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Modified zero-reference deep curve estimation for contrast quality enhancement in face recognition

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ABSTRACT

Face recognition systems remain challenged by variable lighting conditions. While zero-reference deep curve estimation (Zero-DCE) effectively enhances low-light images, it frequently induces overexposure in normal- and high-brightness scenarios. This study introduces modified Zero-DCE combined with three established enhancement techniques: contrast stretching (CS), contrast limited adaptive histogram equalization (CLAHE), and brightness preserving dynamic histogram equalization (BPDHE). Evaluations employed the extended Yale face database B and face recognition technology (FERET) datasets, with 10 representative samples assessed using the blind/referenceless image spatial quality evaluator (BRISQUE) metric. Modified Zero-DCE with BPDHE produced optimal enhancement quality, achieving a mean BRISQUE score of 16.018. On the extended Yale face database B, visual geometry group 16 (VGG16) integrated with modified Zero-DCE and CLAHE attained 83.65% recognition accuracy, representing a 6.08-percentage-point improvement over conventional Zero-DCE. For the 200-subject FERET subset, residual network 50 (ResNet50) with modified Zero-DCE and CLAHE achieved 67.41% accuracy. Notably, standard Zero-DCE with CLAHE demonstrated superior robustness in extremely low-light conditions, highlighting the illumination-dependent performance characteristics of these enhancement approaches.

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1. INTRODUCTION

Face recognition is crucial for identifying and verifying facial claims [1]. However, face recognition systems face challenges due to dynamic environments, particularly dynamic lighting and low-light scenarios. These affect the facial features, reducing accuracy and increasing misidentification [2], [3]. Addressing these challenges requires innovative approaches to enhance image quality before recognition, emphasizing the need for effective preprocessing methods.

One promising approach, zero-reference deep curve estimation (Zero-DCE) [4], has proven effective in enhancing the contrast quality of low-light images. Zero-DCE is lightweight and computationally efficient, making it suitable for real-time applications [5]. However, its limitations such as overexposure in normal or high-brightness images highlight the need for modifications to improve adaptability across broader lighting conditions [6]. Overexposure can lead to loss of facial features, decreasing face recognition accuracy or causing misidentification [7], [8]. Previous studies have proposed various enhancements to Zero-DCE, such as Zero-DCE++ [5] and Zero-DCE Tiny [9], but these modifications often fall short of significantly improving image quality. These limitations underscore the need for alternative approaches to balance efficiency and performance.

This study proposes modified Zero-DCE, designed to overcome these shortcomings through architectural changes and integration with traditional contrast enhancement methods: contrast stretching (CS) [10], contrast limited adaptive histogram equalization (CLAHE) [11], and brightness preserving dynamic histogram equalization (BPDHE) [12]. These traditional methods have been widely used in domains like medical imaging and facial recognition due to their adaptability to varying brightness levels. By combining the strengths of both traditional and deep learning-based methods, we aim to address dynamic lighting challenges more effectively.

To evaluate the proposed method, we employ two complementary metrics: the blind/referenceless image spatial quality evaluator (BRISQUE) [13] and classification accuracy. BRISQUE measures perceptual quality without requiring a reference image, making it ideal for assessing contrast enhancement effects. Classification accuracy directly evaluates the performance of face recognition models (visual geometry group 16 (VGG16) [14] and residual network 50 (ResNet50) [15]) preprocessed with our methods. These metrics comprehensively understand the enhancements' impact on image quality and recognition accuracy.

The datasets used in this study are the extended Yale face database B [16] and face recognition technology (FERET) [17], [18], chosen for their diverse lighting conditions and subject variability. The extended Yale face database B includes images captured under controlled lighting variations, while FERET offers a wide range of poses, expressions, and subject demographics. The inclusion of the low-light dataset (LOL) [19] or training modified Zero-DCE ensures the model is optimized for low-light conditions, aligning with the study's objective to address lighting challenges comprehensively.

This study bridges Zero-DCE's adaptability gap in dynamic lighting by combining modified Zero-DCE with traditional enhancement methods, improving both contrast quality and recognition accuracy. The approach enhances reliability for real-world applications like surveillance and mobile authentication. Results demonstrate modified Zero-DCE's potential to advance face recognition adoption, underscoring contrast enhancement's critical role in optimizing deep learning models.

2. LITERATURE REVIEW

Research on facial recognition explores various methodologies. A common approach involves convolutional neural networks (CNN) with pretrained models like VGG16 and ResNet50 [20], [21]. When tested on the extended Yale face database B, VGG16 and ResNet50 achieved 46.64 and 46.73% accuracy, respectively [20]. Another study reported higher accuracies of 70.78 and 64.87% [21]. Despite improvements, these models struggle with brightness variations, requiring additional enhancements.

Zero-DCE improves contrast in low-light images [4]. Zero-DCE is lightweight, fast, and superior in non-uniform lighting conditions and low-lighting cases [5]. Li *et al.* [22] used Zero-DCE for drowsiness detection, increasing accuracy from 73.56 to 86.75%. Zhou [23] applied it for blink detection, improving accuracy from 58.80 to 76.50% (right eye) and 70.60 to 94.10% (left eye). Guo *et al.* [4] found Zero-DCE nearly matched RetinexNet in precision-recall but outperformed other methods like low-light image enhancement (LIME) and EnlightenGAN. Wei *et al.* [6] modified Zero-DCE to operate in the hue, saturation, and value (HSV) color space, achieving the highest peak signal-to-noise ratio (PSNR) of 16.75 dB and lowest mean absolute error (MAE) of 98.78, outperforming EnlightenGAN and RetinexNet. However, variants like Zero-DCE++ [5] and Zero-DCE Tiny [9] showed minimal improvement. More advanced modifications, including zero-reference residual attention deep curve estimation (Zero-RADCE) [24], zero-reference low-light image enhancement with intrinsic noise reduction (Zero-LEINR) [25], and Bézier curve estimation (BézierCE) [26], enhance contrast and reduce noise.

Traditional contrast enhancement techniques, such as CLAHE, have also improved face recognition. Without enhancement, CNN achieved 97.2% accuracy, but with enhancements, accuracy rose to 99.8% [27]. Similar improvements were noted with CS and histogram equalization on facial emotion recognition (FER) datasets [28]. Other studies applied CS to magnetic resonance imaging (MRI) images [29], CLAHE to facial skin images [30], and BPDHE to X-ray images [31]. When applied to particular research objects, the CS, CLAHE, and BPDHE methods are the superior contrast quality enhancement methods. However, further research is needed to determine which method is suitable for overcoming the weaknesses of the Zero-DCE method on facial images with brightness problems.

This study modifies Zero-DCE to create modified Zero-DCE and evaluates CS, CLAHE, and BPDHE combined with Zero-DCE for face recognition using VGG16 and ResNet50. Methods are compared using BRISQUE [13] for contrast quality and classification accuracy. The best enhancement method has the lowest BRISQUE, and the best model achieves the highest accuracy.

3. METHOD

This section describes the dataset, methodology, and key modifications to Zero-DCE for LIME. It introduces the original Zero-DCE, the proposed modified Zero-DCE, and traditional contrast enhancement techniques. Finally, it discusses the face detection and deep learning models used for evaluation.

3.1. Datasets

This study utilizes the extended Yale face database B [16] and FERET [17], [18] for face recognition and the LOL dataset [19] to train modified Zero-DCE. The extended Yale face database B, with 2,414 images of 38 subjects, was chosen for its controlled lighting variations, while the FERET dataset, containing 14,051 images of 1,204 subjects, provides diverse poses and expressions. The LOL dataset was selected to maintain consistency with the original Zero-DCE training setup, ensuring a fair comparison.

Some FERET classes contain only two images, making dataset splitting impractical. To address this, images were duplicated to create ten per class, increasing the dataset size to 14,291 images. This duplication differs from augmentation, as duplicated images remain unchanged but can still undergo augmentation during training. Face detection using multi-task cascaded convolutional networks (MTCNN) [32] was applied to FERET images before training the face recognition model. Samples of the extended Yale face database B and FERET datasets are shown in Figures 1 and 2.

Figure 1. The extended Yale face database B samples [16]

Figure 2. FERET samples [17], [18]

The LOL dataset consists of 500 low-bright and 500 normal-bright images. Since Zero-DCE and modified Zero-DCE rely on deep curve estimation network (DCE-Net), an unsupervised learning method, training does not require standard brightness images. Modified Zero-DCE was trained using 485 low-brightness images for training and validation. Figure 3 shows a sample of the low-brightness LOL dataset.

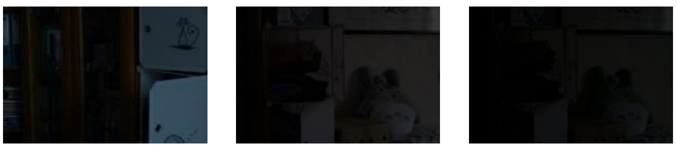


Figure 3. LOL samples [19]

3.2. Method design

This research method consists of three stages: modifying Zero-DCE, preprocessing, and face recognition modeling. In modifying Zero-DCE, we remove a loss function with minimal impact and adjust the DCE-Net architecture by modifying hyperparameters or layers, inspired by prior studies [33] showing that certain loss functions contribute little to contrast enhancement. Figure 4 illustrates this process, which involves selecting an approach, removing a loss function, modifying the DCE-Net, and evaluating results to finalize the modified Zero-DCE.

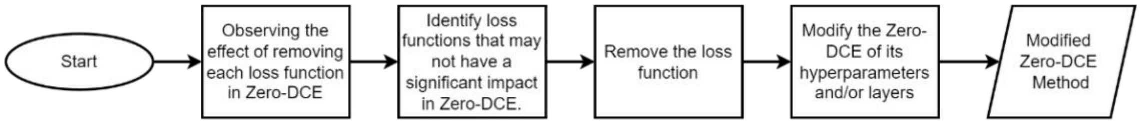


Figure 4. Modifying Zero-DCE stage

The preprocessing stage involves applying Zero-DCE or modified Zero-DCE, converting images to grayscale, and optionally enhancing contrast using CS, CLAHE, or BPDHE, resulting in six dataset variations. BRISQUE scores are calculated on a subset of 10 images from the extended Yale face database B and FERET datasets to assess enhancement effectiveness, followed by evaluations on the full datasets for validation. Figure 5 outlines this preprocessing stage before moving to face recognition modeling.

In the face recognition modeling stage, the datasets are split into 60% training, 20% validation, and 20% test data, with augmentation techniques applied. VGG16 and ResNet50 models are trained for 20 epochs using Adam optimization with a 0.001 learning rate and decay rates of 0.9 and 0.999. Figure 6 details this stage, where models are tested for accuracy to determine the best approach for handling brightness variations in face recognition.

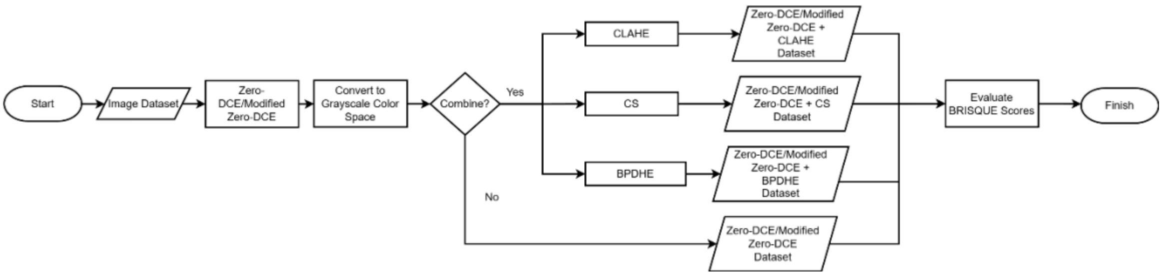


Figure 5. Preprocessing stage

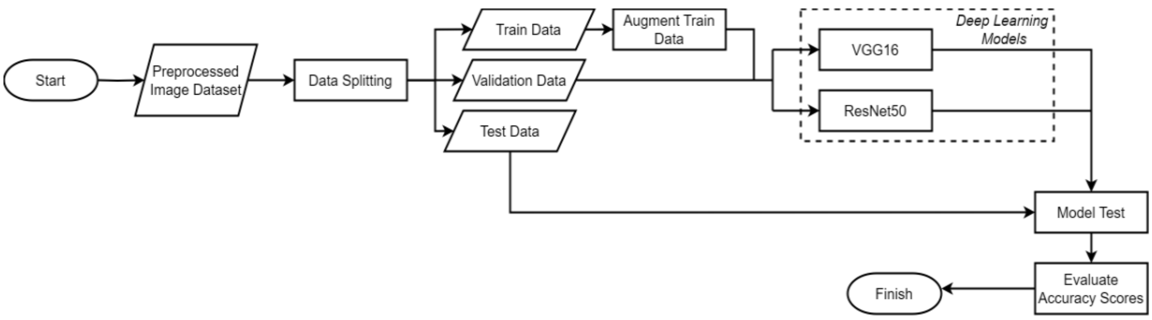


Figure 6. Face recognition modeling stage

To evaluate the impact of our modifications, we use BRISQUE for image quality assessment and classification accuracy for model performance. BRISQUE, a no-reference metric, is essential for datasets like the extended Yale face database B and FERET, which lack normal illumination references. By combining perceptual quality assessment with classification accuracy, we ensure that the proposed modifications enhance both image quality and face recognition performance.

3.3. Zero-reference deep curve estimation

Zero-DCE [4] enhances low-light image contrast by estimating high-order curves that adjust pixel-wise dynamic range, improving brightness while preserving contrast. Unlike CNN- or generative adversarial network (GAN)-based methods, it operates without paired or unpaired training data. The enhancement is driven by the light-enhancement curve (LE-curve), based on a quadratic function, within the DCE-Net, as shown in Figure 7.

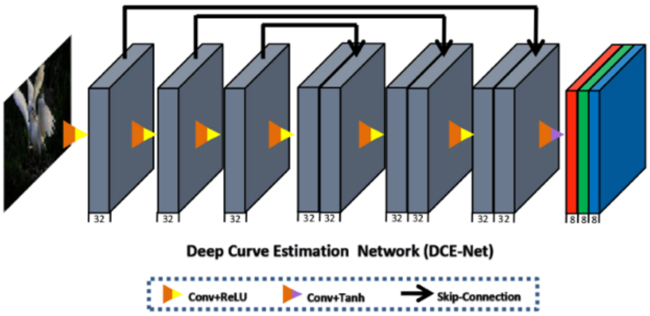


Figure 7. DCE-Net architecture [4]

DCE-Net consists of seven convolution layers with symmetrical skip connections. The first six layers use 32 convolution kernels (3×3, stride 1) with ReLU activation, while the final layer has 24 kernels (3×3, stride 1) with Tanh activation, generating 24 curve parameter maps for eight iterations (three per RGB channel). As an unsupervised method, Zero-DCE relies on four loss functions: spatial consistency, exposure control, color constancy, and illumination smoothness.

Spatial consistency loss is shown in (1).

$$L_{spa} = \frac{1}{K}\sum_{i=1}^{K}\sum_{j\in\Omega(i)}\left(\left|Y_i - Y_j\right| - \left|I_i - I_j\right|\right)^2 \quad (1)$$

Where K is the number of local regions, Ω(i) is the pixel adjacent to the center pixel, Y and I are the average intensity values of the local regions in the upscaled and original image, respectively. Exposure control loss is shown in (2).

$$L_{exp} = \frac{1}{M}\sum_{k=1}^{M}\left|Y_k - E\right| \quad (2)$$

Where M is the number of local non-overlapping regions, and E is the good exposure level (default value is 0.6). Color constancy loss is shown in (3).

$$L_{col} = \sum_{\forall(p,q)\in\varepsilon}(J^p - J^q)^2,\ \ \varepsilon = \{(R,G),(R,B),(G,B)\} \quad (3)$$

Where J^p is the average intensity value of channel p of the enhanced image, J^q is the average intensity value of channel q, (p,q) is the channel pair, R is red channel, G is green channel, and B is blue channel. Illumination smoothness loss is shown in (4).

$$L_{tv_A} = \frac{1}{N}\sum_{n=1}^{N}\sum_{c\in\xi}\left(\left|\nabla_x A_n^c + \nabla_y A_n^c\right|\right)^2, \xi = \{R,G,B\} \quad (4)$$

Where A_n^c is the pixel-wise alpha map for one of R, G or B channel at the n-th iteration, N is the number of iterations, ∇_x and ∇_y are the horizontal and vertical gradient operations. These gradients measure how the intensity in A_n^c changes across adjacent pixels. The total loss of the four loss functions is described in (5).

$$L_{total} = L_{spa} + L_{exp} + W_{col}L_{col} + W_{tv_A}L_{tv_A} \quad (5)$$

Where W_{col} and W_{tv_A} are loss weights.

3.4. Modified Zero-reference deep curve estimation

A modification experiment was conducted by removing one loss function from the four loss functions in Zero-DCE. The results of removing one loss function were tested on an image from the extended

Yale face database B. The results of the loss function removal experiments are shown in Figure 8. Figure 8 illustrates the impact of removing each loss function. Figure 8(a) is the input image, while Figure 8(b) shows Zero-DCE with all losses. Removing spatial consistency loss (L_{spa}) (Figure 8(c)) leads to overexposure, while removing exposure control loss (L_{exp}) (Figure 8(d)), affects luminance control. Figure 8(e) shows color constancy loss (L_{col}) removal, reducing color fidelity, and Figure 8(f) illustrates how removing illumination smoothness loss (L_{tv_A}), introduces artifacts. While all losses are important, L_{spa} had minimal impact on brightness and facial details. Removing it in modified Zero-DCE improved efficiency without sacrificing contrast, useful for real-time face recognition. The formula for total loss used in modified Zero-DCE, initially shown in (5), now changes to (6).

$$L_{total} = L_{exp} + W_{col}L_{col} + W_{tv_A}L_{tv_A} \tag{6}$$

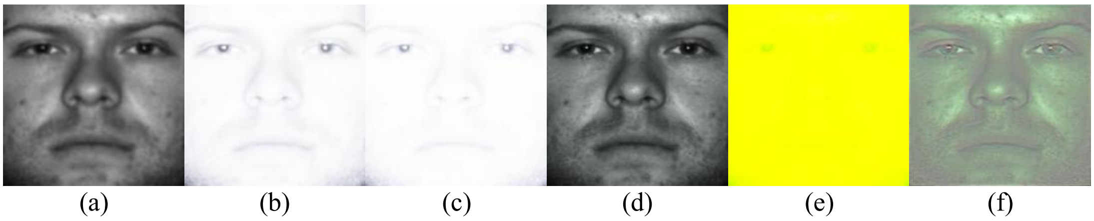


Figure 8. The results of the loss function removal experiments of (a) input image, (b) Zero-DCE, (c) without L_{spa}, (d) without L_{exp}, (e) without L_{col}, and (f) without L_{tv_A}

The architecture of modified Zero-DCE (modified DCE-Net) is not too different from that of Zero-DCE (DCE-Net). The model uses fewer filters (8 instead of 32) in the convolution layer. It also includes an extra pooling layer (MaxPool2D) after each concatenation and dropout layer. This pooling layer is inspired by the spatial attention mechanism in Zero-RADCE [24]. Figure 9 illustrates the architecture of modified Zero-DCE, i.e., modified DCE-Net.

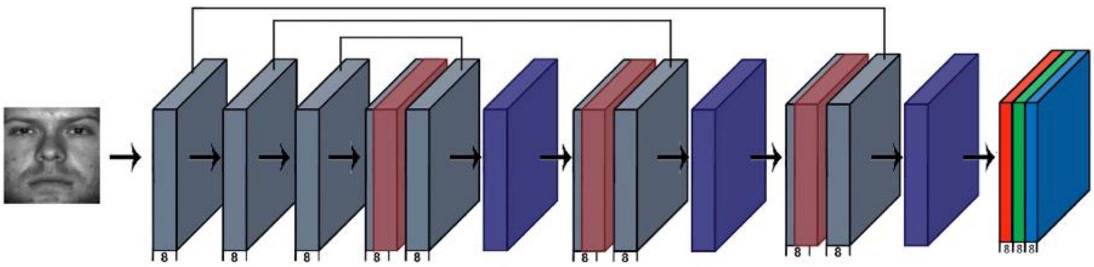


Figure 9. Modified Zero-DCE architecture

In Figure 9, the gray block is the convolution layer, the red block is the dropout layer, and the blue block is the pooling layer. Modified DCE-Net has 7,776 parameters, significantly fewer than DCE-Net's 79,416, due to reduced filters per layer. This makes it lighter and faster for image enhancement. Since L_{spa} does not have a significant effect on the Zero-DCE based on Figure 10, an attempt was made to eliminate L_{spa} in the modified Zero-DCE. The results of the Zero-DCE and modified Zero-DCE comparison stage with and without L_{spa} are shown in Figure 10.

Figure 10 compares Zero-DCE and modified Zero-DCE with and without L_{spa}. As a baseline, Figure 10(a) shows the input image used for enhancement. Figures 10(b) and 10(d) show minimal differences when L_{spa} is present. However, Figures 10(c) and 10(e) reveal that removing L_{spa} in modified Zero-DCE effectively reduces overexposure, contradicting L_{spa}'s intended function in Zero-DCE. This highlights the need for further analysis of L_{spa} in modified Zero-DCE. Since modified Zero-DCE has been found, it can be used for face image preprocessing along with Zero-DCE, CS, CLAHE, and BPDHE, then combined and evaluated using BRISQUE and ended with a comparative study.

(a) (b) (c) (d) (e)

Figure 10. Comparison of Zero-DCE and modified Zero-DCE with and without L_{spa} of (a) input image, (b) Zero-DCE, (c) Zero-DCE without L_{spa}, (d) Modified Zero-DCE with L_{spa}, and (e) Modified Zero-DCE without L_{spa}

3.5. Traditional contrast quality enhancement methods

This study used three traditional contrast enhancement methods: CS, CLAHE, and BPDHE. CS stretches image contrast by expanding intensity values between the minimum and maximum pixel limits [28], typically for 8-bit images (0-255). CLAHE reduces noise and artifacts by dividing the image into sub-blocks, computing histograms, and applying a transformation with a clip boundary parameter [34]. The modified histograms are interpolated to adjust pixel intensity. BPDHE, introduced by Ibrahim and Kong in 2007 [12], normalizes contrast while preserving average intensity. It follows five steps: histogram smoothing, detecting local maxima, mapping partitions, equalizing partitions, and normalizing contrast. BPDHE requires no parameter tuning, introduces minimal artifacts, and is suitable for real-time systems.

3.6. Face detection

The FERET dataset contains non-face characteristics, requiring face detection before training a recognition model. MTCNN [32] was used for this task, as it accurately detects faces and five key landmarks. This step ensures high-quality face localization before applying VGG16 and ResNet50, improving recognition accuracy under varied lighting. However, some images were not detected, reducing the dataset from 14,291 to 13,783 images. Figure 11 shows the face detection result for the first subject.

Figure 11. Face detection results on the first subject of the FERET dataset

3.7. Deep learning models

The deep learning models used in this study are VGG16 and ResNet50. VGG16 [14] is a CNN with 13 convolution layers, five pooling layers, and three fully connected layers, trained on ImageNet with 224×224 RGB images. It uses five max-pooling layers and ends with a SoftMax activation function. ResNet50 [15] is a deeper CNN with 50 convolution layers, offering lower error rates and faster classification than VGG16. Both models are widely used in facial recognition, with VGG16 excelling in accuracy and ResNet50 benefiting from residual connections for efficiency. This provides a balanced comparison of contrast enhancement effects on different network depths.

4. RESULTS AND DISCUSSION

This section evaluates the modified Zero-DCE method, analyzing its behavior and characteristics. It discusses the results of applying modified Zero-DCE and other methods for image enhancement. Finally, it presents the face recognition modeling results to assess the method's impact.

4.1. Modified Zero-reference deep curve estimation analysis

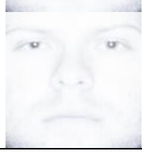
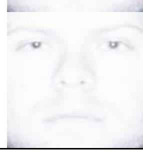
Ten images were randomly selected, five from the extended Yale face database B and five from FERET. Zero-DCE and modified Zero-DCE were applied, with results shown in Figures 12 and 13, where modified Zero-DCE produced clearer images. The analysis examines L_{spa}'s contradictory effects, considering pooling, dropout, reduced filters (8 vs. 32), and L_{spa} removal, with results summarized in Table 1, where "W/o" stands for "without."

Figure 12. Zero-DCE results

Figure 13. Modified Zero-DCE results

Table 1 shows that while both the pooling layer and L_{spa} utilize spatial characteristics, the number of convolution filters has the most significant impact on Zero-DCE results. In modified Zero-DCE, pooling is more effective than L_{spa} in reducing overexposure, allowing luminance adjustment without equalizing local regions. This modification improves image clarity and reduces computational load.

Table 1. Observation results based on the number of filters

Observation	*Pooling + w/o* L_{spa}	*Pooling + w/o* L_{spa}	*W/o pooling +* L_{spa}	*W/o pooling + w/o* L_{spa}
Using 8 filters				
Using 32 filters				

The second focus of analysis is the effect of the dropout layer in modified Zero-DCE, where the model uses 8 filters, pooling, and no L_{spa}. The dropout layer helps reduce overfitting by randomly setting some element values to zero in feature mapping, affecting the loss function calculation. Table 2 shows that while dropout slows total loss convergence, it accelerates convergence in specific loss components, such as L_{tv_A}. The results of the modified Zero-DCE output image with and without the dropout layer can be seen in Figure 14.

Table 2. Observation results based on the number of filters

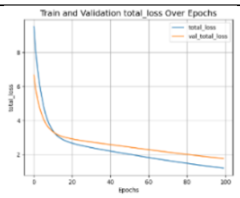
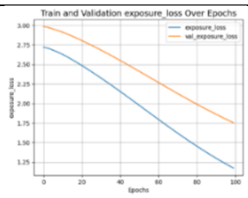
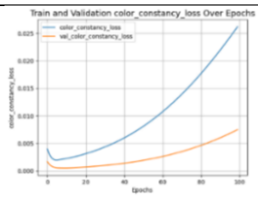
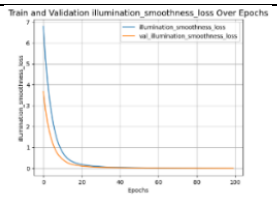
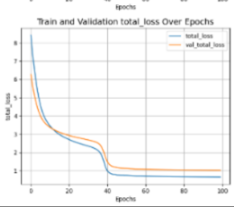
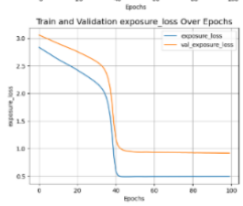
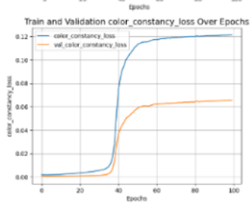
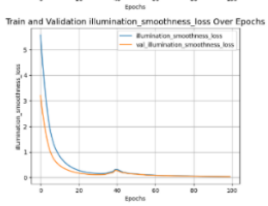
Dropout layers	L_{total}	L_{exp}	L_{col}	L_{tv_A}
Exist				
Not Exist				

Figure 14 compares the output of modified Zero-DCE with and without the dropout layer. Figure 14(a) shows the result with dropout, while Figure 14(b) shows the result without dropout. The dropout layer significantly impacts the model by setting some element values to zero in feature mapping, preventing over-brightening and enhancing image quality. The presence of dropout amplifies the absence of L_{spa}, affects the behavior of convolution filters, and improves the effectiveness of pooling. These modifications collectively contribute to reducing overexposure and enhancing luminance adjustment. As a result, modified Zero-DCE achieves a more balanced image enhancement process. Processing speed tests were conducted on 2,414 images from the extended Yale face database B using an Intel Core i5-8250U laptop without a GPU. Table 3 shows that modified Zero-DCE processes images four times faster than Zero-DCE. This result highlights the efficiency of the proposed method in real-world applications. The next step is to combine this approach with traditional contrast enhancement methods and perform a quantitative evaluation using BRISQUE. The green-colored cells indicate the best.

(a) (b)

Figure 14. Comparison of modified Zero-DCE of (a) with dropout layer and (b) without dropout layer

Table 3. Time comparison results of Zero-DCE and modified Zero-DCE

Methods	Total time (s)	Average time (s)
Zero-DCE	767.3902	0.3179
Modified Zero-DCE	206.8746	0.0857

4.2. Preprocessing stage results

The combination process was first tested on ten selected images using Zero-DCE and modified Zero-DCE with CS, CLAHE, and BPDHE. Evaluation was conducted with and without traditional contrast enhancement methods, and the results for the first sample are shown in Table 4, with the best results highlighted in green. To confirm robustness, all images from the extended Yale face database B and FERET datasets were tested.

Table 4. BRISQUE evaluation results of first sample

Input	Zero-DCE	Zero-DCE + CS	Zero-DCE + CLAHE	Zero-DCE + BPDHE	Modified Zero-DCE	Modified Zero-DCE + CS	Modified Zero-DCE + CLAHE	Modified Zero-DCE + BPDHE
								
Score	57.8683	48.4495	43.6969	37.5207	37.5892	35.5319	32.8356	31.7629

The average BRISQUE value was calculated for each image and contrast enhancement method, with and without combination. Table 5 presents the average BRISQUE scores for the ten sample images, helping to determine the most effective approach for minimizing scores while preserving facial details. From the results, modified Zero-DCE+BPDHE achieved the best performance with an average BRISQUE score of 16.0177, while BPDHE outperformed CS and CLAHE when applied to Zero-DCE.

Table 5. Average BRISQUE evaluation results of 10 samples

Methods	W/o combination	CS	CLAHE	BPDHE
Zero-DCE	43.6404	36.6863	27.9842	23.7520
Modified Zero-DCE	29.3021	26.5361	19.7596	16.0177

Without traditional contrast enhancement, both Zero-DCE and modified Zero-DCE yielded lower scores, demonstrating the effectiveness of conventional methods. The combination of these methods consistently improved BRISQUE scores compared to using them alone. Additionally, modified Zero-DCE exhibited superior processing efficiency and better contrast quality than Zero-DCE. The next step is calculating the average BRISQUE score for each image contrast enhancement method and dataset. Furthermore, the average BRISQUE score for the extended Yale face database B dataset can be seen in Table 6. The green-colored cell indicates the best.

For the extended Yale face database B dataset, Table 6 shows that Zero-DCE combined with CLAHE achieved the best BRISQUE score of 18.1781. The use of CLAHE and BPDHE significantly improved results, particularly for LOL datasets. Modified Zero-DCE also performed well, enhancing outcomes compared to Zero-DCE alone. These findings confirm that traditional contrast methods are essential for improving BRISQUE scores. Table 7 presents the average BRISQUE scores for the FERET dataset. The green-colored cell indicates the best.

Table 6. Average BRISQUE evaluation results of the extended Yale face database B

Methods	W/o combination	CS	CLAHE	BPDHE
Zero-DCE	30.8752	29.8683	18.1781	22.2609
Modified Zero-DCE	28.1670	27.9141	22.2711	21.7172

Table 7. Average BRISQUE evaluation results of FERET

Methods	W/o combination	CS	CLAHE	BPDHE
Zero-DCE	43.2518	18.5525	12.1491	9.3183
Modified Zero-DCE	22.0140	10.3947	10.5732	7.2470

Table 7 presents the average BRISQUE scores for the FERET dataset, where modified Zero-DCE+BPDHE achieved the best result with an average BRISQUE score of 7.2470. The effectiveness of BPDHE in improving both Zero-DCE and modified Zero-DCE is evident, as it consistently produced scores under 10. Modified Zero-DCE performed well on the FERET dataset, which has normal or slightly dark brightness levels, whereas Zero-DCE often caused overexposure. As shown in Tables 5 and 6, combining traditional contrast enhancement methods yields better BRISQUE scores than without combination.

From Tables 5 to 7, Zero-DCE consistently had the highest BRISQUE scores, indicating that modifications and contrast enhancement methods significantly improved image quality. Modified Zero-DCE, even without combination, outperformed Zero-DCE. Given the wide intensity range of dataset images, CLAHE and BPDHE yielded better improvements than CS. The next step is to divide the data into training, validation, and test sets for the face recognition model.

4.3. Face recognition modeling results

The classifier and transfer learning architecture selection are illustrated in Figure 15, showcasing the best-performing models based on the experimental results. In this configuration, the final fully connected layer of VGG16/ResNet50 is removed. Feature extraction is performed from the last convolutional block, and the resulting features are then passed through a batch normalization layer.

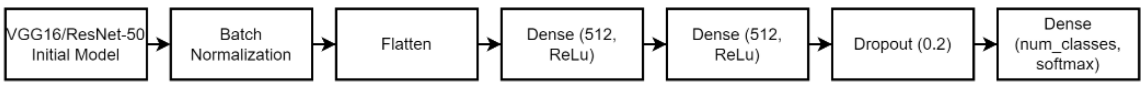


Figure 15. Transfer learning architecture

The accuracy results of the face recognition model for the extended Yale face database B are shown in Table 8. The green-colored cell indicates the best-performing model based on accuracy metrics. This comparison highlights the impact of different contrast enhancement methods on recognition accuracy, demonstrating the effectiveness of modified Zero-DCE in improving facial feature clarity.

Table 8 presents accuracy results. The best performance (83.65%) is achieved by VGG16+modified Zero-DCE+CLAHE, showing a 6.08% improvement over Zero-DCE alone. While Zero-DCE slightly outperforms modified Zero-DCE in extreme low-light cases, the latter combined with CLAHE significantly enhances accuracy. For ResNet50, Zero-DCE reduces accuracy, but modified Zero-DCE alone reaches

78.33%, highlighting its effectiveness in contrast enhancement. Compared to prior studies [20], [21], VGG16+modified Zero-DCE+CLAHE improves accuracy by up to 12.86%. Next, the FERET's face recognition model's accuracy results are shown in Table 9. The green-colored cell indicates the best.

Table 9 shows ResNet50+modified Zero-DCE+CLAHE achieving 67.41%, surpassing ResNet50+CS by 0.34%. In VGG16, modified Zero-DCE alone outperforms other enhancement techniques, confirming its effectiveness in VGG16-based face recognition. However, it falls short of previous results [35], where support vector machines reached 72.70%.

Among the face recognition models tested, BPDHE is ineffective as it causes pixelation and detail loss, particularly when combined with Zero-DCE. Its Gaussian filter smooths facial features but reduces clarity. In contrast, CS and CLAHE effectively preserve image details, leading to higher recognition accuracy.

Table 8. Accuracy result of the extended Yale face database B face recognition model

Methods	W/o combination (%)	CS (%)	CLAHE (%)	BPDHE (%)
VGG16	68.06	77.95	74.71	78.14
VGG16+Zero-DCE	73.00	76.01	77.57	74.71
VGG16+modified Zero-DCE	72.43	73.38	83.65	76.62
ResNet50	67.30	75.86	73.76	63.12
ResNet50+Zero-DCE	64.64	71.40	59.51	58.17
ResNet50+modified Zero-DCE	78.33	64.83	78.14	69.58

Table 9. Accuracy result of FERET face recognition model

Methods	W/o combination (%)	CS (%)	CLAHE (%)	BPDHE (%)
VGG16	59.48	56.37	52.24	54.14
VGG16+Zero-DCE	59.14	53.10	53.97	51.38
VGG16+modified Zero-DCE	61.72	57.76	56.89	55.00
ResNet50	65.69	67.07	60.34	55.52
ResNet50+Zero-DCE	46.38	52.07	49.31	40.34
ResNet50+modified Zero-DCE	61.55	64.31	67.41	51.38

5. CONCLUSION

This study demonstrates that integrating Zero-DCE and modified Zero-DCE with traditional contrast enhancement methods, such as CS, CLAHE, BPDHE, improves both BRISQUE scores and face recognition accuracy. Modified Zero-DCE, optimized via reduced filters, added pooling and dropout layers, and removal of L_{spa}, mitigates overexposure while achieving faster processing and greater noise robustness. Of the ten sample images, modified Zero-DCE with BPDHE achieved the highest BRISQUE score of 16.02, indicating superior image quality. In the extended Yale B dataset, it significantly enhanced extremely dark images with BRISQUE scores under 10, while in FERET, it outperformed Zero-DCE in normal or slightly dark conditions. The best models were VGG16 with modified Zero-DCE and CLAHE, achieving 83.65% accuracy on extended Yale B, and ResNet50 with the same enhancements, reaching 67.41% on FERET. However, BPDHE's tendency to blur facial features limited its recognition performance. These results highlight the task-dependent efficacy of contrast enhancement combinations. Further research is needed to address Modified Zero-DCE's limitations in extreme low-light scenarios, potentially through adaptive hybrid approaches.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest regarding the publication of this paper.

DATA AVAILABILITY

The datasets used in this study include the Extended Yale Face Database B [16], the FERET dataset [17], [18], and the LOL dataset [19]. The Extended Yale Face Database B was acquired in 2022. While both the FERET and LOL datasets were acquired in 2023 from their respective official repositories. At the time of writing, public access to these datasets may be restricted or discontinued. The original download links were:

– Extended Yale Face Database B: http://vision.ucsd.edu/~leekc/ExtYaleDatabase/ExtYaleB.html
– FERET: https://www.nist.gov/itl/products-and-services/color-feret-database
– LOL Dataset (via BMVC 2018 paper): https://daooshee.github.io/BMVC2018website/

Copies of these datasets are retained by the authors and are available upon reasonable request for academic, non-commercial use, in accordance with the original licensing terms.

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