HANOI UNIVERSITY OF SCIENCE AND TECHNOLOGY SCHOOL OF ELECTRICAL AND ELECTRONIC ENGINEERING



REPORT

Beautification Filters on Face Detection and Recognition

Course: Digital Image Processing Course Code: ET4591E

Supervisor: Prof. Tran Thi Thanh Hai

Supervisor: Prof. Le Thi Lan

Member: Tran Minh Ha 20224309

Member: Nguyen Mai Huong 20224314

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First Member Nguyen Mai Huong ET-E16 02

huong.nm224314@sis.hust.edu.vn

Second Member Tran Minh Ha ET-E16 01

ha.tm224309@sis.hust.edu.vn

This project introduces a comprehensive system for applying beautification filters in real-time video processing through a webcam. Utilizing advanced image processing techniques and facial landmark detection, the system features multiple filter categories: color adjustments, accessory overlays, and skin enhancement. Each filter dynamically adapts to facial movements and varying environmental conditions, providing seamless and accurate results. The evaluation demonstrates the system's effectiveness in real-time performance, robustness in different lighting conditions, and adaptability. Future work will include integrating machine learning models for personalized beautification and optimizing performance for mobile platforms.

1. Introduction

1.1. Problem Statement

The rapid rise of social media and augmented reality applications has increased demand for real-time beautification filters. These filters aim to improve facial aesthetics, enhance user experience, and add entertaining elements through virtual accessories. However, implementing such filters presents challenges, including accurate facial landmark detection, real-time performance, and consistency under dynamic conditions like head movements and poor lighting.

1.2. Input/Output

- Input: Real-time video feed from a webcam
- Output: Enhanced video feed with applied beautification filters (e.g., color adjustments, skin smoothing, virtual accessories).

1.3. Challenges

- Maintaining accurate filter placement during facial movements.
- Ensuring real-time performance without noticeable latency.

- Adapting to varying lighting conditions and camera distances.
- Integrating multiple filters while maintaining system stability.

This project bridges the gap between practical deployment and theoretical advances in image processing, focusing on robust filter application using a lightweight and scalable approach.

2. Related works

The domain of real-time facial beautification has gained significant attention with the proliferation of augmented reality (AR) applications and computer vision technologies. This section explores the foundational works and advancements related to the three primary aspects of this project: facial landmark detection, beautification techniques, and accessory overlays.

2.1. Facial Landmark Detection

Facial landmark detection is a cornerstone of many computer vision applications, providing the structural basis for tasks like filter alignment, expression recognition, and facial morphing.

Traditional Methods

Early approaches to facial detection relied heavily on handcrafted features:

- Viola-Jones Algorithm (2001): A breakthrough in object detection, this method utilized Haar-like features combined with an AdaBoost classifier to perform real-time face detection. Despite its efficiency, the algorithm struggled with non-frontal faces and lighting variations, making it less suitable for dynamic applications like AR[8].
- Active Shape Models (ASMs) and Active Appearance Models (AAMs): These statistical shape models used annotated datasets to locate facial landmarks. However, they required significant computational resources and were sensitive to initialization errors.

Modern Approaches

Modern techniques leverage machine learning and deep

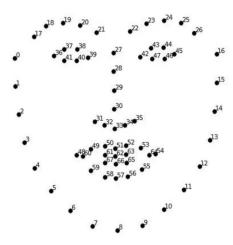


Figure 1. Visualization of Dlib's 68-point facial landmarks.

learning for more robust landmark detection:

- Dlib's 68-point Landmark Model: Based on Histogram of Oriented Gradients (HOG) and Support Vector Machines (SVM), this model provides precise facial feature localization across varying conditions. It is widely used in real-time applications due to its balance between accuracy and computational efficiency[5].
- Deep Learning Models: Methods like MediaPipe Face Mesh and OpenCV's deep neural network (DNN) modules provide high-density facial landmarks. These models utilize convolutional neural networks (CNNs) trained on large datasets, enabling robustness against occlusions and extreme poses[3].

2.2. Beautification Techniques

Beautification techniques aim to enhance facial aesthetics by improving image quality, reducing imperfections, and applying artistic effects.

Traditional Image Processing

Conventional methods include:

- **Histogram Equalization:** Enhances brightness and contrast, especially under low-light conditions. This technique works by redistributing pixel intensity values to achieve uniform histogram distribution. However, it often leads to overexposed or unnatural results in certain regions[2].
- Gaussian Blur and Bilateral Filtering: While Gaussian blur smoothens textures, bilateral filtering preserves edges, making it ideal for skin smoothing[6].

Advanced Techniques

Machine learning has revolutionized facial beautification:

• GAN-based Beautification: Generative adversarial networks (GANs) have been employed for tasks like makeup transfer (e.g., BeautyGAN) [9] and skin texture refinement. GANs learn mappings between input and output

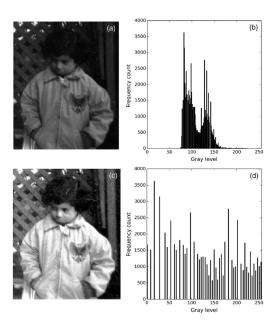


Figure 2. Example of histogram equalization for brightness adjustment



Figure 3. Comparison of Gaussian blur and bilateral filtering for skin smoothing.

domains, enabling realistic transformations.

• Edge-preserving Filters: Algorithms such as guided filters and anisotropic diffusion enhance specific regions without affecting the overall structure.[4]

2.3. Accessory Overlays and Augmented Reality

Virtual accessory overlays, such as hats, glasses, dog noses, cat faces, and floral crowns, play a pivotal role in enhancing user interaction in augmented reality (AR) applications. The implementation of these overlays involves precise alignment, scaling, and orientation to seamlessly integrate them with facial features. In the context of this project, accessory filters are dynamically adjusted in real-time to maintain accurate placement despite facial movements and changes in perspective.

Traditional Methods

Early methods for accessory overlays were limited by their reliance on static templates and pre-defined facial regions:

- **Template-based Approaches:** These methods employed fixed templates for accessory placement, often resulting in inaccuracies when applied to dynamic facial movements or diverse facial geometries[7].
- Shape-based Models: Approaches such as Active Shape Models (ASMs) provided basic adaptability but struggled with real-time applications due to computational constraints and sensitivity to noise.

Advances in Landmark-based Overlay Placement

The introduction of robust facial landmark detection has significantly enhanced the accuracy and adaptability of accessory overlays:

- **Geometric Transformations:** Using the coordinates of key facial landmarks, geometric transformations[2] like scaling, rotation, and translation are applied to align the accessory images with the user's face. For example:
 - Hats: Positioned above the eyebrows, with dynamic adjustments for tilt and scale based on the distance and angle between the eyes and the forehead.
 - Glasses: Placed over the eyes, with scaling determined by the distance between the outer corners of the eyes.
- Angle Correction: Facial orientation is calculated using landmarks such as the eyes and nose. Rotation matrices are applied to the accessories to match the face's tilt accurately.

This project builds upon existing works by combining robust facial landmark detection with lightweight, customizable filters to deliver real-time performance on standard hardware.

3. Proposed methods

The proposed methods in this project leverage advanced image processing techniques and geometric transformations to implement a suite of beautification filters. These methods are designed to operate in real time, ensuring seamless integration of color adjustments, facial enhancements, and accessory overlays with webcam video streams.

3.1. Data Structure and Workflow

The "Selfie Beautification Filter" system is designed for real-time facial enhancement and customization. The workflow is described as follows:

• Trackbar Initialization: Trackbars are created for selecting RGB values dynamically, enabling real-time adjustments for effects like lipstick and eye color:

Trackbars: Blue, Green, Red (Range: 0-255).

• **Video Capture:** The system continuously captures video frames from a webcam using OpenCV:

Frame = cv2.VideoCapture(0).

• Facial Landmark Detection: Dlib's facial landmarks are used to detect key facial features, enabling precise application of filters and effects:

Landmarks: eyes, lips, cheeks, etc..

- **Effect Application:** Based on the user-selected effect (*current_effect*), various transformations are applied:
 - Smooth Skin: Applies a bilateral filter to the facial region.
 - Eye Color: Changes the pupil color based on RGB values.
 - **Fish Eye:** Creates a bulging effect around the eyes.
 - Blush: Adds a soft blush effect to the cheeks.
 - Lipstick: Enhances the lip region with the selected color.
 - Accessory Overlays: Adds virtual elements like glasses, hats, or crowns.
 - Artistic Filters: Applies filters such as Negative, Sepia, and Cool Tone.
- Button and Mouse Interaction: Interactive buttons allow users to switch between effects. A mouse callback function handles button clicks and effect selection dynamically.
- **Image Capture:** Users can capture a frame by pressing the 'c' key, saving the enhanced image:

Saved Image: PICTURE.jpg.

• Keyboard Shortcuts:

- 'g': Set eye color to green.
- 'b': Set eye color to blue.
- 'r': Set eye color to red.
- 'p': Set eye color to purple.
- 'o': Reset to the original eye color.
- 'q': Exit the application.
- **Real-Time Display:** The final processed frame is displayed in a window titled "Selfie Beautification Filter," updated continuously with user-selected effects.
- Exit: The program exits cleanly when the user presses the 'q' key, releasing resources and closing all windows.

This workflow provides a highly interactive and customizable experience, enabling users to enhance their appearance in real-time.

3.2. Detailed Algorithm

3.2.1. Face Detection and Landmark Detection

The project begins with precise face detection and landmark extraction to enable accurate placement of filters and overlays.

• Face Detection: The Histogram of Oriented Gradients (HOG) method is employed to detect faces. The image is divided into small regions, and gradient direction histograms are calculated for each region. A linear Support

Vector Machine (SVM) classifier then identifies faces.

$$HOG(x,y) = \sqrt{\sum_{i=1}^{n} \left(\frac{\partial I}{\partial x}\right)^{2} + \left(\frac{\partial I}{\partial y}\right)^{2}}$$

where I(x, y) is the pixel intensity.

• Facial Landmark Detection: Dlib's 68-point facial landmark detector is used. This model is trained on ensemble regression trees to predict landmark locations.

3.2.2. Color Adjustment Filters

Color adjustment filters enhance the overall aesthetic of the video feed by manipulating pixel values. Below are the specific filters used:

 Sepia Filter: This filter transforms the image into a warm, vintage-like tone using a linear transformation of RGB values.

$$\begin{bmatrix} R' \\ G' \\ B' \end{bmatrix} = \begin{bmatrix} 0.393 & 0.769 & 0.189 \\ 0.349 & 0.686 & 0.168 \\ 0.272 & 0.534 & 0.131 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

where R', G', B' are the transformed pixel values.

• **Negative Filter:** Inverts pixel intensities to produce a negative effect:

$$I'(x,y) = 255 - I(x,y)$$

• Brightness Adjustment: Adjusts the brightness β and contrast α of the image:

$$I'(x,y) = \alpha \cdot I(x,y) + \beta$$

• **Histogram Equalization:** Histogram equalization adjusts pixel intensities in the Y channel:

$$Y_{\text{equalized}} = \text{cdf}(Y) \cdot (L-1)$$

where cdf(Y) is the cumulative distribution function, and L is the number of intensity levels.

• Gaussian Blur: The Gaussian kernel G(x, y) is given by:

$$G(x,y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right)$$

3.2.3. Geometric Transformations

• Face Orientation Estimation: Determines the tilt or rotation angle of a face based on the relative positions of the eyes. Used for aligning filters like glasses, hats, or masks with the face orientation.

$$\theta = -\arctan\left(\frac{y_2 - y_1}{x_2 - x_1}\right)$$

where (x1, y1) and (x2, y2) are coordinates of the left and right eyes, respectively.

• Filter Alignment Rotation: Rotates accessory filters (e.g., hats, glasses) to align with the face angle

$$M = \begin{bmatrix} \cos \theta & -\sin \theta & t_x \\ \sin \theta & \cos \theta & t_y \end{bmatrix}$$

where t_x and t_y are translation adjustments.

• **Scaling:** The size of the accessory is dynamically adjusted based on the distance between landmarks, such as:

Width =
$$k \cdot (landmark_{16} - landmark_0)$$

3.2.4. Accessory Overlay Placement

Accessory placement involves mapping virtual objects onto the face with precision:

• Landmark Mapping: Identify key landmarks for positioning accessories.

Example: The glasses align with the corners of the eyes (landmarks 36 to 45) and hats align with the top forehead region (landmarks 19 to 24).

Alpha Blending: Merge accessory images with the original frame:

$$I'(x,y) = \alpha \cdot A(x,y) + (1-\alpha) \cdot I(x,y)$$

where A(x,y) is the accessory image and α is its transparency

3.2.5. Wide-Angle Distortion

This algorithm applies a wide-angle distortion effect, simulating a fisheye or wide-lens view. It uses intrinsic parameters (camera matrix) and distortion coefficients to remap pixel coordinates. Pixels further from the center are distorted more significantly than those closer, creating a bulging effect.

• Distortion Model:

$$x' = x(1 + k_1r^2 + k_2r^4) + 2p_1xy + p_2(r^2 + 2x^2)$$

$$y' = y(1 + k_1r^2 + k_2r^4) + p_1(r^2 + 2y^2) + 2p_2xy$$

where r is the radial distance from the center, and k_1, k_2 ... are distortion coefficients.

• Camera matrix The matrix K represents intrinsic camera parameters:

$$K = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix}$$

where:

 f_x, f_y : Focal lengths in pixels along x and y axes.

 c_x, c_y : Principal point coordinates (usually the image center).

3.2.6. Fisheye Effect for Eyes

The fisheye effect is applied to the eye regions to create a bulging or distorted appearance, enhancing the aesthetic or stylistic impact. The algorithm consists of the following steps:

- **Region of Interest (ROI):** The left and right eye regions are extracted based on the Dlib facial landmarks. Specifically:
 - The ROI for the left eye is determined using landmarks 37 to 41.
 - The ROI for the right eye is determined using landmarks 43 to 47.

The bounding box around each eye is extended by a specified radius to allow for the fisheye effect.

 Barrel Distortion: The fisheye effect is achieved using barrel distortion, which remaps pixels based on their radial distance from the center:

$$r = \sqrt{x^2 + y^2}$$
, where x, y are normalized pixel coordinates.

The distortion equation modifies the radial distance:

$$r_{\text{new}} = r - k \cdot r \cdot \cos(\pi \cdot r),$$

where k controls the intensity of the distortion. Pixels beyond the maximum radius (r > 0.5) are not distorted.

• **Remapping:** The distorted radial coordinates are used to calculate the new pixel positions:

$$x_{\text{new}} = r_{\text{new}} \cdot \frac{x}{r}, \quad y_{\text{new}} = r_{\text{new}} \cdot \frac{y}{r}.$$

The new coordinates are scaled back to the original image dimensions and used for pixel remapping.

- Applying the Effect: The barrel distortion is applied independently to the left and right eye regions. The distorted regions are then blended back into the original image, preserving the rest of the facial features.
- Output: The final image contains bulging eyes with the fisheye effect applied, while the rest of the face remains untouched.

This algorithm leverages radial distortion to create a dramatic fisheye effect, adding a unique stylistic element to the eyes while maintaining realism in the surrounding facial features.

3.2.7. Skin Smoothing Algorithm

The skin smoothing algorithm is designed to smooth facial textures while preserving edge details. The following steps summarize the approach based on the provided code:

• Face Region Masking: The algorithm uses Dlib's facial landmarks to create a mask around the facial region. Points along the jawline (landmarks 0 to 16) are extracted and used to define the mask:

$$\operatorname{mask}(x,y) = \begin{cases} 1 & \text{if } (x,y) \in \operatorname{face_region}, \\ 0 & \text{otherwise}. \end{cases}$$

• **Smoothing with Bilateral Filter:** A bilateral filter is applied to the entire image to smooth textures while retaining edges. The filter is defined as:

$$B(x,y) = \frac{1}{W} \sum_{i,j} \exp\left(-\frac{\Delta_s^2}{2\sigma_s^2}\right) \exp\left(-\frac{\Delta_r^2}{2\sigma_r^2}\right)$$

where:

$$\Delta_s = \sqrt{(x_i - x)^2 + (y_i - y)^2}, \quad \Delta_r = I_i - I,$$

and σ_s controls spatial filtering, and σ_r controls intensity filtering.

• **Mask Application:** The smoothed image is combined with the mask to isolate the filtered face region:

face_smoothed
$$(x, y) = B(x, y) \cdot \text{mask}(x, y)$$
.

Background Preservation: The original image is preserved outside the face region:

$$\mathsf{background}(x,y) = I(x,y) \cdot (1 - \mathsf{mask}(x,y)).$$

 Final Combination: The smoothed face region and the original background are combined using bitwise operations:

$$I'(x,y) = \text{face_smoothed}(x,y) + \text{background}(x,y).$$

This method ensures that only the facial region is smoothed, maintaining natural transitions between the face and the background.

3.2.8. Eye Color Adjustment

The eye color adjustment algorithm changes the color of the pupil region in the eyes while maintaining a natural appearance. The steps of the algorithm are as follows:

- **Region of Interest (ROI):** The algorithm identifies the pupil region for both eyes using Dlib's facial landmarks:
 - **Left Eye:** The pupil region is defined using landmarks 37, 38, 40, and 41.
 - **Right Eye:** The pupil region is defined using landmarks 43, 44, 46, and 47.

A mask is created by filling the polygon formed by these landmarks for each eye.

• Color Application: A solid color (e.g., green, red, or blue) is applied to the masked pupil region. The algorithm creates a blank image of the same size as the input image and fills the mask with the desired color:

$$\operatorname{eye_color}(x,y) = \begin{cases} \operatorname{color} & \text{if } (x,y) \in \operatorname{pupil_region}, \\ 0 & \text{otherwise}. \end{cases}$$

• **Smoothing:** To ensure a natural transition between the colored pupil and the surrounding area, the colored region is smoothed using a Gaussian blur:

$$G(x,y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right),\,$$

where σ is the blur radius.

• **Blending:** The colored and blurred pupil region is blended with the original image using weighted addition:

$$I'(x,y) = \alpha \cdot \text{eye_color}(x,y) + (1-\alpha) \cdot I(x,y),$$

where α controls the intensity of the applied color.

• **Output:** The final image has the pupil regions of both eyes adjusted to the specified color while preserving the overall natural appearance.

This algorithm provides a seamless way to enhance the eye color dynamically, making it suitable for real-time beautification or stylistic applications.

3.2.9. Blush Effect

The blush effect algorithm adds a natural-looking blush to the cheek regions, blending seamlessly with the original image. The following steps describe the implementation:

- **Region of Interest (ROI):** The algorithm identifies the cheek regions using specific Dlib facial landmarks:
 - **Left Cheek:** The region between landmarks 31 (side of the nose) and 2 (jawline).
 - **Right Cheek:** The region between landmarks 35 (side of the nose) and 14 (jawline).

The cheek centers are calculated as the midpoints between the top and bottom of each cheek region.

• **Blush Mask:** A mask is created for each cheek region using a Gaussian-like radial fading. For each pixel within a specified radius (r) of the cheek center:

$$\alpha = \exp\left(-0.5 \cdot \left(\frac{\text{distance}}{r}\right)^2\right),$$

where α determines the transparency of the blush color at that pixel. The mask is filled with a light pink color ([180, 105, 255]) weighted by α .

• **Blurring:** To ensure a smooth and natural transition, the mask is blurred using a Gaussian blur:

$$G(x,y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right),$$

where σ is the blur radius.

• **Blending:** The blush mask is blended with the original image using weighted addition:

$$I'(x,y) = (1 - \text{intensity}) \cdot I(x,y) + \text{intensity} \cdot \text{mask}(x,y),$$

where intensity controls the strength of the blush effect.

• Output: The final image features a soft blush effect applied to the cheeks, enhancing facial aesthetics while maintaining a natural appearance.

This algorithm provides a realistic and customizable blush effect, suitable for beautification and photo editing applications.

3.2.10. Lipstick Application

The lipstick application algorithm enhances the lip region by applying a customizable color overlay. The following steps describe the implementation:

• Region of Interest (ROI): The lip region is extracted using Dlib's facial landmarks, specifically points 48 to 60, which define the outer and inner contours of the lips. A mask is created by filling the polygon formed by these points:

$$\max(x,y) = \begin{cases} 1 & \text{if } (x,y) \in \text{lips_region,} \\ 0 & \text{otherwise.} \end{cases}$$

• Color Selection: The RGB values for the lipstick color are retrieved dynamically using trackbars, allowing real-time adjustment:

$$color = (blue, green, red),$$

where blue, green, and red are the trackbar positions.

• Color Layer Creation: A color layer is generated with the selected lipstick color and is restricted to the lip region using the mask:

$$\label{eq:lips_color} \begin{aligned} \operatorname{lips_color}(x,y) = \begin{cases} \operatorname{color} & \operatorname{if } \operatorname{mask}(x,y) = 1, \\ 0 & \operatorname{otherwise}. \end{cases} \end{aligned}$$

• **Smoothing:** To ensure a natural appearance, the color layer is smoothed using a Gaussian blur:

$$G(x,y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right),\,$$

where σ is the blur radius.

• **Blending:** The smoothed color layer is blended with the original frame using weighted addition:

$$I'(x,y) = (1-\alpha) \cdot I(x,y) + \alpha \cdot \text{lips_color}(x,y),$$

where $\alpha=0.4$ controls the intensity of the applied lipstick color.

• Output: The final image features the lip region enhanced with the selected color, providing a realistic lipstick effect.

This algorithm allows for dynamic and customizable lipstick application, making it suitable for real-time beautification tools and photo editing applications.

3.3. Complexity Analysis

- Face Detection: O(n) per frame, where n is the number of faces in a frame.
- Landmark Extraction: O(m) where m=68 (Dlib's model).
- Filter Application: Ranges from O(k) for color adjustments to $O(k^2)$ for skin smoothing.

4. Experiment

4.1. Experimental Setup

- **Hardware Configuration:** The evaluation was performed on a standard consumer-grade laptop with a webcam.
- Input Source: Live feed from the webcam.
- Evaluation Metrics: FPS, PSNR, and MSE were computed for 100 frames for each filter. For filters where these metrics are insufficient, visual assessment was employed.

4.2. Evaluation Metrics

This project implements a wide range of beautification filters to enhance live webcam feed images. The evaluation of these filters involves both quantitative metrics and qualitative observations:

4.2.1. FPS (Frames Per Second):

FPS was calculated for each filter to measure the computational efficiency and real-time performance of the system. For each filter, the program captured 100 frames while applying the filter in a continuous loop. The total elapsed time for processing these frames was recorded, and FPS was computed as:

$$FPS = \frac{Total\ Frames}{Elapsed\ Time\ (seconds)}$$

4.2.2. Peak Signal-to-Noise Ratio and Mean Squared Error

Applied to filters that modify pixel intensities, such as "Smooth Skin" and "Lipstick"

Peak Signal-to-Noise Ratio (PSNR): PSNR was used to measure the quality of the processed image compared to the original. A higher PSNR value indicates better preservation of image details after applying filters

$$PSNR = 10 \cdot \log_{10} \left(\frac{MAX^2}{MSE} \right)$$

where:

• MAX: Maximum possible pixel value (e.g., 255 for an 8-bit image).

Mean Squared Error (MSE): MSE calculates the average squared difference between pixel intensities of the original and processed images. Lower MSE values correspond to higher visual similarity between the filtered and original images.

$$\text{MSE} = \frac{1}{H \cdot W} \sum_{i=1}^{H} \sum_{j=1}^{W} \left(I_{\text{ref}}(i, j) - I_{\text{filtered}}(i, j)\right)^{2}$$

where

- H, W: Height and width of the images.
- I_{ref}, I_{filtered}: Pixel intensity values of the reference and filtered images.



Figure 4. Output of 22 filters

4.2.3. Visual Inspection:

Used for accessory filters (e.g., hats, glasses) and creative effects where numerical metrics may not fully capture user satisfaction.

Each filter was tested over 100 frames, recording FPS and, where applicable, PSNR and MSE values. For visual inspection, accessory filters were applied during live interaction, with alignment and aesthetic quality observed under varying head movements and expressions.

4.2.4. Implementation

The evaluation was conducted as follows:

- The system applied each filter to live video frames captured from the webcam.
- For FPS, the system processed 100 frames per filter, and the average FPS was calculated.
- For PSNR and MSE, the original and filtered frames were compared in real-time. The metrics were computed for each frame, and their averages were calculated over the test period.

4.3. Experimental Results

Table 1. Summarizes the performance of filters based on FPS, PSNR, and MSE $\,$

Filter	FPS	PSNR (dB)	MSE
Smooth Skin	9.98	49.72	0.69
Blush	9.42	48.37	0.95
Lipstick	10.02	50.03	0.65
Negative	10.01	27.16	124.97
Sepia	10.00	28.70	87.68
Wide Angle View	10.01	29.06	80.82
Edge	10.01	27.75	109.13
Black and White	10.04	30.85	53.50
Cool Tone	10.00	29.07	80.57
Brighten and Contrast	10.00	27.93	104.77
Rainbow Overlay	10.01	inf	0.00

- **Performance (FPS):** Most filters achieved FPS values above 10, supporting real-time usability.
- Quality Metrics: Enhancement filters like "Smooth Skin" and "Lipstick" exhibited high PSNR (49 dB) and low MSE, demonstrating minimal distortion. Artistic filters (e.g., "Negative," "Sepia") showed lower PSNR due to intentional alterations, aligning with their aesthetic purpose.
- Accessory Filters: All accessory filters displayed clearly and maintained good quality with stable face tracking. However, due to limitations of the Dlib model in handling extreme head rotations, the filters sometimes failed to align accurately when the head was turned significantly to either side. Additionally, filters such as "Bunny Hat" and "Frog Hat" showed misalignment when the distance between the face and the camera changed, resulting in the filters not perfectly matching the face's proportions or position. These issues highlight the need for more dynamic and adaptable tracking systems for such scenarios.

These results demonstrate the system's ability to balance real-time performance and visual quality effectively. Future work could explore further optimization of accessory filters and the inclusion of adaptive techniques for dynamic environments.

5. Conclusion

The "Selfie Beautification Filter" project effectively demonstrates the application of image processing and real-time facial enhancement techniques. By leveraging the robust capabilities of Dlib's facial landmark detection and OpenCV's dynamic filters, the system showcases a wide range of beautification features, including skin smoothing, color adjustments, and creative accessory overlays.

The evaluation of the system highlights several key strengths:

- **Real-Time Performance:** With most filters achieving an FPS of 10, the system meets the requirements for real-time usability.
- Visual Quality: Enhancement filters such as "Smooth Skin" and "Lipstick" demonstrated excellent PSNR values and minimal MSE, ensuring that the aesthetic quality of the filtered images is preserved.
- User Interaction: Accessory filters like hats and glasses performed well visually, with stable face tracking under normal conditions. However, limitations in extreme head rotations or changes in camera distance point to areas for improvement.

This project balances computational efficiency and visual fidelity, making it suitable for live applications. Nevertheless, the challenges encountered, such as occasional misalignment of accessory filters under extreme conditions, underline the potential for further optimization. Incorporating advanced techniques like deep learning-based tracking or

adaptive algorithms could address these issues in future iterations.

The success of this project sets the foundation for integrating more personalized beautification options, optimizing performance for mobile devices, and expanding the scope of real-time augmented reality applications. Through ongoing enhancements, the "Selfie Beautification Filter" has the potential to make significant contributions to the field of digital image processing and user-centered design. [1]

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