

Selective Image Enhancement for Robust GentleBoost Face Detection under Uncontrolled Illumination

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Abstract

Although significant progress has been achieved in computer vision, detecting faces under different lighting conditions and poses remains challenging. This issue is particularly crucial for biometric and surveillance applications, where lighting cannot be controlled. While the machine learning based Gentle Boost cascade provides stability benefits, it has not been studied extensively in face detection research. This paper introduces Selective Image Enhancement (SIE), a lightweight preprocessing technique designed to enhance image quality prior to detection. SIE operates on the (L) channel of the Commission Internationale de l'Éclairage CIELAB (LAB) color space, breaking down the (L) channel into illumination and detail components. It employs Gaussian filtering, gamma correction, and thresholding to selectively enhance image pixels while minimizing artifacts. Features are extracted using Local Binary Patterns Histogram (LBPH) and then classified with the Gentle Boost cascade, trained on the CelebA dataset and evaluated on 500 images. A comparative evaluation was conducted against gamma correction and Contrast Limited Adaptive Histogram Equalization (CLAHE). The proposed SIE method achieved 0.9800 recall, 0.9684 precision, and an F1-score value of 0.9742, with an average IoU of 0.7161 ± 0.0938 . Although CLAHE achieved higher recall and F1-score value, SIE obtained the highest mean IoU among the evaluated enhancement methods. The unenhanced images achieved a slightly higher IoU of 0.7193 ± 0.0926 . These results indicate that SIE provides competitive detection performance and a balance between image enhancement quality and localization accuracy.

Keywords: Uncontrolled Illumination, CIELAB, CLAHE, Face Detection, GentleBoost, Cascade Classifier, LBPH.

1. Introduction

Human face detection serves as a fundamental step in many computer vision applications, ranging from biometric identity verification systems to wide-area surveillance systems. Face detection involves extracting facial features from human faces using numerous techniques. It identifies human faces within an image and returns their spatial coordinates as a bounding box [1], [2]. The evolution of face detection has progressed from early statistical methods through classical feature-based approaches to machine learning techniques and

deep learning architectures. The evolution of face detection was significantly marked by the Viola-Jones detector [3], which introduced real-time detection using boosted cascade classifiers with Haar-like features. Other studies adopted local texture descriptors such as Local Binary Patterns Histogram (LBPH) to efficiently capture local texture information for face recognition applications [4].

Most current methods rely on deep learning techniques, usually through Convolutional Neural Networks (CNNs) showing strong efficiency in image classification and object detection, as presented in a review paper [2]. This highlights the benefits of deep learning and vision transformers over traditional approaches for face detection in complex conditions and occlusions, utilizing multi-scale, and attention-based features.

However, they face limitations including high computational requirements and resource constraints and potential overfitting on small or occlusion-specific datasets [1]. Recent Retinex-based neural methods decompose low-light images into reflection and illumination components and use neural networks for denoising and illumination enhancement, achieving improved objective quality [5].

Consequently, many studies still rely on boosting-based framework methods since they offer low computational cost and processing time making them well-suited for low-power devices and mobile applications [6]. Despite significant advances in face detection techniques, considerable challenges persist under uncontrolled real-world conditions, with different poses, occlusions, illumination changes, and dataset specific variations [7], along with changes in facial position, scale, lighting, image quality, and facial expressions [8].

To address challenging uncontrolled image conditions, this paper proposes a selective image enhancement method that decomposes image luminance into illumination and detail layers, followed by pixel-level enhancement. The resulting preprocessing pipeline is integrated with a GentleBoost cascade classifier [9]. Although GentleBoost has received limited research attention over the past decade, this work investigates whether a well-designed classical pipeline with improved preprocessing can achieve competitive performance and establishes a baseline for future classical cascade optimisation.

2. Related Work

The demand for face detection drives research to develop faster, more accurate, and robust face detection methodologies. [3], established the foundational framework based on approaches that extract Harr-like features and the AdaBoost cascade classifier. The success of AdaBoost inspired the development of further boosting variants. The authors in [9] modified AdaBoost, creating the GentleBoost algorithm which employs Newton stepping for more stable and robust weak-learner updates. A study in [10] compared GentleBoost, RealBoost, and AdaBoost, for face detection using a weak classifier and Haar-like feature, empirically finding that GentleBoost outperforms the other approaches in computational complexity and accuracy. Despit these advantages, a limited number of works have applied Gentle Boost specifically to face detection. [11] developed a two stage GentleBoost cascade, using pixel-intensity and partial-mean features, although the method was faster processing than Haar-AdaBoost, its detection rate was lower on detection self-recorded dataset. [12] compared Gentle AdaBoost, Real AdaBoost, Discrete AdaBoost, and LogitBoost using Multi-Block Local Binary Patterns (LBP) features to detect faces, finding that GentleBoost achieved the highest rate of true

positives. The authors in [13] combined Gentle AdaBoost with rotation-invariant LBP, and Canny-based features for multi pops detection, significantly improving detection rate and speed.

Our literature review found limited recent research on GentleBoost-based face detection after 2019, suggesting that this classical approach remains relatively underexplored.

Nevertheless, a recent study has revisited the algorithm and applied it to other classification tasks. For instance, [14] applied GentleBoost for medical diagnosis, while [15] proposed online GentleBoost as an extension of the original batch algorithm, providing theoretical and empirical justification that consistently improves upon its weak learner. Despite significant advances in both software and hardware, accurate face detection under uncontrolled imaging conditions remains a challenging and active research problem. A study [16] evaluated face image quality by considering specific facial properties, including resolution, pose angle, illumination parameters, and occlusion, demonstrating that these factors significantly degrade system performance. Image quality will significantly degrade under extreme lighting conditions (bright, dark) or if the image contains noise [17].

Since nonuniform illumination distorts key facial features, which is critical for face analysis, several studies have investigated image enhancement techniques for challenging real-world face detection. A study [18] found that illumination preprocessing improves face detection under different lighting, and the combined Gamma Correction plus Histogram Equalization method achieved, 92.79% precision, 87.49% accuracy, and 89.61% recall.

The Haar cascade algorithm was improved in [19] by integrating area analysis and adaptive thresholding, significantly boosting detection from 67.22% to 96.11%.

These studies indicate that image enhancement can improve classical face-detection pipelines without relying on deep-learning models. Although recent lightweight detectors generally provide stronger performance under severe occlusion, the GentleBoost cascade classifier [9] with HLBP remains relevant for CPU-based, resource-constrained, and legacy systems because of its low complexity and interpretable features. Therefore, SIE is investigated as a lightweight, training-free preprocessing method for improving GentleBoost–HLBP detection under varying illumination. GentleBoost has received limited recent attention in face-detection research; therefore, this study revisits its use with selective image enhancement.

3. Proposed Methodology

Inconsistent lighting requires nonuniform enhancement. Our method, the Selective Image Enhancement (SIE) framework, targets only affected regions in two stages. The first is a lightweight image preprocessing stage that converts the input image to the CIELAB (LAB) color space, separating luminance from color information. The luminance channel (L) is decomposed into an illumination component estimated using Gaussian blur [20] and a detail component obtained from their difference. Gamma correction [18] is applied directly to (L) to adjust brightness in poorly illuminated regions. The corrected (L) and detail components are then selectively merged, and the resulting image is converted back to RGB format. The second stage employs a GentleBoost cascade classifier with LBPH to detect faces from the enhanced image. The proposed framework pipeline is explained in Figure 1.

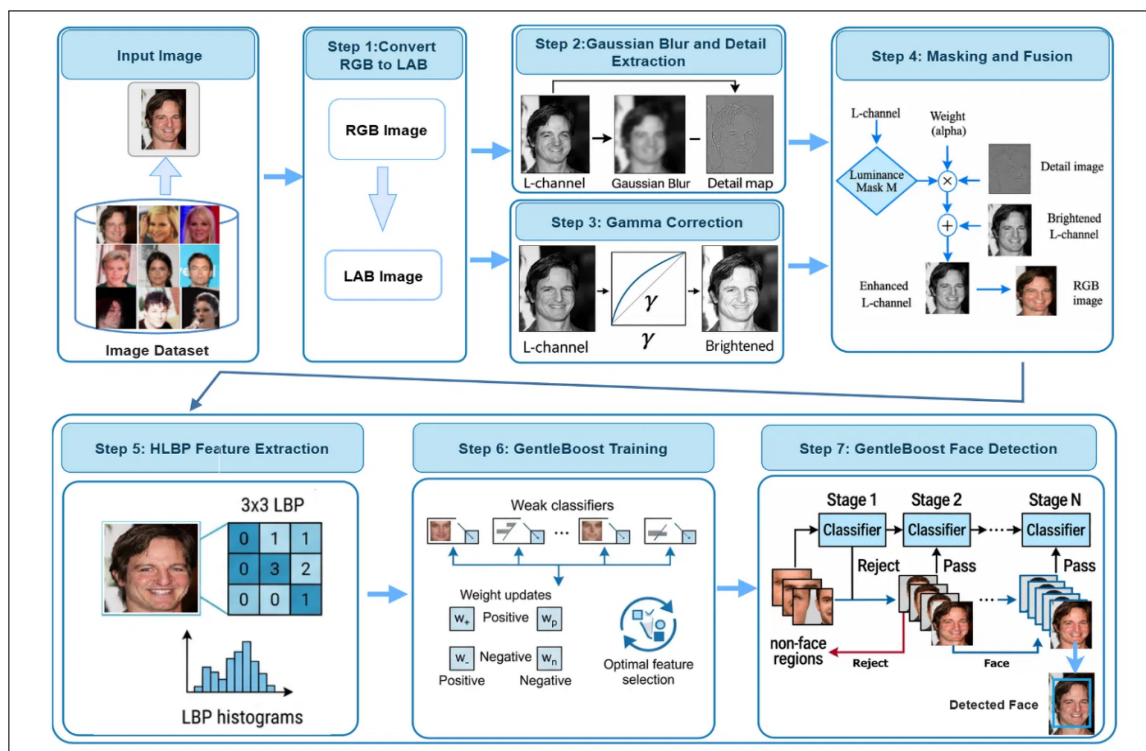


Figure 1. Overview of the SIE-GentleBoost pipeline

3.1 Dataset and Training Setting

The Gentleboost classifier was trained using face samples from the CelebA dataset [21], a large-scale celebrity face benchmark containing 200,599 images of size 178×218 pixels. Each image contains a single annotated face captured under varying pose, expression, and illumination. The training subset comprised (3,507) negative samples of non-face samples and (5,000) positive face patches, each of size 64×64 pixels. Positive samples were extracted from faces in CelebA images (000001.jpg–005000.jpg), using the available CelebA bounding box annotation. The original images, CLAHE, gamma correction, the proposed SIE enhancement method, and ablation configuration were quantitatively evaluated using the same 500 images numbered (195000.jpg–195499.jpg). These images were not included in positive, negative, or training samples, ensuring no overlap between the training and test sets. The selected CelebA subset includes visible variance in facial appearance, illumination, facial expression, near-frontal and side-pose faces, makeup, hairstyles, hats, eyeglasses, indoor and outdoor scenes, and background content. Automatic screening identified approximately 100 dark, 100 bright, and 100 non-uniform-illumination images (20% each). These categories were not manually verified or balanced and may overlap.

To assess the generalization strength of the proposed enhancement method, the Labeled Faces in the Wild (LFW) dataset [22] was used for qualitative evaluation. The images were resized from 250×250 to 160×250 pixels before passing to the detection pipeline. The LFW dataset contains facial images captured under unconstrained real-world conditions, providing natural variations in illumination, pose, facial expression, and background.

3.2 Code Implementation

All experiments were performed on a Lenovo-IdeaPad, 510-15IKB laptop running Windows 10, powered by an Intel® Core™ i7-7500U processor with 2.70 GHz and 8 GB RAM. The experiments were performed in Python using only CPU processing.

4. The Proposed Face Detection Framework

The proposed Selective Image Enhancement (SIE) method corrects illumination variation while preserving the natural detail of facial image structure. Enhancement is exclusively applied to the luminance channel (L) of the CIE LAB color space, which decouples luminance from chrominance, enabling illumination correction without chromatic distortion. The LAB color space consists of L (Luminance), a (green–red chrominance), and b (blue–yellow chrominance) [23]. Human perception of spatial structure, edges, contours, and texture is driven primarily by luminance contrast rather than color. Operating exclusively on the L channel preserves skin tone and facial hue, as luminance adjustment in this space does not propagate to other channels as in RGB color space. While pre-processing can improve detection with poor illumination, inappropriate or aggressive processing degrades detector effectiveness, as demonstrated by a study in [20]. Instead of uniformly modifying the whole image. Table 1 explains the adopted parameters of the proposed SIE algorithm.

Table 1. Parameter justification

Parameter	Value	Justification
Gaussian kernel	51×51	Capture illumination variation, reject fine detail
Gamm (γ)	0.90	Luminance-correction strength
Threshold	180	target shadow and mid-tone regions
Detail weight (α)	0.2	Subtle detail recovery without noise amplification

All parameter values were determined experimentally by evaluating detection performance across multiple configurations on the training data.

Image areas are enhanced selectively, by applying the following three main steps:

1. A (51×51) Gaussian filter is applied to the luminance channel (L) to estimate the illumination (L_{illu}). The detail component (D) is then obtained from the difference between (L) and (L_{illu}), as defined in Equation (1).

$$D = L - L_{illu} \quad (1)$$

2. Gamma correction applies to the (L) channel using power-law transformation [25], as in Equation (2) to adjust the overall brightness, where $\gamma = 0.90$

$$L\gamma = 255 \times \left(\frac{L}{255} \right)^\gamma \quad (2)$$

3. Selective enhancement is then performed, using a binary mask (M), which restricts detail enactment to pixels whose luminance is below a threshold, as expressed in Equation (3):

$$M(x, y) = \begin{cases} 1, & \text{if } L(x, y) < 180 \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

4. The final step represented in Equation 4 computes the enhanced (L) channel (L_{enh}):

$$L_{enh} = clip(L\gamma + \alpha \cdot D \cdot M, 0, 255) \quad (4)$$

Where $L\gamma$ is the gamma corrected luminance and (D) is the detail residual from Equation (1). (M) is the binary mask, and $\alpha=0.2$ controls detail recovery strength. Clipping bounds output to [0,255]. (L_{enh}) replaces the original (L) channel. The image is reconstructed by merging (L_{enh}) with the (a,b) channels and converting back to RGB, producing the final enhanced image (En_img). The complete steps are given in Algorithm 1.

Algorithm 1: Selective Image Enhancement (SIE)

INPUT: RGB img

OUTPUT: En_img

1. Transform img from RGB to LAB color space: $[L, a, b] \leftarrow RGB2LAB(img)$
 2. Estimate illumination layer: $L_{illum} \leftarrow GaussianBlur(L, 51 \times 51, \sigma=0)$
 3. Extract the fine detail: $D \leftarrow L - L_{illum}$
 4. Apply gamma correction on the luminance: $L_{\gamma} \leftarrow (L/255)^{0.90} \times 255$
 5. Construct a binary mask: $M \leftarrow (L < 180)$
 6. Merge corrected luminance with the detail: $L_{enh} \leftarrow clip(L_{\gamma} + 0.2 \cdot D \cdot M, 0, 255)$
 7. Reconstruct the final RGB image: $En_img \leftarrow LAB2RGB([L_{enh}, a, b])$
- return En_img
-

Since each pixel is processed independently, using a fixed Gaussian kernel, gamma correction, and threshold masking, the overall SIE method complexity scales linearly $O(N)$, where N is the number of pixels.

A threshold of 180 was set, based on experimental results with approximately 70.6% of the luminance range falling below it, spanning the shadow and mid-tone regions. Pixels in this lower range correspond to areas of insufficient illumination, whereas pixels above the threshold are already well-lit, so enhancing them further tends to introduce more harm than benefit. Restricting enhancement to the lower range avoids generating artificial edges or structure, which experimentally caused clipping artifacts and false positives in the GentleBoost. Rather than using an adaptive formulation a fixed exponent $\gamma = 0.90$ was selected empirically, since it delivers a consistent, mild luminance boost across the dataset while avoiding saturation in highlight regions. Experimental evaluation confirmed that excluding bright pixels from detail injection eliminated the clipping artifacts and false positive detections that were observed when detail was applied globally in the GentleBoost cascade. Furthermore, values of α above 0.1 introduced clipping artifacts and increased false positives, while values below 0.1 produced negligible detail recovery with no measurable improvement in detection performance.

Contrast Limited Adaptive Histogram Equalization (CLAHE) has been employed as an illumination-invariant preprocessing method for face detection [18]. Unlike CLAHE, which redistributes contrast uniformly across all pixel intensities within each tile, the proposed SIE method restricts detail injection to under-illuminated regions through a thresholding operation using a mask M . This avoids over-sharpening bright facial areas, a behavior that experimentally increased the false positive ratio for the cascade classifier.

5. Face Detection Stages

5.1 LBPH Feature Extraction

The first step in face detection is extracting feature vectors from each candidate window. The LBPH is used for feature extraction due to its effectiveness [4]. For each pixel, LBP describes the local texture by comparing it with its local neighbours and encoding the resulting pattern. LBPH works by partitioning the image into a non-overlapped grid of cells, calculating an LBP histogram within each cell, and then concatenating them into a single vector that captures both local texture and spatial facial structure. In this work, LBP features are computed with a radius value of 1 and 8 sampling points over a non-overlapped (10×10) grid, yielding 100 cell histograms per face window. Each histogram contains 10 bins, resulting in a 1000-dimensional feature vector.

5.2 GentleBoost Classifier

GentleBoost is an ensemble learning algorithm [9] introduced as a numerically stable variant of AdaBoost. Unlike AdaBoost, which employs exponential loss, machine learning based GentleBoost minimizes logistic loss by fitting real-valued regression trees, resulting in gentler weight updates. In this work, a GentleBoost cascade classifier is trained to discriminate face from non-face regions using LBPH feature vector. The cascade consists of subsequent stages of increasing complexity: early stages rapidly reject non-face regions to reduce computational cost. Later stages apply progressively stricter criteria to remaining candidates. The detector comprises three cascade stages with 80, 120, and 160 decision trees and maximum depths of 3, 6, and 6, respectively. These parameters were selected empirically based on detection performance. During testing, a 64×64 pixel sliding window scans the image at multiple scales with a step size of 12 pixels; the image is downsampled by a factor of 0.85 at each level, enabling the detection of faces of varying sizes. Overlapping detections are merged using OpenCVs (cv2.groupRectangles) function with a similarity tolerance (eps) of 0.4 and group threshold = 1. Table 2 presents the multiscale sliding-window detection parameters used during inference.

Table 2. Multi-Scale detection parameters

Parameter	value
Image scale factor per level	0.85
Sliding window step size	12 pixels
Grouping tolerance	0.4
Group threshold	1

6. Evaluation Metrics

6.1 Image Quality Metrics

The enhanced images were evaluated using Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), Average Mean Brightness Error (AMBE) and entropy to quantify enhancement quality [24].

PSNR measures pixel-level fidelity, where higher values indicate higher similarity to the reference image, SSIM evaluates structural similarity by considering contrast, luminance and structural information; a value of 1, refer to an identical image. Entropy measures the

information content and intensity distribution of an image; a higher value generally indicates greater retained image information. AMBE is calculated as the absolute difference between the input and output mean brightness; lower values indicate less change in mean brightness and close preservation of the original brightness.

These metrics indicate whether the image enhancement stage improves image quality and preserves the facial contrast, texture and brightness consistency required for effective HLBP feature extraction, ensuring that preprocessing does not distort the facial structures for detection. However, they do not directly measure face-detection accuracy. Therefore, detection metrics were also calculated.

6.2 Detection Performance Metrics

Following [25], detection performance is quantified by computing precision (the ratio of correctly predicted faces), recall (the ratio of ground-truth faces successfully detected), and F1-score, which is the harmonic mean of precision and recall. The Intersection over Union (IoU) computes the overlap between a predicted bounding box and the ground-truth bounding box. In this study, a detection was considered correct when $\text{IoU} \geq 0.5$, consistent with PASCAL VOC convention, while mean IoU was calculated for correctly detected faces to assess localization accuracy. A False Positive (FP) occurs when a non-face region is incorrectly detected as a face; a False Negative (FN) occurs when an actual face is undetected by the model. Higher values of Precision, Recall, F1, and IoU reflect superior performance, whereas lower FP and FN are preferable.

All methods were evaluated on the same 500 images using the same GentleBoost detector, HLBP features, and ground-truth bounding boxes, with metrics computed per detected instance and averaged across the full test set, ensuring unbiased and consistent comparison.

7. Results and Discussion

7.1 Image Enhancement Results

The proposed SIE technique is tested on 500 test images that were not used in training, selected from the CelebA dataset [21]. Figure 2 presents representative examples from the evaluated subset, illustrating variations in illumination and facial viewing angle. These examples are intended to illustrate the diversity of the test images and do not replace condition-specific quantitative evaluation. The proposed SIE method was compared with two baselines methods, namely CLAHE and gamma correction. Qualitative results across four challenging conditions are shown in Figure 2 low-contrast pose (Row 1), side view (Row 2), bright background (Row3), and low light (Row 4). In these cases, the proposed method preserves natural skin tones while improving local visibility. CLAHE introduced visible artifacts in smooth regions due to over-amplified local contrast, and gamma correction over-brightened highlight areas, resulting in a loss of facial detail.

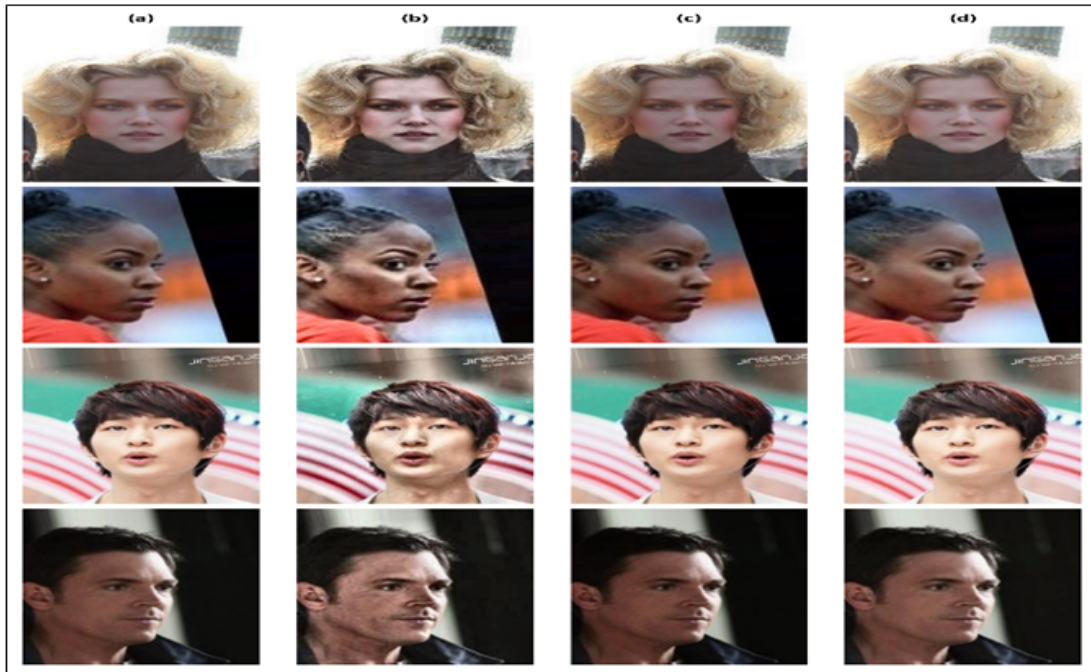


Figure 2. Image enhancement results: a.) Origin, b.) CLAHE, c.) Gamma, d.) proposed SIE

Table 3 reports the quantitative image quality results across the 500-test images. The original image entropy is 7.1157 ± 0.4837 which is used as the information-content baseline for all comparisons. Among the three enhancement methods, gamma correction achieves the highest structural fidelity to the original image as indicated by the PSNR and SSIM but with a low AMBE value, reflecting a slightly overall enactment, it minimizes pixel deviation from the original image. CLAHE produces the largest structural distortion in PSNR, SSIM, and AMBE metrics and the highest entropy (7.4458 vs. original image 7.1157), suggesting artificial histogram inflation that increased contrast and over sharpens the image details without improving structural fidelity. These effects were visible in the enhanced images, as shown in Figure 2- column b.

Table 3. Image-Enhancements metrics of 500 image

Metrics	CLAHE	Gamma	Proposed SIE
PSNR	20.831 ± 1.701	30.843 ± 1.121	26.032 ± 1.725
SSIM	0.8273 ± 0.0566	0.9826 ± 0.0141	0.9630 ± 0.0158
Entropy	7.4458 ± 0.4153	7.0674 ± 0.5172	7.0921 ± 0.5281
AMBE	11.6788 ± 6.5832	6.8707 ± 1.1880	9.7970 ± 3.1561
Time/ms	2.01 ± 7.50	0.33 ± 0.16	4.65 ± 1.46

Although SIE achieved intermediate PSNR and SSIM, its entropy (7.0921) was the closest to the original image (7.1157), with a deviation of 0.0236 versus 0.0483 for gamma and 0.331 for CLAHE. This confirms that SIE better preserved the information distribution of the original image texture and retained realistic skin tone and background structure, as presented in Figure 2. The resulting enhanced image metrics demonstrate that pixel-level fidelity metrics alone, without visual evaluation, are insufficient to predict visual quality for detection performance.

Processing times across all methods were measured using a trimmed mean (5th–95th percentile) over 500 images. SIE required about 4.56 ms per image, which was higher than the two comparison methods because it involves multiple processing stages, including thresholding.

Nevertheless, its computational cost remained in the millisecond range and was substantially lower than the subsequent GentleBoost detection stage.

7.2 Face Detection Results

Figure 3 presents qualitative detection results on test images, where green boxes correspond to detections and red boxes denote the ground truth annotation. The proposed SIE method, shown in column (d) achieved higher localization accuracy than other enhancement methods and successfully detects face. CLAHE also detected faces reliably, while the gamma correction method in column (c) yielded false detections with an extra box in most the images. However, all methods could not precisely detect the face with a side pose in row 2.



Figure 3. Detection results:(a) original, (b) CLAHE, (c) gamma correction, (d) proposed SIE

Table 4 presents face-detection metrics for the four evaluated conditions. The reported detection metrics are point estimates followed by percentile-bootstrap 95% confidence intervals, calculated from 10,000 resamples of the 500 per-image results. Gamma correction achieves the highest image quality with PSNR (30.843 dB) and SSIM (0.9826), but yields the lowest detection F1-score (0.9567) which is even below the performance without applying image enhancement preprocessing. Conversely, CLAHE produces the worst image quality (PSNR of 20.831 dB, SSIM of 0.8273), with low visual quality, likely because of aggressive contrast amplification. Yet, it achieves the best detection performance across recall, precision, and F1-score metrics. SIE achieved a slightly higher average IoU than CLAHE (0.7161 vs. 0.7143). The results indicate that higher image-quality scores do not necessarily correspond to better face-detection performance. For the HLBP-GentleBoost detector, local contrast and discriminative texture features have a more significant impact on detection accuracy than image-quality scores alone.

Table 4. Face detection metrics of 500 test images

Metrics	No Enhancement	CLAHE	Gamma	Proposed SIE
TP	488	495	486	490
FP	28	12	30	16
FN	12	5	14	10
Precision	0.9457 (0.9254–0.9648)	0.9763 (0.9611–0.9900)	0.9419 (0.9210–0.9625)	0.9684 (0.9528–0.9822)
Recall	0.9760 (0.9620–0.9880)	0.9900 (0.9800–0.9980)	0.9720 (0.9560–0.9860)	0.9800 (0.9660–0.9920)
F1-score	0.9606 (0.9444–0.9753)	0.9831 (0.9722–0.9930)	0.9567 (0.9393–0.9724)	0.9742 (0.9603–0.9861)
Avg. IoU	0.7193 (0.7111–0.7272)	0.7143 (0.7068–0.7216)	0.7160 (0.7076–0.7243)	0.7161 (0.7078–0.7242)

The proposed SIE improved detection performance compared with the unenhanced images, increasing precision from 0.9457 to 0.9684, recall from 0.9760 to 0.9800 and F1-score from 0.9606 to 0.9742. It also reduced the number of false positives from 28 to 16.

SIE achieved an IoU of (0.7161 ± 0.0938) , a slightly higher score than gamma correction (0.7160 ± 0.0953) and CLAHE (0.7143 ± 0.0832) but slightly lower than the unenhanced images (0.7193 ± 0.0926) . The differences in mean IoU were very small, indicating comparable localization performance rather than a substantial improvement. The mean IOU absolute pairwise difference among the four evaluated conditions was only 0.0025, indicating that the methods exhibited very similar localization performance. CLAHE achieved higher precision, recall, and F1-score than SIE. While gamma correction produced the lowest metric values.

As an additional validation, the proposed SIE was evaluated on an expanded set of 800 images. It achieved precision, recall, F1-score, and average IoU values of 0.9582, 0.9738, 0.9659, and 0.7148, respectively. Although the performance values were slightly lower on the expanded evaluation, they remained comparable to those obtained on the 500-image set.

In terms of detection computation time, the face detection process required an average of 12.24 ± 1.96 s per image using CPU processing. The image-enhancement stage required substantially less processing time, whereas the sliding-window face-detection stage constituted the primary computational bottleneck. Although the cascade architecture reduces computation through early-stage rejection, LBPH feature extraction is performed prior to cascade entry, which limits the resulting computational saving.

The computational cost of the face detection stage depends mainly on the number of sliding-window positions, LBPH feature extraction, and cascade evaluation across image scales. Although early cascade rejection reduces computation, extracting LBPH features before cascade evaluation limits this saving.

To provide an external qualitative assessment beyond the CelebA dataset the LFW dataset was additionally evaluated. The LFW images were reprocessed and resized before being passed to the detection process. Since LFW bounding-box annotations were not incorporated in this study, only qualitative detection results are presented in Figure 4.



Figure 4. Images enhanced with SIE, and detection results on LFW

7.3 Discussion of Detection Performance

The results demonstrate that image quality metrics do not directly correspond to face detection performance. Among the evaluated methods, CLAHE achieved the highest detection performance, with a precision of 0.9763, recall of 0.9900, and F1-score of 0.9831, despite producing the lowest PSNR and SSIM values. Its strong detection performance may be associated with local contrast enhancement, which can strengthen local texture patterns, providing more discriminative LBPH features for the GentleBoost classifier. The increased local contrast may also help more candidate windows satisfy the minimum-variation criterion before classification. Gamma correction achieved the highest image quality score, but produced a lower detection metrics than the unprocessed and the proposed SIE method. This comparison suggests that pixel-level similarity to the original image alone is insufficient to predict detection performance. The contribution of SIE lies in balancing detection performance, localization preservation, and enhanced quality. Although it did not outperform CLAHE in precision, recall, or F1-score, it achieved competitive detection performance and localization comparable to other evaluated methods. It also maintained a more natural visual appearance than CLAHE. Thus, SIE may be considered a competitive alternative for applications in which perceptual quality and localization preservation are important alongside detection accuracy.

A two-sided Wilcoxon signed-rank test was performed on 500 paired per-image IoU scores. Although SIE produced slightly higher IoU (0.7161 ± 0.0938) than CLAHE (0.7143 ± 0.0832) the difference was not statistically significant ($W=52.570.5$, $p=0.141$). Thus, SIE and CLAHE demonstrated comparable localization performance. Paired bootstrap confidence-interval analysis showed that SIE improved precision over the unenhanced images by 0.0226 (95% confidence interval: 0.0037–0.0428). The F1-score increase was 0.0135 (95% confidence interval: -0.0003 –0.0284). Therefore, the results support a statistically significant improvement in precision, but not in F1-score, over the unenhanced images.

This study has some limitations: the gamma value was fixed at $\gamma=0.90$, and the evaluation used a fixed. Broader testing across gamma values and image condition-annotated datasets is needed. It should be noted that quantitative evaluation was conducted on single-face portrait images from CelebA.

7.4 Ablation Study

Table 5 presents the component-ablation results of SIE. The gamma-only configuration removes the Gaussian/detail branch, whereas the no-gamma, no-threshold and no-details configuration remove only their respective components. The full SIE configurations use a 51×51 Gaussian kernel, a threshold of 180 and $\alpha = 0.2$. The complete SIE configuration achieved the highest F1-score among the tested component configuration, indicating its

effectiveness. It should be noted that the Gamma baseline used in Table 4 applies BGR lookup-table correction, therefore, it is treated as separate experiment.

Table 5. Image enhancement component-ablation metrics on 500 images

Metrics	Gamma Only	No Gamma	No Threshold	No Detail	Full SIE $\alpha = 0.2$
PSNR	26.457 $\pm$ 1.827	30.259 $\pm$ 1.844	25.454 $\pm$ 1.517	26.457 $\pm$ 1.827	26.032 $\pm$ 1.725
SSIM	0.9819 $\pm$ 0.0090	0.9585 $\pm$ 0.0255	0.9628 $\pm$ 0.0155	0.9819 $\pm$ 0.0090	0.9630 $\pm$ 0.0158
Entropy	7.0014 $\pm$ 0.5195	7.0683 $\pm$ 0.5475	7.1378 $\pm$ 0.5439	7.0014 $\pm$ 0.5195	7.0921 $\pm$ 0.5281
AMBE	10.5813 $\pm$ 3.0728	3.6496 $\pm$ 2.2881	10.6550 $\pm$ 3.0779	10.5813 $\pm$ 3.0728	9.7970 $\pm$ 3.1561
TP	490	490	489	491	490
FP	23	23	21	18	16
FN	10	10	11	9	10
Precision	0.9552	0.9552	0.9588	0.9646	0.9684
Recall	0.9800	0.9800	0.9780	0.9820	0.9800
F1 Score	0.9674	0.9674	0.9683	0.9732	0.9742
Avg. IoU	0.7166 $\pm$ 0.0931	0.7166 $\pm$ 0.0931	0.7182 $\pm$ 0.0928	0.7201 $\pm$ 0.0941	0.7161 $\pm$ 0.0938

The complete quantitative sensitivity results are reported in Table 6. The sensitivity analysis was evaluated on a 31 $\times$ 31 Gaussian kernel, alternative threshold values and different α values. The selected configuration ($\alpha = 0.2$) achieved the highest precision and F1-score, whereas other settings produced slightly higher IoU, precision, or recall. Increasing α to 0.3 reduced the F1-score to 0.9644 and the 31 $\times$ 31 kernel produced the lowest performance among the tested kernel sizes. These findings indicate that no single configuration is optimal for every metric.

Table 6. SIE Parameter-sensitivity analysis on 500 images

Metrics	Kernel 31 $\times$ 31	SIE $\alpha=0.05$	SIE $\alpha=0.1$	SIE $\alpha=0.3$	SIE-Thr =160	SIE-Thr =200	Full SIE $\alpha = 0.2$
PSNR	26.376 $\pm$ 1.795	26.424 $\pm$ 1.816	26.353 $\pm$ 1.794	25.545 $\pm$ 1.641	26.464 $\pm$ 1.813	26.241 $\pm$ 1.768	26.032 $\pm$ 1.725
SSIM	0.9773 $\pm$ 0.0103	0.9793 $\pm$ 0.0099	0.9751 $\pm$ 0.0114	0.9479 $\pm$ 0.0209	0.9752 $\pm$ 0.0114	0.9751 $\pm$ 0.0114	0.9630 $\pm$ 0.0158
Entropy	7.0960 $\pm$ 0.5201	7.0941 $\pm$ 0.5166	7.0988 $\pm$ 0.5200	7.0769 $\pm$ 0.5347	7.0962 $\pm$ 0.5200	7.1068 $\pm$ 0.5198	7.0921 $\pm$ 0.5281
AMBE	10.3324 $\pm$ 3.1009	10.3942 $\pm$ 3.0993	10.1831 $\pm$ 3.1172	9.4523 $\pm$ 3.2002	10.0674 $\pm$ 3.1023	10.3222 $\pm$ 3.1336	9.7970 $\pm$ 3.1561
TP	485	489	489	487	489	491	490
FP	25	25	24	23	23	18	16
FN	15	11	11	13	11	9	10
Precision	0.9510	0.9514	0.9532	0.9549	0.9551	0.9646	0.9684
Recall	0.9700	0.9780	0.9780	0.9740	0.9780	0.9820	0.9800
F1 Score	0.9604	0.9645	0.9654	0.9644	0.9664	0.9732	0.9742
Avg. IoU	0.7169 $\pm$ 0.0943	0.7192 $\pm$ 0.0922	0.7185 $\pm$ 0.0941	0.7136 $\pm$ 0.0937	0.7200 $\pm$ 0.0920	0.7196 $\pm$ 0.0918	0.7161 $\pm$ 0.0938

Figure 5 presents representative detection results for selected SIE parameter settings. From left to right, the examples show a 31×31 Gaussian kernel, $\alpha=0.05$, $\alpha=0.1$, thresholds of 160 and 200 and the proposed SIE configuration (51×51 Kernel, threshold =180, $\alpha=0.2$). The examples illustrate how parameter selection affects face detection and localization.

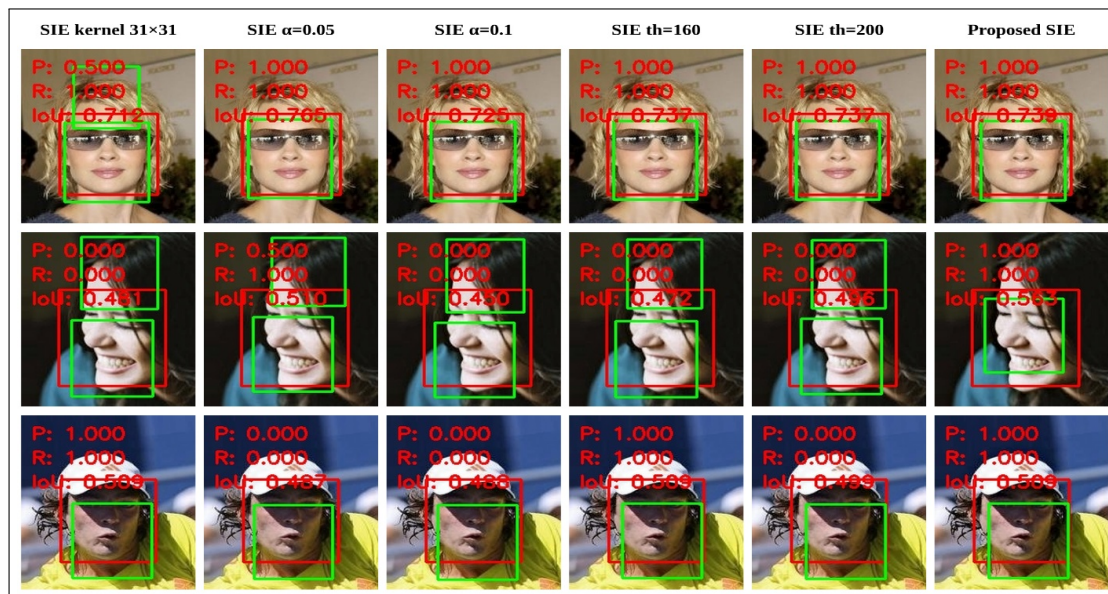


Figure 5. Qualitative comparison of SIE parameters (kernel size, α , and threshold)

8. Conclusion

A Selective Image Enhancement (SIE) framework was built as a lightweight preprocessing method for face detection under varying illumination. The method selectively enhances luminance regions using Gaussian filtering, gamma correction, a thresholding operation, and detail fusion. Enhanced images were processed using a GentleBoost cascade classifier with LBPH features. Experiments on 500 test images showed that gamma correction achieved the best image quality values for PSNR, SSIM and AMBE but this did not yield stronger detection performance. CLAHE outperformed all methods in detection with an F1-score of 0.9831, but produced the lowest PSNR, SSIM and AMBE. The proposed SIE configurations, a 51×51 Gaussian kernel, threshold of 180 and $\alpha = 0.2$, achieved an F1-score of 0.9742, exceeding the unenhanced baseline and gamma correction, although remaining below CLAHE. SIE also produced the highest mean IoU among the enhancement methods (0.7161 ± 0.0938) however, the unenhanced images achieved a slightly higher mean IoU (0.7193 ± 0.0926). Overall, the results demonstrate that pixel-level image-quality metrics do not directly predict face-detection performance. SIE provides a reasonable balance between face detection accuracy, localization preservation, and perceptual image quality on the evaluated dataset, although CLAHE remains superior in detection metrics. The enhancement stage requires only a few milliseconds per image, whereas the GentleBoost sliding-window detector remains the primary computational bottleneck. Future work will evaluate the method on challenging datasets with explicit illumination, pose, and occlusion annotations, to enable condition-specific analysis. GPU acceleration will be investigated to reduce the processing time of the sliding-window detection stage. The method will also be evaluated for multi-face detection and enhanced using deep-learning-based feature extraction to improve its applicability to real-time, uncontrolled environments.

Acknowledgment

The author would like express his gratitude to the University of Mosul, College of Computer Science and Mathematics for its institutional support.

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