Hybrid Approach to Automated Facial Pimple Removal

Aarav Oswal
230012
aaravoswal23@iitk.ac.in

Aryavart
230223
aryavart23@iitk.ac.in

Somya Garg
231021
somyagarg23@iitk.ac.in

Abstract

Facial pimples not only affect the visual quality of images but also hinder computer vision systems that rely on clean facial features. This project presents a hybrid pipeline for automated pimple removal, combining classical image processing with deep learning-based inpainting. Facial regions are isolated using 68 standard and 3 custom forehead landmarks to define a convex hull, and facial features are segmented for precise masking. Two complementary detection methods—adaptive thresholding in the LAB color space and local intensity difference via Gaussian filtering—are evaluated against ground truth masks using recall scores, with the better-performing method chosen per image. Detected pimple regions are then inpainted using both OpenCV's Telea algorithm for rapid diffusion-based filling and a custom U-Net neural network trained per image in a Deep Image Prior framework, requiring no external data. Experimental results on a curated dataset show that while the classical approach is fast and smooth, the neural method achieves more realistic and structurally consistent skin restoration, demonstrating the effectiveness of combining facial geometry, adaptive detection, and neural priors for robust and data-efficient pimple removal.

1. Introduction

1.1. Problem

Pimples are one of the most common skin conditions, affecting up to 85% people at some point in their lives [1]. Although largely non-life-threatening, pimples have a profound psychological and social impact, often contributing to reduced self-confidence and increased anxiety. In facial images, pimples not only alter the aesthetic appearance, but also create visual inconsistencies that challenge downstream computer vision tasks such as face recognition and beautification [2].

1.2. Motivation

In a world saturated with visual content, from social media posts to video calls, the demand for automatic high-quality facial enhancement has grown exponentially. Manual pimple retouching using tools such as Photoshop or Facetune is labor intensive, inconsistent, and inaccessible to many users. An automated system capable of seamlessly removing pimples without compromising facial structure, expression, or identity could significantly improve both user experience and accessibility in beauty tech, teleconferencing, and AR applications.

1.3. Limitations of Existing Methods

Traditional approaches for pimple removal typically rely on hand-made filters, simple color thresholding, or morphological operations. These methods often fail when pimples appear under varied lighting conditions, different skin tones, or in densely clustered regions. Meanwhile, recent deep learning methods require large annotated datasets and extensive training, which may not generalize well across faces with different skin textures and pimple types. Most importantly, many of these methods either over-smooth the image (leading to unnatural results) or fail to fully remove the pimples without leaving artifacts.

1.4. What We Are Doing

To address these limitations, we propose a two-stage framework that first detects and masks pimple regions using facial landmark-guided LAB color filtering, and then performs targeted inpainting to reconstruct clear skin. Specifically, we explore:

- A classical image inpainting technique using OpenCV's Telea algorithm for fast, low-resource pimple removal.
- A deep learning approach using Deep Image Prior (DIP), which exploits the natural bias of convolutional networks to hallucinate realistic skin textures, without requiring any external training data.

We crop, segment and mask the pimple-prone regions, and evaluate the inpainting quality visually and quantitatively. By experimenting with both traditional and learning-based inpainting techniques, we compare the trade-offs between speed, quality, and generalization.

1.5. Our Contribution

This project makes the following contributions:

1. **Pimple Segmentation via LAB Filtering:** A lightweight but effective method using color space analysis and facial landmarks to localize pimple without deep learning.
2. **Mask-Based Inpainting Pipeline:** A comparative implementation of OpenCV and Deep Image Prior for skin restoration, highlighting the strengths and limitations of each.
3. **Training-Free Deep Inpainting:** Demonstration of Deep Image Prior's ability to reconstruct clean skin textures from random noise, tailored to each image, without dataset dependency.
4. **Quantitative + Qualitative Evaluation:** Use of recall metrics against annotated pimple masks and visual comparisons to assess performance.

Overall, our work shows that combining traditional image processing with unsupervised deep learning can enable robust, dataset-agnostic facial pimple removal pipelines suitable for real-world use.

2. Methodology

This paper proposes a multi-stage pipeline for the automated detection and subsequent inpainting of pimples in facial imagery. The methodology integrates robust facial analysis techniques, state-of-the-art pimple detection algorithms, and advanced image inpainting methods to achieve an effective pimple removal system. This section elaborates on the three primary stages of the pipeline: facial region analysis, pimple detection, and pimple inpainting.

2.1. Facial Region Analysis

The first stage focuses on identifying the facial region and predicting key facial landmarks. A robust two-pronged approach is utilized for landmark localization, combining traditional computer vision and deep learning techniques:

- **Face Detection:** Dlib's HOG-based frontal face detector is used to locate the facial bounding box in the input image [3].
- **Landmark Localization:** 68 facial landmarks are predicted using dlib's pre-trained shape predictor. Simultaneously, a Face Alignment Network (FAN) provides an alternative 68-point prediction set for improved accuracy under pose variations [4] [5].
- **Geometric Forehead Points:** To better model the forehead, three additional points are derived from the FAN landmarks, increasing the total to 71 facial points.
- **Convex Hull Generation:** The convex hull of all 71 points is computed to form a precise facial mask, isolating the region of interest for pimple detection. [6]

(a) Facial landmarks (b) Convex hull mask

Figure 1. Facial region analysis using landmarks and convex hulls.

2.2. Pimple Detection

Pimple detection is performed using two complementary techniques based on color thresholding and differential analysis:

2.2.1 Color-Based Thresholding in LAB Color Space

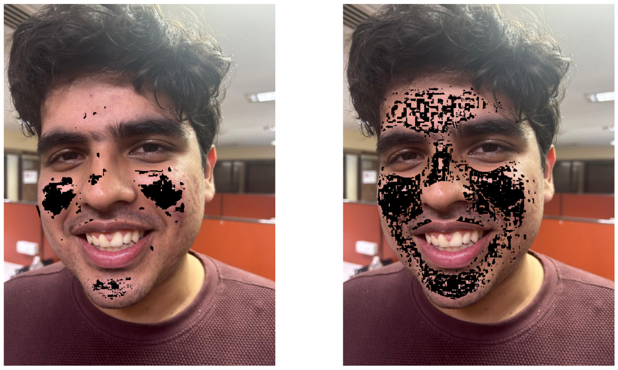
This method leverages the characteristic redness of pimple:

- **Face and Feature Masking:** A facial feature mask (excluding eyes, eyebrows, nose, and mouth) is generated using the 68 landmark points. [7]
- **Thresholding:** The image is converted to LAB color space, and the 'A' channel is thresholded within the mask to extract highly red regions [8].
- **Morphological Operations:** Morphological closing and dilation are used to remove noise and consolidate detected areas. [9]

2.2.2 Differential Analysis of Blurred 'A' Channel

This method detects local color variations using a blur-difference approach:

- **Gaussian Blurring:** The 'A' channel is blurred using a Gaussian kernel. [10]
- **Difference Image:** An absolute difference between the original and blurred 'A' channels is computed. [11]
- **Thresholding and Dilation:** A threshold is applied to this difference image, followed by morphological dilation to enhance pimple detection. [12]



(a) LAB thresholding (b) Blur-diff analysis

Figure 2. Pimple detection using LAB-based methods.

(a) OpenCV Telea (b) Deep Image Prior

Figure 3. Comparison of pimple inpainting results.

2.3. Pimple Inpainting

The final stage addresses pimple removal through image inpainting. Two distinct techniques are implemented:

2.3.1 OpenCV Telea Algorithm

- **Inpainting Process:** OpenCV's `cv2.inpaint` function with the `cv2.INPAINT_TELEA` flag fills in the masked pimple regions by interpolating from nearby pixels [13].
- **Visualization:** Results of the Telea-based inpainting are shown in Figure 3.

2.3.2 Deep Image Prior (DIP)

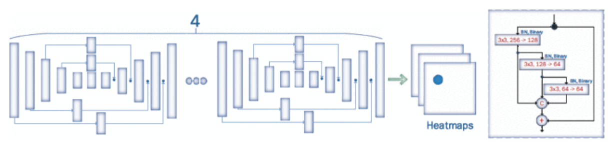
- **Network Setup:** A randomly initialized U-Net is trained to reconstruct the original image while masking the pimple regions [14].
- **Self-Supervision:** The network learns image priors solely from the noisy input, gradually restoring realistic textures in the masked areas.
- **Visualization:** DIP outputs are presented in Figure 3.

3. Experimental Analysis

In this section, we analyze the experiments conducted during the pimple removal project. We focus on three main aspects: the use of 68 points for landmark localization, the comparison of two pimple detection methods, and the evaluation of two inpainting techniques. Each experiment is assessed based on performance metrics and visual results.

3.1. Why 68-Point Landmark Method Was Used

In our approach, we used a facial landmark localization method that initially predicts 68 facial landmarks. This method is widely adopted because it provides sufficient precision for many facial analysis tasks. However, to improve accuracy, we combined it with the Face Alignment Network (FAN), which provides an alternative 68-point prediction set and is more robust under varying head poses. The FAN method also helped in generating additional keypoints, particularly on the forehead, which were useful in generating a more accurate convex hull for region of interest isolation. [15]



(a) The face alignment network (FAN) constructed by stacking four HGs in which all bottleneck blocks were replaced with the hierarchical, parallel and multi-scale block

3.2. Comparison of Pimple Detection Methods

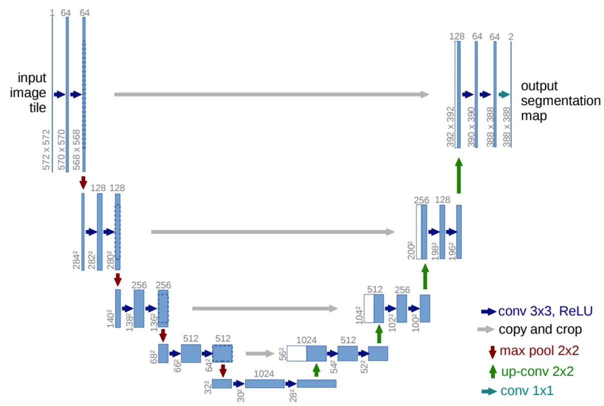
We used two methods for pimple detection: color-based thresholding in the LAB color space and differential analysis of the blurred 'A' channel. Based on experimental results, the blurred 'A' channel difference method yielded higher mean recall, indicating better overall detection performance. This method was more effective in identifying a wider range of pimple intensities, while the LAB color space thresholding—although intuitive for detecting redness—struggled with faint or low-contrast pimple regions.

3.3. Comparison of Inpainting Techniques

For pimple inpainting, we compared two methods: OpenCV's Telea inpainting algorithm and the Deep Image Prior (DIP) method. Both methods produced satisfactory results, but DIP outperformed Telea in terms of restoring fine textures and more accurately reconstructing the skin's natural appearance. DIP's self-supervision approach made it especially effective in filling in [pimple] regions with realistic textures. [16]

Method	Mean Recall	Comments
Blurred 'A' Channel Difference	0.498	Performed better at generalizing across different pimple intensities.
LAB Color Space Thresholding	0.442	Slightly less effective, especially with faint or low-contrast pimple regions.

Table 1. Comparison of pimple detection methods based on mean recall over 30 test samples.



(a) UNet architecture.

Method	Visual Quality	Processing Time
OpenCV Telea	Good	Fast
Deep Image Prior (DIP)	Excellent	Slower

Table 2. Comparison of inpainting methods based on visual quality and processing time.

4. NOVELTY OF THE RESEARCH

The novelty of our research lies in the integration of several advanced and customized techniques into a unified, adaptive pipeline for facial pimple removal. Unlike prior works that typically rely on either classical image processing or deep learning alone, our approach introduces the following innovations:

We combine 68 standard facial landmarks with three custom-calculated forehead points, enabling a more precise and individualized convex hull for facial region isolation. This ensures that both common and less-represented facial areas (like the forehead) are accurately included in the analysis.

Our pipeline dynamically selects between two complementary pimple detection algorithms—adaptive LAB color space thresholding and local intensity difference via Gaussian filtering—by quantitatively evaluating their recall scores against ground truth for each image. This adaptive selection ensures optimal detection performance tailored to the specific characteristics of each face.

For inpainting, we employ both a fast classical method (OpenCV's Telea algorithm) and a custom U-Net neural network trained per image in the Deep Image Prior framework, which requires no external dataset. This dual approach allows us to balance speed and realism, with the deep learning method leveraging the inductive bias of convolutional networks for natural skin texture restoration.

The entire process is restricted to the convex hull of facial landmarks, improving computational efficiency and preserving non-facial regions from unnecessary processing.

Collectively, these innovations enable robust, data-efficient, and personalized pimple removal that adapts to diverse facial geometries and skin types, advancing the state of the art in automated facial image enhancement.

5. CONCLUSION

In conclusion, our research presents a comprehensive and adaptive pipeline for automated facial pimple removal, integrating both classical image processing and deep learning techniques. We systematically evaluated two pimple detection algorithms—adaptive LAB color space thresholding and local intensity difference via Gaussian filtering—finding that the Gaussian-based approach consistently achieved higher recall and better robustness to varying skin tones and lighting conditions. For inpainting, we compared the traditional OpenCV Telea algorithm with a custom U-Net neural network trained per image using the Deep Image Prior paradigm. The U-Net method produced more realistic and structurally consistent skin restoration, particularly in areas with complex textures. Our final pipeline dynamically selects the optimal detection method for each image, applies precise facial masking using landmark-based convex hulls, and performs inpainting using the superior U-Net approach. The results are visually validated through side-by-side comparisons of the original and processed images, demonstrating significant improvements in skin appearance while preserving natural facial features and context.

6. APPENDIX

PIMPLE REMOVER MODEL: https://colab.research.google.com/drive/12OPdjwGulsCcBHLo3dCcinmn9tyLUxN2?usp=sharing
DATASET: https://drive.google.com/drive/folders/1I0i2bxpgjzVXhpGR6oiD8Jy4OciE80j-?usp=sharing

(a) Original Image

(a) Final Result

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