coherence.

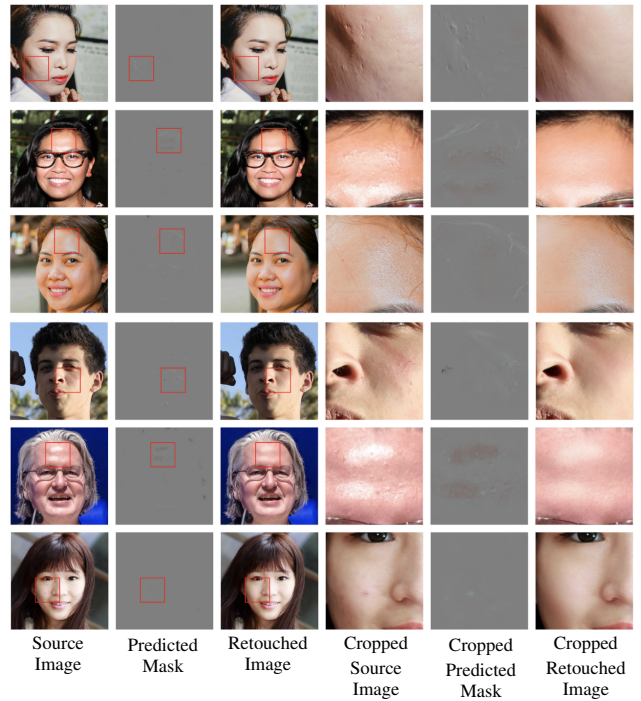


Figure 3: Qualitative results on FFHQR dataset. Our method effectively identifies and removes facial blemishes and skin imperfections while preserving natural skin texture and facial features. The predicted masks accurately localize regions requiring retouching, and the cropped regions (right-most three columns) demonstrate detailed improvements in skin appearance with minimal artifacts.

Task	PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$
General Retouching (FFHQR)	45.33	0.9934	0.0124
Wrinkle Removal (In-house)	45.73	0.9927	0.0074
Shine Reduction (In-house)	43.74	0.9951	0.0054

Table 2: Performance evaluation across different facial enhancement tasks using identical model architecture.

## Experimental Validation and Results

### Dataset Strategy and Evaluation Framework

**FFHQR Baseline Evaluation:** We conduct comprehensive experiments using FFHQR (Shafaei, Little, and Schmidt 2021b), containing 70,000 high-definition face images with professionally retouched counterparts (56,000/7,000/7,000 train/val/test split). This enables direct comparison with existing state-of-the-art methods using established benchmarks.

**Addressing Dataset Limitations:** FFHQR primarily contains subtle retouching scenarios with minimal severe blemishes, potentially masking the texture preservation advantages of our approach. To provide comprehensive evaluation, we curated specialized datasets:

- **Wrinkle Removal Dataset:** 20,000 image pairs targeting age-related facial lines

Method	General Retouching (FFHQ)			Wrinkle Removal (In-house)			Shine Reduction (In-house)		
	PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$	PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$	PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$
MSE	44.89	0.9921	0.0156	45.12	0.9913	0.0089	42.03	0.9918	0.0092
MSE + Perc.	45.15	0.9929	0.0138	45.51	0.9921	0.0081	43.29	0.9925	0.0076
MSE + Perc. + TV	45.33	0.9934	0.0124	45.73	0.9927	0.0074	43.74	0.9951	0.0054

Table 3: Cross-task ablation study showing consistent improvement with additional loss components across different facial enhancement tasks.

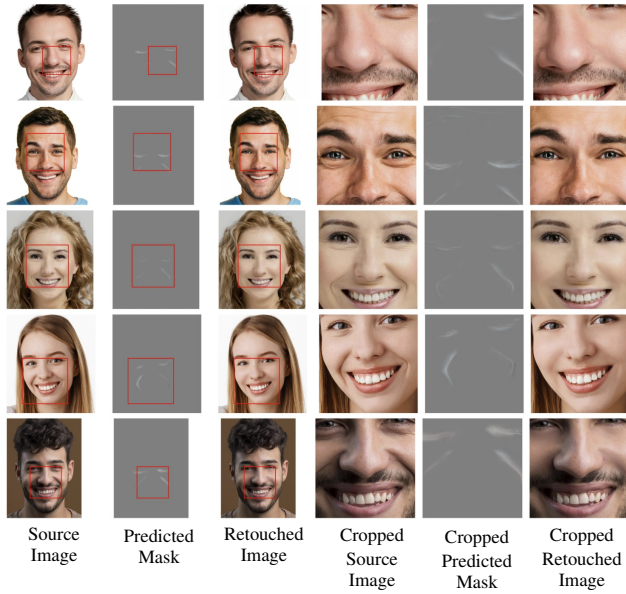


Figure 4: Qualitative results on wrinkle removal.

- **Facial Shine Dataset:** 20,000 image pairs addressing oily skin shine removal

These datasets, manually retouched by professional photographers using traditional Photoshop techniques, enable precise evaluation of texture preservation capabilities in challenging scenarios where binary-mask approaches typically fail.

## Implementation and Training Details

**Technical Specifications:** Model implementation uses PyTorch with distributed training across 8 NVIDIA L4 GPUs using data parallel training. We employ Adam optimizer with initial learning rate  $5 \times 10^{-5}$  and batch size 2 per GPU (effective batch size 16). Learning rate decreases by  $10\times$  every 50 epochs using StepLR scheduler over 150 total epochs.

**Deployment Optimization:** FP8 quantization (Rokh, Azarpeyvand, and Khanteymooori 2023) reduces the final model to 6MB while maintaining quality standards, making edge deployment feasible for professional photography environments typically running on laptop configurations.

## Quantitative Results and Competitive Analysis

**Benchmark Performance:** Our method achieves competitive quality metrics on FFHQ while providing substantial deployment advantages (Table 1). Key results demon-



Figure 5: Qualitative results on FaceShine removal.

strate that blend map prediction preserves visual quality better than reconstruction-based methods while offering significant efficiency improvements.

**Cross-Task Generalization:** Evaluation across test datasets reveals consistent performance—PSNR, LPIPS and SSIM scores (Horé and Ziou 2010; Zhang et al. 2018) remain stable across wrinkle removal, blemish removal, and shine reduction tasks. This validates the generalizability of our blend map prediction approach across diverse retouching scenarios (Table 2).

## Ablation Studies and Design Validation

**Loss Component Analysis:** Systematic ablation reveals that perceptual loss proves crucial for maintaining visual quality standards expected in professional photography. Total variation regularization ensures spatial coherence in predicted blend maps, preventing artifacts that would be immediately apparent to professional photographers (Table 3).

**Resolution Strategy Validation:** Processing at  $512 \times 512$  instead of  $1024 \times 1024$  achieves  $4\times$  inference speedup due to quadratic computational relationships. Our upsampling strategy with bilinear interpolation and convolutional refine-

ment maintains output quality while achieving substantial efficiency gains essential for real-time professional applications.

## Path to Deployment and Commercial Viability Development Strategy and Market Readiness

**Current Implementation Status:** The system architecture supports immediate integration into professional photo editing workflows through local processing capabilities, maintaining the data privacy essential for professional photographers handling sensitive client content. Our lightweight design specifically addresses computational constraints typical in professional photography environments where expensive GPU infrastructure isn't feasible.

### Integration Roadmap:

- **Phase 1 (Q3 2025):** Internal testing within controlled environments with select professional photographers
- **Phase 2 (Q4 2025):** Limited beta release gathering feedback from 100+ professional photographers across different specializations
- **Phase 3 (Q1 2026):** Full production deployment with usage analytics and performance monitoring

**Success Metrics and Commercial Impact:** Performance targets include sub-100ms processing time across 95% of test cases, > 95% photographer satisfaction scores, and < 5% manual intervention requirements. For typical wedding photographers processing 300 images per event, our solution reduces workflow from 10-15 hours of manual retouching to 5 minutes of automated processing plus 1 hour of selective refinement—representing a 90% reduction in retouching time while maintaining professional quality standards.

### Technical Readiness and Competitive Advantage:

Extensive experimental validation demonstrates technical readiness for professional deployment. Our approach addresses the primary barrier preventing widespread adoption of automated retouching: the quality-efficiency trade-off that forces photographers to choose between speed and professional results. Professional photographers use diverse hardware configurations and work across extreme lighting diversity—from controlled studio lighting to harsh outdoor conditions. Our 6MB model and additive approach handle this variability naturally, eliminating hardware upgrade requirements while adapting to cultural and aesthetic preferences through blend map modifications rather than imposed generated content.

## Technical Results and Performance Analysis Comprehensive Evaluation and Limitations

**Performance Validation:** Evaluation on FFHQ demonstrates competitive performance with state-of-the-art methods while achieving dramatic efficiency improvements. Testing on wrinkle and shine datasets reveals superior texture preservation compared to reconstruction-based methods that consistently produce over-smoothed results. Real-world validation with professional photographers processing actual client work confirms laboratory results translate to

practical scenarios, with 90%+ satisfaction with automated results.

**Current Limitations and Mitigation:** Extreme lighting conditions (harsh shadows, overexposure) occasionally require manual adjustment, very severe scarring may need traditional reconstruction approaches, and color cast correction remains outside current scope. Our system includes confidence scoring that identifies challenging cases requiring manual attention, ensuring professional photographers maintain control over quality standards while benefiting from automation in routine scenarios.

## Future Development and Impact

### Technical Innovation and Broader Vision

We present a fundamental shift in automated face retouching through lightweight U-Net architecture achieving professional-quality results via additive mask prediction. Our 6MB model processes images in sub-100ms while maintaining texture preservation essential for professional applications, mathematically implementing traditional dodge-and-burn techniques through learnable blend maps.

Planned enhancements include expanded training data addressing challenging lighting scenarios, advanced user controls based on direct feedback from beta deployment, and integration with RAW processing pipelines. Beyond immediate commercial applications, this work establishes a framework for AI-assisted creative tools that preserve human artistic intent while automating routine technical tasks, potentially inspiring similar approaches across creative industries where maintaining original content characteristics while enabling selective enhancement represents both technical and economic value.

## Conclusion

We have presented a lightweight neural approach that successfully bridges traditional photographic techniques with modern AI capabilities, achieving professional-quality face retouching while maintaining computational efficiency. Our additive blend map prediction method demonstrates that texture preservation and automated enhancement can be achieved simultaneously through architectures that respect the fundamental principles of photography rather than replacing them.

## Acknowledgments

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