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Research Article

A Color Space-Based Framework for Enhancing Low-Light Images Using CIELAB Transformation

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ABSTRACT

Image processing dates to the 1960s when it was first applied to improve image quality. With the increased use of digital products in the form of smartphones and cameras, low-light image improvement has come into sharp focus. Several methods have been adopted such as histogram equalization, illumination map estimation, normalizing flows, neural networks, and dark region-aware enhancement. This study offers a function for RGB to CIELAB color space transformation and a step-by-step improvement process. Transformation into CIELAB color space offers the feature of separating brightness and color details and improving contrast and image quality. The device-independent CIE 1976 (L*, a*, b*) formula that is well adapted to improve images from different sources is employed. An easy-to-use interface has been implemented, enabling users to download low-light photos and restore the improved ones.

1. Introduction

The history of image processing was initiated in the 1960s 1, when an experiment was performed to improve the quality of the medical imaging picture, video telephony picture, character recognition picture, and satellite picture. It was created to enhance the visual image of low-quality images and offer a replacement for a high-quality image 2. From then on, different types of image processing have evolved, such as image compression, encoding, restoration, and image enhancement 3.

Nowadays, electronic equipment such as smartphones and digital cameras is highly prevalent 4. Low light, however, degrades image quality significantly by losing luminance, contrast, and colour detail 5. Various techniques have been suggested by researchers to enhance the quality of images in the low-light regime, such as histogram equalization, illumination map estimation 6, normalization flow 7, neural networks 8, and dark region-aware low-light image enhancement 9.

To optimize the low-light image enhancement algorithm to some extent, conversion of colour space is performed to convert RGB colour space to CIELAB or HSI colour space. CIELAB-to-RGB conversion and step-by-step performance of the conversion and enhancement process are given here. The project also includes a simple interface to download images snapped in dark and download the enhanced images, and a comparison box to show the enhancement from the original to enhanced image.

Low-light image enhancement technique was created generally to improve the low-light image which has been taken in the dark or low light conditions. Existing low-light image enhancement methods work well when it comes to dark enhancement. However, there are still weaknesses that depend on the technique. In Histogram Equalization and Illumination Map Estimation, which are known as traditional methods for enhancing low-light images, the weakness of these methods is obvious because the image brightness is overexposed, and the colors are distorted. This may not serve the right to the original purpose of implementing the technique which the brightness of the image is enhanced to view the object in the dark side and if the image is overexposed the results will not be suitable for display or further image analysis.

Besides, modern methods such as Normalizing Flow, Neural Network, and Dark Region-Aware have also significantly improved the weaknesses of traditional methods but require a large amount of data to perform proper training for the system to work effectively. As a result, there are many techniques that come together with color transformations and dehazing methods to help the image retain the color and reduce haze while the improvement process is going on. Since the RGB color space is not consistent with human visual perception, it is difficult to ensure that all Red, Green, Blue channels in that image are enhanced according to an appropriate ratio. Due to this, the image needs to be transformed into different color spaces such as HSI and CIELAB which have better representation than RGB color space. This study is to develop a system with applications that is based on CIELAB color space method.

2. Methodology

2.1. Histogram Equalization (HE)

To improve contrast in images, histogram equalization, a computer image processing technique, is utilized. This technique is accomplished by effectively broadening the intensity range of the image and allocating the most frequent intensity levels. When payload is expressed in terms of values near contrast, this technique typically enhances overall contrast of images. This enables areas of low local contrast to be given increased contrast. Histogram equalization alters intensity distributions. If there is an image with a histogram with lots of peaks and valleys, they will still exist after equalization but will be translated. This is why histogram equalization is more appropriately called “spreading” instead of “flattening” During histogram equalization, a new intensity is given to each pixel depending on the past intensity 10.

Depending upon which transformation function is utilized, it can be separated into two branches: global histogram equalization (GHE) and local histogram equalization (LHE). While GHE is extremely quick and convenient, its capacity to augment contrast is weak. In this situation, the histogram transformation function is obtained from the histogram of the entire input image. This compresses and expands the dynamic range of the image histogram. Global contrast is improved. Alternatively, LHE can further enhance the global contrast. Also, due to histogram flattening, it can potentially drastically alter the mean brightness of an image, which is not always a good thing when preserving an image's native mean brightness is better.

2.2. Illumination Map Estimation (LIME)

Unlike variational models, illumination map estimation represents a novel approach to low-light image enhancement. The Low-light Image Enhancement via Illumination Map Estimation (LIME) approaches estimates illumination maps for individual RGB channels based on structural data from images. In addition, LIME provides alternative illumination enhancement procedures, which extend image brightness beyond image decomposition, distinguishing it from variational models.

LIME, proposed by Guo et al. 6, is thought to be a milestone in the area and one of the state-of-the-art traditional algorithms for low-light image enhancement. LIME relies on the Retinex theory and attempts to strengthen the low-light images by approximating and modifying the illumination map. The illumination map is enhanced with priority in Retinex-based methods to optimize the visual quality of low-light images.

Though useful, these techniques are prone to side effects like overexposure, halo artifacts, low contrast, and unnecessary smoothing. Some Retinex-based techniques have an intrinsic tendency to over-enhance the image, resulting in unnatural or aesthetically displeasing images.

2.3. Normalizing Flow (NF)

A normalizing flow is a sequence of invertible and differentiable mappings that transform a tractable probability distribution, say the standard normal distribution, into a more complicated one. This framework allows one to calculate the probability density function (PDF) of the sample exactly by back-projection onto the base distribution. This is possible by designing the network layers to be well engineered in a way that the determinant of the Jacobian matrix as well as its inversion can be obtained easily. These constraints limit the model’s design flexibility but ensure that the network remains invertible and tractable.

To enhance the expressive power of normalizing flows, several architectural innovations have been introduced, including 1×1 convolutions, partitioning and concatenation, permutation operations, and affine coupling layers. Wang et al. 11 successfully implemented such methods to address limitations in modeling local pixel correlations, which previously hindered the ability to capture global image properties such as color saturation. In their approach, the normalizing flow effectively learned both local and global image features by modeling the distribution of normally exposed images.

Although this method improved saturation enhancement and reduced color distortions 12, it still occasionally resulted in unnatural color appearances in the enhanced images.

2.4. Neural Network (CNN)

In recent years, numerous image enhancement methods based on neural networks have emerged, each adopting different architectural strategies. For instance, LLCNN incorporates convolutional blocks in its pipeline, drawing inspiration from architectures like Inception. It also utilizes the concept of residual connections from ResNet to create two separate pathways for illumination and reflection. This approach, detailed by Li et al. 8, shows promise; however, as a residual neural network is still a form of artificial neural network, enhanced images often suffer from visible visual artifacts.

Meanwhile, Mehwish et al. 12 introduced a color-wise attention network that performs color balancing on lowfrequency components using a sigmoid activation function. Their method simultaneously preserves image contrast and reduces excessive color saturation. The implementation successfully improved image contrast while minimizing visual artifacts 15, 22.

Recent research has shown growing interest in integrating advanced computational techniques to improve user-centric visual processing tasks, such as low-light image enhancement. Methods that prioritize real-time responsiveness and efficiency have proven particularly valuable in resource-constrained environments 15. For instance, Baker et al. demonstrated the application of neural collaborative filtering and prefetching to optimize web performance, which shares similarities with adaptive enhancement techniques in visual systems 16. Similarly, motion detection frameworks that utilize deep learning architectures like YOLOv8 and R-CNN have illustrated the potential of combining spatial analysis with real-time processing—principles that can be extended to color-based enhancement in image restoration tasks 17. Additionally, the implementation of recurrent neural networks such as GRU and LSTM for intelligent automation reflects the increasing use of learning-based models for perceptual improvements and adaptive feedback in image systems 18. Optimization strategies including factorization machines and collaborative filtering have also contributed to personalized and context-aware computing, which are relevant to dynamic contrast and color adjustments in low-light scenarios 19, 20. These developments support the use of a CIELAB-based framework by aligning with broader efforts to enhance computational perception and improve image quality in user-interactive systems.

Additionally, Lore et al. 13 pioneered the use of deep neural networks in low-light image enhancement with the development of LLNet, the first deep learning-based approach in this field. LLNet employs a variation of a stacked sparse denoising and contrast-enhancement autoencoder. Despite lacking convolutional layers, the method significantly outperformed traditional low-light enhancement techniques.

However, one common limitation of these neural network-based methods is their reliance on large datasets. Substantial training data is required to achieve optimal performance and generalization for low-light image enhancement tasks.

2.5. Dark Region-Aware Low-light Enhancement (DALE)

This approach utilizes two primitive components: a visual attention network and an enrichment network. The attention network is used to create an attention map to detect dark areas within an image, and the enrichment network is used to enrich these low-light areas 14, 15.

However, with most neural network-based approaches, this approach needs huge amounts of training data to be effective 21. The system's performance largely relies on having huge and varied datasets for the sake of guaranteeing sound training and generalization.

3. Method

3.1. Accuracy of numerical integration

CIELAB is one of the most widely used color spaces that have been designed such that they are perceptually linear to a larger degree than RGB. CIELAB separates the data of colors into three categories: L for luminance, A for red-green axis, and B for blue-yellow axis.

The formula developed in this paper is an image enhancement method in low-light conditions that alters the lightness component (L) and retains the chroma and hue information constant. The formula is:

The image's chroma is a color intensity measure and is the square root of the sum of the square of the A and B components of the CIELAB color space:

$$\text{Chroma} = \sqrt{(A^2 + B^2)} \quad (1)$$

The hue of the image is computed as arctangent of the ratio of B to A component, resulting in the color angle within the CIELAB color space:

$$\text{Hue} = \tan^{-1}(B / A) \quad (2)$$

The intensity of the image overall is calculated by averaging the red (R), green (G), and blue (B) channels:

$$I = (R + G + B) / 3 \quad (3)$$

Alpha is then derived from the image intensity. It will then be employed to normalize the lightness component, leading to brightness enhancement:

$$\text{Alpha} = (255 - I) / 255 \quad (4)$$

The new lightness value is calculated by adding 1 to the alpha and multiplying it with the original (old) lightness value:

$$\text{newL} = (\text{Alpha} + 1) \text{ x oldL} \quad (5)$$

Next, the ratio between the new and old lightness values is computed:

$$\text{Ratio} = \text{newL} / \text{oldL}$$

$$\text{Ratio} = \text{Alpha} + 1 \quad (6)$$

This ratio is subsequently applied to compute the new chroma value, thus the intensity of the color remains:

$$\text{new Chroma} = \text{Ratio} \times \text{Chroma} \quad (7)$$

To transform the color channels, new A and new B are derived from the cosine and sine of the hue angle, respectively:

$$\text{newA} = \text{new Chroma} \times \cos(\text{Hue}) \quad (8)$$

$$\text{newB} = \text{new Chroma} \times \sin(\text{Hue}) \quad (9)$$

Finally, the adjusted newL, newA, and newB values are combined and converted back into the RGB color space. This technique maintains image brightness with the original color characteristics, paving the way to a clearer and improved-looking image.

3.2. *System Interface*

The LLIE system interface must be minimalistic and consistent in such a manner that users won't waste much time figuring out how the system functions. The system was thus created based on the study of such interfaces with features of image uploading, converting, comparing, and downloading. The LLIE system employs Tkinter, an active and robust Python GUI library, to establish its interface.

3.3. *Main Interface*

The user opens the application and is given the main interface as shown in Figure 1.

Figure 1 Main Interface.

3.4. *Choose File*

The user clicks on the "Choose File" button to choose a file for an image from his/her hard drive. This can open a file dialog box that enables the user to find the file to be opened as in Figure 2.

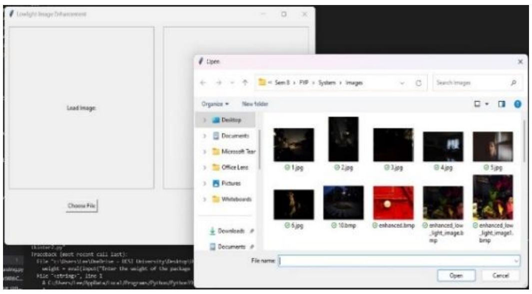

Figure 2 Choose File Function.

3.5. *Open Image*

As soon as the user clicks on the file, the program displays the image in the main window and opens the image (Figure 3). The user can now see and edit the image accordingly.

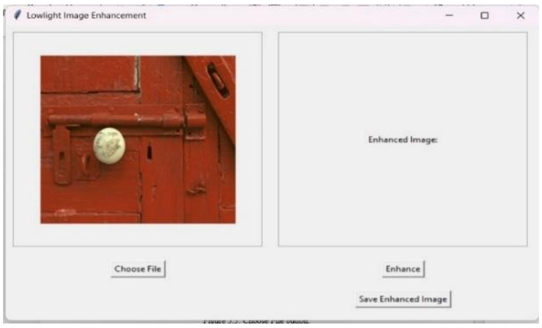

Figure 3 Display the Chosen Image.

3.6. *Enhance Image*

When the user is ready to enhance the image, they click the "Enhance" button. This could launch a dialog box that allows the user to choose from various enhancement options, or it could simply apply a default enhancement algorithm to the image.

3.7. *Display Enhanced Image*

After the application enhances the image, it displays the enhanced version in a separate box or window. This allows the user to compare the original and enhanced images side-by-side as shown in Figure 4.

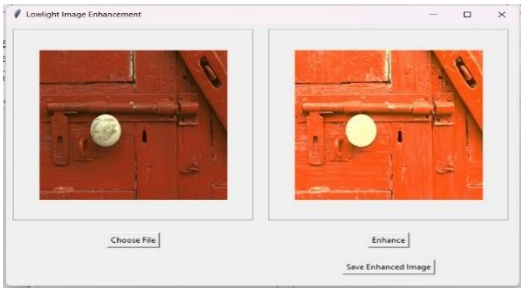

Figure 4 Enhanced and Display the Image.

3.8. *Save Enhanced Image*

If the user is satisfied with the enhancement, they can click the "Save Enhanced Image" button to save the enhanced image to their computer. This could launch a file dialog box that allows the user to choose a file name and location for the saved image (Figure 5).

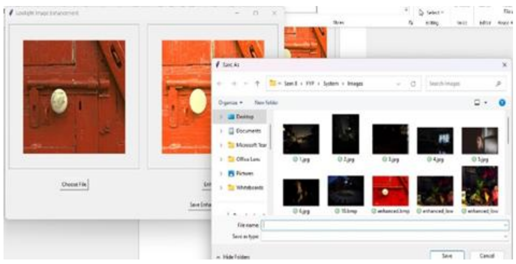

Figure 5 Save Image.

The user can repeat the process with other images as needed.

4. Result

After applying the color space method, Figure 6, Figure 7, Figure 8 present the results of the low-light image enhancement system, along with the interface used to compare the original and enhanced images.

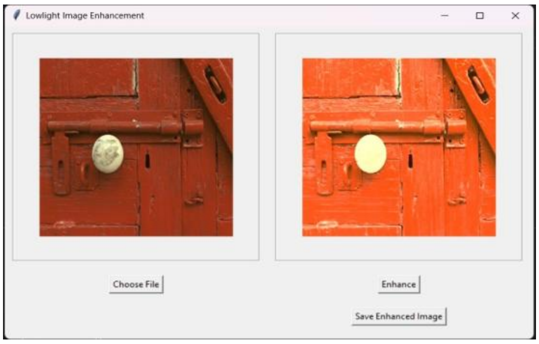

Figure 6 Door Lock Images.

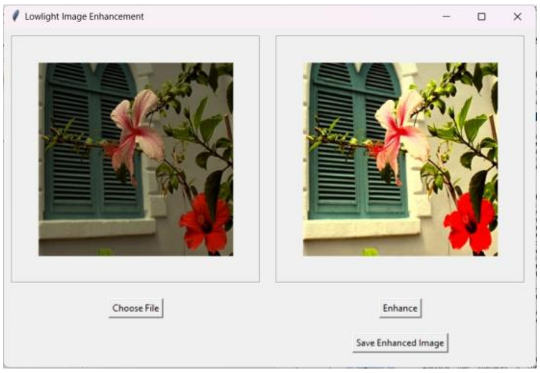

Figure 7 Flower Images.

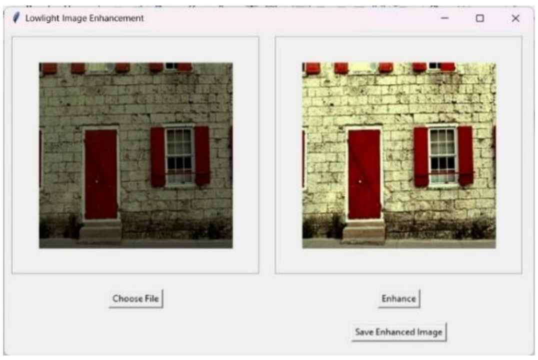

Figure 8 Wall Images.

5. Discussion

5.1. Limitations

While the proposed technique of colour transformation from RGB to CIELAB for low-light image enhancement can provide significant improvements in image quality, there are some limitations to consider. Firstly, this technique may not work effectively in extreme low-light conditions where the input image has very little information to begin with. In such cases, more advanced techniques may be needed. Secondly, the proposed technique may not work well with images that have a high dynamic range, as it relies on a specific range of luminance values for the enhancement process.

Another limitation is the absence of direct comparative evaluation with existing state-of-the-art methods such as Histogram Equalization (HE), LIME, and CNN-based approaches. These comparisons would provide stronger empirical evidence of the advantages of the proposed method but due to page limitations, these results could not be included in the current manuscript.

Lastly, the application of the technique might also involve technical skills and knowledge that would be beyond the ability of most individuals. The time to process large images might also be very long, and that would be a limitation for use in situations where every second counts.

5.2. Recommendations and Enhancement

Incorporating the use of the formula into more generalized colour spaces might offer a more generalized approach that can be applied to a greater diversity of uses. As a matter of instance, colour spaces HSL and HSV are extensively used for computer graphics and image-processing algorithms, and having the capability to apply such a formula to these colour spaces would be handy.

Apart from that, it would also be interesting to see how machine learning methods can be employed to further enhance the performance of the formula. With an ML model trained using a large dataset of low-light images, the model would then be able to learn to adjust the lightness component automatically without damaging the chroma and hue information in a more computationally efficient manner than the formula implementation. This can result in even superior outcomes and more precise adjustments.

Finally, it will also prove useful to give users a easy interface or software through which they can apply the formula to process their pictures with ease. This could be in the form of a plugin for image processing software or a web-based tool that allows users to upload and process their images online. Such a tool would make it easier for non-experts to use the formula and improve the brightness and clarity of their images.

6. Conclusion

The proposed application enhances the overall brightness of an image, allowing users to view objects more clearly with improved color representation. However, its current implementation is limited and performs effectively only on specific types of images. Therefore, further research is needed to expand its applicability to a broader range of image types. While brightness and color enhancement improve visual clarity, there are still limitations that need to be addressed in future work.

References

1. Pratt, W.K.: Digital Image Processing: PIKS Inside. John Wiley & Sons, Hoboken, 2007.
2. Wang, L., Zhao, L., Zhong, T., Wu, C.: Low-light image enhancement using generative adversarial networks. Sci. Rep. 14(1), 18489, 2024.
3. Feng, Y., Hou, S., Lin, H., Zhu, Y., Wu, P., Dong, W., Zhang, Y.: Difflight: integrating content and detail for low-light image enhancement. In: Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit., pp. 6143–6152, 2024.
4. Statista: Number of mobile phone users worldwide from 2019 to 2026 (in billions). https://www.statista.com/statistics/274774/forecast-of-mobile-phone-users-worldwide/ (2022). Accessed 15 Sept 2025.
5. Gonzalez, R.C., Woods, R.E.: Digital Image Processing. Pearson Education India, New Delhi, 2018.
6. Guo, X., Li, Y., Ling, H., Wu, J.: LIME: Low-light image enhancement via illumination map estimation. IEEE Trans. Image Process. 26(2), 982–993, 2017.
7. Chen, C., Chen, Q., Xu, J., Koltun, V.: Learning to see in the dark. In: Proc. IEEE Conf. Comput. Vis. Pattern Recognit., pp. 3291–3300, 2018.
8. Li, C., Ren, W., Fu, D., Tao, D., Feng, D.: LLNet: A deep autoencoder approach to natural low-light image enhancement. IEEE Trans. Image Process. 27(6), 2608–2622, 2018.
9. Chen, Z., Yang, J., Li, F., Feng, Z.: Real-time low-light image enhancement method for train driving scene based on improved Zero-DCE. In: Int. Conf. Electrical and Information Technologies for Rail Transportation, pp. 9–18. Springer, Singapore, 2023.
10. Ismael, A.N.: A comparative study of image enhancement techniques for natural images. J. Al-Qadisiyah Comput. Sci. Math. 14(4), 53–65, 2022.
11. Wang, Y., Wan, R., Yang, W., Li, H., Chau, L.P., Kot, A.: Low-light image enhancement with normalizing flow. In: Proc. AAAI Conf. Artif. Intell. 36(3), 2604–2612, 2022.
12. Atoum, Y., Ye, M., Ren, L., Tai, Y., Liu, X.: Color-wise attention network for low-light image enhancement. In: Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. Workshops, pp. 506–507, 2020.
13. Lore, K.G., Akintayo, A., Sarkar, S.: LLNet: A deep autoencoder approach to natural low-light image enhancement. Pattern Recognit. 61, 650–662, 2017.
14. Yu, X., Bo, L., Xin, C.: Low light combining multiscale deep learning networks and image enhancement algorithm. J. Image Video Process. 2(4), 0215–0232, 2022.
15. Tan, W.Y., Subaramaniam, K., Shibghatullah, A.S.B., Mansor, N.F.: Enhancement of low-light image using homomorphic filtering, unsharp masking, and gamma correction. Int. J. Adv. Comput. Sci. Appl. (IJACSA) 13(9), 53–60, 2022.
16. Baker, O., Li, W., Liu, D.: Advanced web optimization: Leveraging neural collaborative filtering and prefetching for enhanced user responsiveness. In: 2024 IEEE 7th Int. Conf. Electrical, Electronics and System Engineering (ICEESE), Kanazawa, Japan, pp. 1–6, 2024.
17. Baker, O., Li, W., Yuan, Q.: Advanced human motion detection and precision movement measurement via mobile devices using YOLOv8, R-CNN, and augmented reality. In: 2024 Int. Symp. Networks, Computers and Communications (ISNCC), Washington, DC, USA, pp. 1–6, 2024.
18. Baker, O., Rehman, A., Basas, O., Liu, J.: Deep learning for intelligent customer service automation: Development of GRU, LSTM, and recurrent neural network architectures for chatbot applications. In: 2024 Int. Conf. Inf. Technol. Res. Innovation (ICITRI), Jakarta, Indonesia, pp. 111–117, 2024.
19. Baker, O., Yuan, Q.: Machine learning: Factorization machines and normalized discounted cumulative gain for tourism recommender system optimisation. In: 2021 IEEE Int. Conf. Comput. (ICOCO), pp. 31–36, 2021.
20. Baker, O., Yuan, Q., Liu, J.: Collaborative filtering-based recommender system using ant colony optimisation for path planning. In: 2021 IEEE 5th Int. Conf. Inf. Technol., Inf. Syst. Electr. Eng. (ICITISEE), pp. 365–370, 2021.
21. Ping, C.O.Q., Hassan, M.F., Subaramaniam, K.: A study on the effectiveness of contrast adjustment function in website for color vision deficiency. AIP Conf. Proc., 2023.
22. Shaiden, A.S.M., Islam, S., Subramaniam, K.: Android based digital steganography application using LSB and PSNR algorithm in mobile environment. EVERGREEN – Joint J. Novel Carbon Resour. Sci. Green Asia Strategy 8(2), 421–427, 2021.

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