



Adaptive image optimization for difficult lighting conditions in face recognition

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Abstract

With the rapid development of the era of artificial intelligence, our lives have become more comfortable, and "face scanning" using facial recognition technology has become a new way of life. Facial recognition is a biometric technology that uses devices such as cameras to take photos containing faces, recognize faces in photos, and obtain information about facial features to match. Facial recognition technology belongs to a broad category of biometric technologies used by government and private institutions to identify people. The system includes the collection and recognition results. This article describes the advanced multiband Retinex algorithm, which allows processing images with uneven lighting and is integrated into the Yolov5 object detection pipeline. To evaluate this method, a dataset was collected from photographs of 3,045 students in various lighting scenarios with controlled changes in illumination achieved using a software light source. This method preserves image details and increases contrast, resulting in better detection accuracy while maintaining computational efficiency. The experimental results showed that the proposed approach can be more effective than traditional methods of obtaining images of faces in uneven lighting conditions.

Keywords: Face recognition, Face recognition, Image processing, Lighting modification, Retinex method.

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1. Introduction

Artificial neural networks are the most common and effective methods for image recognition. The human face recognition algorithm is based on mathematical calculations, and neural networks perform multiple calculations simultaneously.

Facial recognition algorithms perform three main tasks: real-time image, video, or face recognition, and comparison of models in a training set or database for identification or identity verification. Over the past decade, there have been many new algorithms and groundbreaking research in deep learning, as well as new computer vision algorithms.

The purpose of this study is to test an adaptive image optimization algorithm with nonlinear brightness correction based on the Retinex method to improve the accuracy of object recognition using the YOLOv5 model. The proposed algorithm aims to eliminate the influence of difficult lighting conditions (low lighting, uneven lighting, bright glare) on image processing and includes a method for improving image quality in preprocessing by a deep learning detector.

This article describes the extended multi-band Retinex algorithm, which allows you to edit images with uneven lighting. Before processing using the multi-band Retinex algorithm, the image data is pre-processed by a non-linear transformation for uniform illumination. Since the face image contains a lot of textual information, it is difficult to characterize this information with sudden changes in lighting using traditional methods, so the accuracy of subsequent face recognition and the speed of the system are reduced [1-3].

In this article, we present an adaptive image optimization algorithm based on the Retinex nonlinear brightness correction method, which is integrated with the Yolov5 preprocessing process. This eliminates the effect of complex lighting and improves the accuracy of object recognition. The proposed algorithm has high computational efficiency, making it suitable for real-time tasks such as video surveillance systems, autonomous vehicles, and medical diagnostics.

2. Literature Review

Facial recognition is one of the most studied topics in the machine learning community. This technology is highly efficient and accurate and is used in many fields such as video surveillance, financial services, social media, and transportation. However, due to its effectiveness and ease of use, this technology also carries potential risks related to the protection of personal data and personal property. Protecting personal data from misuse is a serious issue that affects all segments of society, ensuring effective management of facial recognition technologies and a balance between the protection and use of personal data.

For years, facial recognition has been studied by traditional methods [4-7]. And is currently being studied with new algorithms based on deep learning [8-13]. To improve the effectiveness of face recognition, mechanisms for normalizing model learning and heuristic models for detecting differences in facial features have been introduced. Li et al. [14] developed a method of multitasking discriminant analysis using a description of local features. Gong et al. [12] it was proposed to use latent factor analysis (HFA) for modeling the factor of signs and the decrease of age differences in identity-related signs.

The problem of lighting, which is one of the main problems of modern facial recognition systems, has become an obstacle for many face recognition applications. Well-known facial recognition models have shown that significant changes in illumination can affect the performance of facial recognition algorithms. Several papers have been proposed, mostly divided into three categories [15]: preprocessing procedures and normalization of facial recognition algorithms, Brunelli and Poggio [16]; Wiskott et al. [17] and Manjunath et al. [18] approaches based on lighting modeling [19-21], and extraction of invariant features [22-25].

The article by Hong et al. [26] explores ways to reduce the effect of uneven lighting on the image, improving the sharpness and uniform brightness of the image. The ordinal ratio between the average brightness of pairs of image regions consistently determines the properties of local image scattering at different light levels. A local binary display is defined as a fixed illumination for face recognition based on a local binary pattern descriptor [27]. The article by Hong et al. [26] explores ways to reduce the effect of uneven lighting on the image, improving the sharpness and uniform brightness of the image. The authors considered the possibility of using 2D RGB images with medium aperture and maps of irregularities and depth obtained from a set of low-exposure images associated with a light field [28].

3. Materials and Methods

Then the face is extracted, and the feature vector is compared with the feature vector in the database for identification. It collects information on a topic in real time using a local camera. Problems such as shifting the angle of the face and uneven light distribution may occur under the camera. Factors such as overexposure, blurred faces, dark faces, and backgrounds make it difficult to collect content.

3.1. Video processing

Direct testing of facial images using low-quality video shows more obvious errors, which significantly increases the error rate. Therefore, pre-processing is necessary to improve video quality and enhance facial features in order to better preserve facial information and increase the likelihood of successful facial recognition.

3.2. The external factor

The pre-created content is processed primarily by aligning the edges and enhancing the image. It is especially important that the direction of the face movement in the video is determined by the system. Regardless of whether the information about the face can be recognized or not, the camera must be sure that it fully recognizes the contours of the face and features of the

eyes, nose, mouth, etc. An object that is used as a landmark in face recognition, and based on this information, algorithms are created to determine the coordinates of the face.

The study examined the effect of lighting changes on the quality of objects and facial recognition using a modified image enhancement method. To test the effect of the parameters on the reliability of the results of facial recognition algorithms, we chose the Python programming language with a library (NumPy library, OpenCV, Dlib, OpenFace). We used the YOLOv5 algorithm for face recognition. To create a face recognition instance model, we used the cvv2 function, face_recognition OpenCV API, and then used the function face_detector.py. The images were captured by a Hikvision DS-2CD1347G0-L digital IP camera in real time. The camera is equipped with a photosensitive 1/3-inch progressive scan CMOS sensor with a resolution of 4 megapixels and the ability to transfer images in the format of 2560 by 1440 pixels at a rate of 25 frames per second.

For the experiment, a separate set of data was collected from photographs of 3,045 students. The data was collected under various indoor lighting conditions. Each participant was invited to take part in filming under different lighting conditions. A) weak light, imitating twilight; B) normal daylight; C) strong and bright light caused by directional lighting. The following values were used to evaluate the effectiveness of the Yolov5 algorithm: image processing speed and average absolute error.

4. Results

4.1. Retinex Algorithm

According to the retinex theory, the brightness value of an image is the result of a combination of the ambient light component and the reflection component from the object's surface. In uneven lighting, the difference in brightness between neighboring areas of the image is significant, so a curved surface consisting of an ambient lighting component significantly changes the spatial area, which affects the image quality [29]. To improve image quality, the proposed algorithm uses a multiband retina to highlight the image's lighting components and perform adaptive brightness correction. The lighting component is usually a low-frequency part that can be extracted using a directional filtering algorithm. Compared to many edge-preserving filtering algorithms, the directional filtering algorithm makes it possible to smooth the surface of the lighting element as much as possible, while preserving the image details around the edges [30, 31]. The image I(x,y) can be expressed as follows:

$I(x, y) = R(x, y) \times L(x, y)$

I(x,y) is the input image, L(x,y) is the light component, R(x,y) is the reflective component. Using I(x,y) as the image control function, the multiband filter direction function is used to filter the processing to ensure a balance between image smoothing and edge detail. The proposed method makes it possible to improve the detailing properties of complex low-quality images by combining images, which allows them to be restored [32].

Due to the difficulties in estimating the brightness of an image in the Retinex algorithm, the image is first converted from the RGB color space to an increasing color space in low light. The brightness component (Y) is then extracted from the enlarged color space, and the original image is created when the light source is turned on. The selected image is processed using gamma correction to obtain an enhanced selected image.

3 stages of the image illumination improvement algorithm were implemented: 1) converting a darkened surface image from RGB color space to YCbCr color space, and obtaining brightness components to create the original illuminated image $R_1(x,y)$; 2) to obtain an improved illuminated image $R_2(x,y)$; obtain an improved image L(x,y) according to the Retinex algorithm(Figure 1).



The main mechanism of the algorithm.

The face image is preprocessed, and then facial features are extracted. First, the face image was cut out of the photo using the coordinates of the face position. Then the estimated viewing angle was adjusted, and the next step was to normalize the image size to 640 x 640 pixels. Finally, the lighting quality of the image determined whether a fill light was needed. Face correction can effectively eliminate the effects of changing face position and lighting on face recognition (Figure 2).

During facial recognition, the Faster RCNN model is loaded first [33]. The accuracy of the model tested on the LFW dataset is 99.05%, and the processor speed is 25 frames per second. Embedding with a dimension of 512 was used for face recognition. Face Net directly compares the face image with the Euclidean space to find the similarity of the images. The face image is then standardized, and the vector image of the face is extracted along with the model after the preprocessing is completed.

3.2. Adaptive Enhancement Algorithm with Nonlinear Brightness Correction

Let's assume that the image size is $M \times N$, and the grayscale level corresponds to L. We set the initial threshold T(k) = k, 0 < k < N - 1. We use it to divide image pixels into two categories according to a threshold value, Kilicaslan, et al. [34] denoted as C_1 and C_2 . The probability of selecting a pixel is:

$$P_1(k) = \sum_{i=0}^k p_i \tag{1}$$

where, p_i indicates that the grayscale level is *i*, and the probability of pixels of class C_2 is

$$P_2(k) = \sum_{i=k+1}^{L-1} p_i = 1 - P_1(k)$$
⁽²⁾

The average grayscale value for the two categories $t_1(k)$, $t_2(k)$ and the average grayscale value $t_{mean}(k)$:

$$t_1(k) = \frac{1}{P_1(k)} \sum_{i=0}^k i p_i,$$
(3)

$$t_2(k) = \frac{1}{P_2(k)} \sum_{i=k+1}^{L} i p_i, \tag{4}$$

 $t_{mean}(k) = P_1(k)t_1(k) + P_2(k)t_2(k).$ (5)

In accordance with Equations 1~5, the interclass variance can additionally be calculated [35]:

$$\delta_B^2(k) = P_1(k)[t_1(k) - t_{mean}(k)]^2 + P_2(k)[t_2(k) - t_{mean}(k)]^2.$$
(6)

for $\delta_B^2(k)$ maximum is the optimal threshold value k^* , so $\delta_B^2(k^*) = \max_{0 \le k \le N-1} \delta_B^2(k)$, if $\delta_B^2(k)$ *If* the maximum value is not unique, then k^* is used as the maximum value equal to k^* and expressed as the average (6).

For images, the proposed adaptive enhancement algorithm with nonlinear brightness correction looks like this (Figure 2).



Figure 2. Block diagram of the proposed algorithm.

Figure 3 shows the resulting images of faces with different levels of dim at 1, 2, and 3 m, respectively.







(c)

Figure 3. Images of faces with different levels of dimming at a distance of 1, 2 and 3 m, respectively.

Figure 3. Images of faces with different dimming levels at distances of 1, 2 and 3 m, (a) images of faces collected from a distance of 1 m, the dimming level from left to right is 20%-100%; (b) images of faces collected from a distance of 2 m, the dimming level is $30\%\sim100\%$ from left to right; (c) Images of faces taken from a distance of 3 m, the dimming level is 40%-100% from left to right.

Figure 4 shows the results of face recognition at different brightness levels at 1, 2 and 3 meters. Recognition efficiency increases with increasing brightness. Tests at 1 m have shown that the speed of face recognition can reach 98% when using a 70% brightness adjustment of the image, which basically corresponds to the recognition speed when the image optimization algorithm is increased.



The speed of face recognition before and after adding an image enhancement algorithm in different light conditions.

At 1 m and a brightness value of 20%, the average face recognition rate is 60.98, and after adding an image enhancement algorithm, this figure increases by 86%. At 1 m and a brightness level of 60%, the average face recognition rate is 97%, and after adding an image enhancement algorithm, this figure increases by 98%. The face recognition system cannot identify faces at a light level of 20% brightness at 2 meters. In such conditions, there is not enough information for analysis, which leads to the interruption of subsequent calculations.

At 2 meters and with a dimming level of 50%, the face recognition rate is 86%. After adding the image optimization algorithm, the face recognition rate increases by 11.00%. At 3 meters and a dimming level of 50%, the face recognition rate is 61.09. After adding the algorithm, the face recognition rate increases by 23.91







Figure 5 shows the average absolute errors before and after switching on the image enhancement algorithm at various dimming levels at 1, 2 and 3 m. As the brightness value increases, after adding an image optimization algorithm, the average absolute errors decrease. This is because as the brightness increases, the face becomes brighter, and the details become clearer. At 1 m and a brightness level of 50%, the average absolute error is 2.63, and after adding an image enhancement algorithm, this indicator decreases by 0.96. At 2 meters and with a dimming level of 50%, the average absolute error is 2.77. After adding the image optimization algorithm, the average absolute error value decreases by 2.60. With 3 meters and a dimming level of 50%, the average absolute error is 2.82. After adding the algorithm, the average absolute error decreased by 2.77.

Table 1 shows the results of comparing the average gray value, recognition speed, and average absolute error before and after adding the image enhancement algorithm at distances of 1, 2, and 3 m. You can see that the average gray value for an image optimized using the algorithm increased at different distances compared to the average gray value for the original image. As the brightness value increases, after adding an image optimization algorithm, the average absolute errors decrease, and the speed of face recognition increases. The facial recognition system could not detect faces with 20% brightness at 2 meters. The face recognition system could not detect faces at illumination levels of 20%, 30%, and brightness at 3 meters.

Table 1.

	Results before the algorithm implementation			Results after implementing the algorithm			
Indicator	Gray mean value	Recognition rate, %	Mean absolute error	Gray mean value	Recognition rate, %	Mean absolute error	
Brightness modulation level, 20%	7.54	60.98	3.56	24. 99	86	3.34	
Brightness modulation level, 30%	10.71	85.56	3.32	30.07	95	3.21	
Brightness modulation level, 40%	13.29	95.44	2.89	37.41	98	2.67	
Brightness modulation level, 50%	25.30	97.00	2.63	56. 61	98	0.96	
Brightness modulation level, 60%	35.89	97.00	2.15	68.77	9898	0.88	
Brightness modulation level, 70%	61.46	97.38	1.59	84.97	98	0.64	
Brightness modulation level, 80%	89.60	97.40	0.81	103. 28	98.60	0.55	
Brightness modulation level, 90%	93.34	97.60	0.54	115.09	98.60	0.42	
Brightness modulation level, 100%	93.21	97.60	0.38	123. 38	98.60	0.22	

Table 2.

The results before and after the implementation of the algorithm at distances of 2 m.

	Results before the algorithm implementation			Results after implementing the algorithm			
Indicator	Gray mean value	Recognition rate, %	Mean absolute error	Gray mean value	Recognition rate, %	Mean absolute error	
Brightness modulation level, 20%	N/A	N/A	N/A	N/A	N/A	N/A	
Brightness modulation level, 30%	10. 87	20.00	3.56	18.90	67.00	3.40	
Brightness modulation level, 40%	17.42	60.00	3.19	30. 11	96.89	3.10	
Brightness modulation level, 50%	26.68	86.00	2.77	43.88	97.00	2.60	
Brightness modulation level, 60%	37. 61	96.00	2.43	57.39	97.00	2.31	
Brightness modulation level, 70%	45.34	96.00	1.89	66. 61	97.00	1.45	
Brightness modulation level, 80%	55. 51	96.30	1.60	79.90	98.00	1.01	
Brightness modulation level, 90%	68.05	97.60	0.84	80.81	98.50	0.79	
Brightness modulation level, 100%	79. 33	97.60	0.42	90. 74	98.50	0.38	

Table 3.

Results before and after the implementation of the algorithm at distances of 3 m.

	Results before the algorithm implementation			Results after implementing the algorithm			
Indicator	Gray mean value	Recognition rate, %	Mean absolute error	Gray mean value	Recognition rate, %	Mean absolute error	
Brightness modulation level, 20%	N/A	N/A	N/A	N/A	N/A	N/A	
Brightness modulation level, 30%	N/A	N/A	N/A	N/A	N/A	N/A	
Brightness modulation level, 40%	15.53	21.02	3.50	35.00	49.00	3.45	
Brightness modulation level, 50%	17.00	61.09	2.82	40.07	85.00	2.77	
Brightness modulation level, 60%	22.12	84.00	2.67	40.23	95.90	2.08	
Brightness modulation level, 70%	30.16	88.67	1.97	51.21	96.0	1.08	
Brightness modulation level, 80%	41.33	96.56	1.19	60.56	98.00	1.00	
Brightness modulation level, 90%	51.22	97.00	0.98	68.00	98.00	0.79	
Brightness modulation level, 100%	61.90	97.00	0.66	71.98	98.00	0.42	

4. Discussion

With simplicity, speed, and ease of use, the advances of technology manufacturers have allowed facial recognition and its applications to spread unnoticed across a variety of scenarios. Currently, the innovative use of digital technologies has become an irreversible trend in society over time. In this context, the use of facial cleansing methods should be legal, reasonable, and safe to balance technological development and the protection of human rights. Security is a prerequisite, but it cannot be used as a reason for abandoning development. Studying the laws of how applications work, applicable scenarios, and formulating proper principles for facial recognition technology is also the only way to deal with the era of artificial intelligence.

The research has confirmed the effectiveness of the proposed adaptive image optimization algorithm based on the Retinex method to improve the accuracy of object detection in difficult lighting conditions. In particular, it was found that the method eliminates the effects of uneven lighting and improves local contrast, which has a positive effect on object recognition using the Yolov5 model.

However, the effectiveness of any approach depends on the correct setting of the algorithm parameters, which may limit its diversity. In addition, the increased image processing time indicates the need for further optimization. In the future, it is planned to integrate the method directly into the Yolov5 architecture, which will reduce preprocessing time and increase real-time applicability. The proposed approach can be used in video surveillance systems, autonomous vehicles, and other applications where accuracy in low-light conditions is important.

5. Conclusion

A face recognition system based on a multitasking convolutional neural network with variable illumination was investigated, which aims to solve the problem of light exposure to the face recognition system. In this article, we present an improved Retinex-based facial recognition method under various lighting conditions.

The algorithm used not only works quickly but also effectively improves the brightness and detail of the image, thereby preventing distortion of brightness and color and obtaining better visual effects. Although the applied image enhancement algorithm in low-light conditions can effectively increase the brightness of the image, the parameters cannot be adjusted to match the image itself; therefore, research on adaptive image enhancement will be conducted in the future.

In conclusion, the proposed approach is more suitable for face recognition in various lighting conditions and is more effective in addressing problems caused by insufficient lighting.

References

- [1] P. Jonathon, P *et al.*, "FRVT 2006 and ICE 2006 large-scale experimental results," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 32, no. 5, pp. 831-846, 2009.
- [2] J. Wright, A. Y. Yang, A. Ganesh, S. S. Sastry, and Y. Ma, "Robust face recognition via sparse representation," *IEEE transactions on pattern analysis and machine intelligence*, vol. 31, no. 2, pp. 210-227, 2008.
- [3] J. Yang, J. Wright, T. S. Huang, and Y. Ma, "Image super-resolution via sparse representation," *IEEE transactions on image processing*, vol. 19, no. 11, pp. 2861-2873, 2010.
- [4] M. Kirby and L. Sirovich, "Application of the Karhunen-Loeve procedure for the characterization of human faces," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 12, no. 1, pp. 103-108, 1990.
- [5] C. Liu and H. Wechsler, "Proc. of the 2nd int. conf. on audio- and video-based biometric person authentication," pp. 211–216, 1999.
- [6] G. G., L. S.Z., and C. K., "IEEE int. conf. on automatic face and gesture recognition," pp. 196–201, 2000.
- [7] W. Y. Zhao, "Pattern recognition 2000. Proc. 15th Int. Conf," vol. 2, pp. 818–821, 2000.
- [8] Y. Sun, D. Liang, X. Wang, and X. Tang, "Deepid3: Face recognition with very deep neural networks," *arXiv preprint arXiv:1502.00873*, 2015.
- [9] E. Zhou, Z. Cao, and Q. Yin, "Naive-deep face recognition: Touching the limit of LFW benchmark or not?," *arXiv preprint arXiv:1501.04690*, 2015.
- [10] I. Stanko, The architectures of geoffrey hinton. in: Skansi S. (eds) guide to deep learning basics. Cham: Springer, 2020.
- [11] Y. Li, L. Song, X. Wu, R. He, and T. Tan, "Anti-makeup: Learning a bi-level adversarial network for makeup-invariant face verification," presented at the In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 32, No. 1). 2018.
- [12] S. Gong, Y. Shi, N. D. Kalka, and A. K. Jain, "Video face recognition: Component-wise feature aggregation network (c-fan)," presented at the In 2019 International Conference on Biometrics (ICB) (pp. 1-8). IEEE, 2019.
- [13] Z. Mutalova, A. Nurpeisova, A. Shaushenova, A. Ispussinov, and L. Zhumaliyeva, "Face recognition system based on neural network," presented at the Patent Republic of Kazakhstan. No. 9870. Ministry of Justice of the Republic of Kazakhstan. Registered on November 29, 2024.
- [14] Z. Li, U. Park, and A. K. Jain, "A discriminative model for age invariant face recognition," *IEEE Transactions on Information Forensics and Security*, vol. 6, no. 3, pp. 1028-1037, 2011.
- [15] A. M. Martinez, "Recognizing imprecisely localized, partially occluded, and expression variant faces from a single sample per class," *IEEE Transactions on Pattern analysis and machine intelligence*, vol. 24, no. 6, pp. 748-763, 2002. https://doi.org/10.1109/TPAMI.2002.1008382
- [16] R. Brunelli and T. Poggio, "Face recognition: Features versus templates," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 15, no. 10, pp. 1042-1052, 2002. https://doi.org/10.1109/34.254061
- [17] L. Wiskott, J.-M. Fellous, N. Krüger, and C. Von Der Malsburg, "Face recognition by elastic bunch graph matching," Routledge, 2022, pp. 355-396.
- [18] B. S. Manjunath, J.-R. Ohm, V. V. Vasudevan, and A. Yamada, "Color and texture descriptors," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 11, no. 6, pp. 703-715, 2001.
- [19] W. Gao, S. Shan, X. Chai, and X. Fu, "Virtual face image generation for illumination and pose insensitive face recognition," in In 2003 International Conference on Multimedia and Expo. ICME'03. Proceedings (Cat. No. 03TH8698) (Vol. 3, pp. III-149). IEEE, 2003.
- [20] A. S. Georghiades, P. N. Belhumeur, and D. J. Kriegman, "From few to many: Illumination cone models for face recognition under variable lighting and pose," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 23, no. 6, pp. 643-660, 2002. https://doi.org/10.1109/34.927464
- [21] H. Shim, J. Luo, and T. Chen, "A subspace model-based approach to face relighting under unknown lighting and poses," *IEEE Transactions on Image Processing*, vol. 17, no. 8, pp. 1331-1341, 2008. https://doi.org/10.1109/TIP.2008.925390
- [22] T. Chen, W. Yin, X. S. Zhou, D. Comaniciu, and T. S. Huang, "Total variation models for variable lighting face recognition," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 28, no. 9, pp. 1519-1524, 2006. https://doi.org/10.1109/TPAMI.2006.195
- [23] X. Tan and B. Triggs, "Enhanced local texture feature sets for face recognition under difficult lighting conditions," *IEEE Transactions on Image Processing*, vol. 19, no. 6, pp. 1635-1650, 2010. https://doi.org/10.1109/TIP.2010.2042645
- [24] T. Zhang, Y. Y. Tang, B. Fang, Z. Shang, and X. Liu, "Face recognition under varying illumination using gradientfaces," *IEEE Transactions on image processing*, vol. 18, no. 11, pp. 2599-2606, 2009. https://doi.org/10.1109/TIP.2009.2028255
- J. Yi, X. Mao, L. Chen, Y. Xue, A. Rovetta, and C.-D. Caleanu, "Illumination normalization of face image based on illuminant [25] direction estimation and improved retinex," PloS one, vol. 10, no. 4, e0122200, p. 2015. https://doi.org/10.1371/journal.pone.0122200
- [26] Y. Hong, R. Pang, Q. Wei, J. Su, and F. Zhao, "Nonlinear adaptive enhancement algorithm for uneven illumination images," *Advances in Lasers and Optoelectronics*, vol. 60, no. 16, 2023. https://doi.org/10.3788/LOP222380
- [27] A. Sepas-Moghaddam, P. L. Correia, K. Nasrollahi, T. B. Moeslund, and F. Pereira, "Light field based face recognition via a fused deep representation," In 2018 IEEE 28th International Workshop on Machine Learning for Signal Processing (MLSP) (pp. 1-6). IEEE, 2018.
- [28] Y. Zhang, Y. Chu, X. Mou, and G. Zhang, "Face recognition under variable lighting using local qualitative representations," in *MIPPR 2007: Pattern Recognition and Computer Vision. https://doi.org/10.1117/12.749831*, 2007, vol. 6788, pp. 417-423.
- [29] K. Wu, J. Huang, Y. Ma, F. Fan, and J. Ma, "Cycle-retinex: Unpaired low-light image enhancement via retinex-inline cyclegan," *IEEE Transactions on Multimedia*, vol. 26, pp. 1213-1228, 2023.
- [30] J. y. Zhang, Y. Ding, and Y. Yang, "ICE workshops Real-time defrag model based on visible and near-infrared information," presented at the IEEE International Conference on Multimedia & Expo Workshops (ICMEW), pg. 1, (2016); https://doi.org/10.1109/icmew.2016.7574749, 2016.
- [31] S. Marsi, G. Impoco, A. Ukovich, S. Carrato, and G. Ramponi, "Video enhancement and dynamic range control of HDR sequences for automotive applications," *EURASIP Journal on Advances in Signal Processing*, vol. 2007, pp. 1-9, 2007.

- F. Chung-Ting, C. Jiang-Ru, and L. Chong-Wei, "Accelerating multi-scale retinex using ARM NEON," presented at the IEEE International Conference on Consumer Electronics Taiwan , pg. 77, (2014). https://doi.org/10.1109/icce-tw.2014.6904110, [32] 2014.
- [33] X. Ding, Q. Li, Y. Cheng, J. Wang, W. Bian, and B. Jie, "Local keypoint-based faster R-CNN," Applied Intelligence, vol. 50, pp. 3007-3022, 2020. https://doi.org/10.1007/s10489-020-01665-9
- M. Kilicaslan, U. Tanyeri, and R. Demirci, "Image retrieval using one-dimensional color histogram created with entropy," [34]
- *Advances in Electrical & Computer Engineering*, vol. 20, no. 2, pp. 79-88, 2020. A. K. Bhandari, A. Ghosh, and I. V. Kumar, "A local contrast fusion based 3D Otsu algorithm for multilevel image segmentation," *IEEE CAA J. Autom. Sinica*, vol. 7, no. 1, pp. 200-213, 2020. [35]