Abstract

Acne detection and removal from facial images is a critical task for applications in skincare visualization, photo editing, and dermatology. Existing manual or semi-automated tools are time-consuming and lack precision. We propose a novel deep learning pipeline that detects pimples in facial images and automatically removes them using inpainting techniques. Our system combines a DLIB-based detection model (95% mAP) with a DLN-based inpainting model to restore skin texture seamlessly. Experiments show 90% user satisfaction in removal quality, offering a robust solution for acne-free skin visualization.

1. Introduction

Pimples, even when temporary, affect self-confidence and photo aesthetics. Automatic skin blemish removal is widely desired for portrait retouching in social media, e-commerce, and virtual makeup applications. Traditional inpainting methods often struggle with small, ill-defined acne lesions, resulting in noticeable artifacts or blurred facial details. Recent learning-based approaches improve results but still suffer from imprecise mask boundaries and over-smoothing. Manual removal in photo editors (e.g., Photoshop) is tedious, while automated tools often produce unrealistic results.

Our contribution:

- *A two-stage system:*

1. *Detect pimples with high precision using DLIB library.*
2. *Remove pimples and reconstruct skin texture using inpainting.*

- *Novelty: Unlike existing tools, our method uses context-aware DLN to preserve skin texture, avoiding "blurry" artifacts common in traditional inpainting.*

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2. Proposed Method

2.1 Overview

System Pipeline

1. *Detection Phase:*
   - *Input: Facial image.*
   - *DLIB library localizes pimples with bounding boxes.*
2. *Removal Phase:*
   - *Masked pimple regions are inpainted using a Deep learning network trained on healthy skin patches.*

2.2 Lesion Detection using DLIB

We use DLIB for pimple detection due to its real time object detection capabilities and superior performance on small object localization. DLIB anchor-free design and strong generalization allow it to detect varying pimple sizes and shapes effectively. The output bounding boxes are converted to binary masks, which are subsequently used by the inpainting module.

The detection loss includes objectness, classification, and localization components, optimized using CIoU loss. Post-processing is done via non-maximum suppression (NMS) with a threshold of 0.4 to remove overlapping detections.

2.3 Inpainting with Gated Convolutions

For inpainting, we adopt the gated convolutional architecture from Yu et al. (2019). The predicted binary mask guides the gating mechanism, allowing the network to focus on hole filling while preserving surrounding context. We train *the inpainting network with a combination of L1 reconstruction loss and perceptual loss.*

Technical Details

- *Detection Model: DLIB trained on ACNE04 dataset (2,500 annotated images).*
- *Inpainting Model: A UNET trained on paired pimple-masked and clean skin images from FFHQ Skin Dataset.*
- *Pre-processing: Face alignment and HSV colour normalization.*

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3. Experiments & Results

3.1 Detection Performance

Model	*mAP@0.5*	*Precision*	*Recall*
DLIB	*0.95*	*0.93*	*0.96*
Faster R-CNN	*0.89*	*0.88*	*0.91*

3.2 Inpainting Quality

Method	*PSNR ↑*	*SSIM ↑*	*User Satisfaction ↓*
Traditional CV	*28.5*	*0.82*	*65%*
Our DLN	*32.1*	*0.91*	*90%*

4. Conclusion & Future Work

Our tool achieves 95% mAP in detection and 90% user satisfaction in seamless pimple removal. Future directions:

- *Real-time video processing for live skincare simulations.*
- *Mobile app deployment with edge-optimized models.*

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Appendix:

https://github.com/Navdeep1331/Pimple-Removal-Tool

Dataset link

FFHQ dataset - ffhq-dataset - Google Drive

ACNE04 Dataset - ACNE04 DATASET - template

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