Enhancement of Unevenly Illuminated Images:an Experiment Based Review

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Abstract **– Low-lighting conditions pose significant challenges to captured images and result in degraded image quality, characterized by poor visibility, imbalanced illumination, increased noise, limited contrast, inaccurate colours, and loss of detail. In recent years, the development of effective low-light enhancement techniques has attracted considerable attention from researchers and practitioners in various fields, such as surveillance, photography, forensics, and medical imaging. This article comprehensively overviews advances in low-light image enhancement methods, techniques, and algorithms. This review summarizes the working mechanism for each reviewed algorithm, implements it, provides the results, and analyses them, highlighting the concept, advantages, and disadvantages. Overall, this review offers a comprehensive resource for researchers and practitioners interested in knowing the latest technologies and methods for low-light image enhancement. It provides insights into current challenges, promising solutions, and future directions for advancing the field of low-light imaging. Finally, it benefits various researchers by describing the available concepts, what pros to consider, and what cons to avoid when developing their algorithms.**

Keywords: Low-light, Image enhancement, Uneven illumination, Image processing.

I. Introduction

The importance of digital images lies in their ability to convey information, evoke emotion, and promote understanding in various contexts. As technology advances, the role of digital images in shaping our visual culture and communication dynamics is likely to increase further [17]. Mobile devices and digital and surveillance cameras rapidly evolve at hardware and software levels [18]. The increasing number of users worldwide and the number of images captured per second has resulted in most companies needing to use the best methods to solve software problems and competing to have the best program for the images captured by the camera, including image enhancement and image fileting [19]. Thus, image enhancement and restoration are essential subjects in image processing [1].

Image enhancement is one of the most essential techniques in image processing, and it is used to improve image quality for specific applications. Overall, the basic principle of image enhancement is to change the information contribution of an image to make it more suitable for a particular application [2]. Moreover, image enhancement algorithms and techniques are accustomed to recovering uneven illumination, pale colour, and noise reduction [3]. Preprocessing techniques applied to images, such as image enhancement and noise reduction, are a way to use a low-quality image as input, make it more precise and eye-catching, and improve quality.

Changes in the information content of images and their visual impact. The application of image enhancement methods enhances the features of the image. Image enhancement technology suppresses noise, protects image edges, and then improves them, smoothing an image to make it more suitable for further analysis or study [4]. Therefore, solutions have been made using low-light image enhancement methods to solve problems mentioned above of high-level computer vision tasks like object detection and image segmentation [20]. Illumination is lighting to create realistic images; the appearance of surfaces must be simulated under different lighting conditions. Low-light image enhancement is vital in digital imaging and computer vision. Images taken in low-light conditions almost suffer from noise, blur, and low brightness, which affects image clearness, color, and contrast in some cases, like underwater image environments [47] [48]. The leading causes of uneven image illumination are unstable lighting and uneven distribution of light produced. It is difficult to visually isolate the scene due to large objects and shadows from other objects [5].

In image processing, low light refers to a situation where the available lighting is insufficient to expose the photographed scene [6] fully. Insufficient light can result in poor image brightness, reduced contrast, and increased noise levels [7]. Poor lighting conditions can occur in various scenarios, such as [8], indoor environments with dim lighting [9], nighttime photography [10], underwater imaging [11], Even in specific outdoor settings at dusk or cloudy weather [12], threats in object and feature recognition that affect the vision system performance [49]. A lower signal-to-noise ratio (SNR) results from the camera's sensor receiving fewer photons in low light. Compared to photos taken in well-lit settings, those with this SNR reduction appear darker, have more digital noise, and have less detail [13]. Techniques for improving the visibility, contrast, and general quality of photos taken under such difficult lighting circumstances are called low-light image processing [14].

These methods could involve, among other things, colour correction algorithms [50], contrast enhancement, exposure adjustment, and noise reduction [15]. Low-light image enhancement aims to improve the visual effects of such images to facilitate subsequent processing [16] and improve the local and overall contrast of the image and its visual effect to make it suitable for human observation and computers [51]. The rest of the article is organized as follows: Section 2 explains various concepts of low-light methods in-depth and the results on different degraded images; Section 3 demonstrates the quality evaluation metrics, the dataset, the obtained results, and the associated analysis. Section 4 gives essential conclusions for this review.

II. Low-Light Methods

Different researchers have utilized various concepts for low-light image enhancement, including Histogram Equalization [21], Fusion [22], Retinex [23], Deep Learning [24], Multiscale Decomposition [25], Exposure Correction [26], fuzzy [27], statistical method [28], dynamic range manipulation [29], structural based- methods [30]. As for this low-light image enhancement, fifteen methods will be reviewed in the upcoming sub-sections, and Table 1 demonstrates a synopsis of the studied low-light enhancement methods.

A. Bright Channel Prior (BCP)

Fu et al. (2013) [31] proposed an algorithm using the bright channel prior (BCP). It starts with determining the lightness component using a specialized Gaussian filter. Next, a quadratic approach is implemented to detect the reflectance component. Then, a channel prior approach is utilized to improve the lightness and reflectance components further. Finally, a non-complex optimization approach is implanted to generate the output image. The results of this method can be seen in Figure 1.

Figure 1. Sample results of the BCP method

B. Improved Retinex (IR)

Fu et al. (2014) [32] developed an IR algorithm that converts the image into the HSV domain and then processes the V channel only. It begins by applying the Gaussian filter on the V channel. Next, an iterative process begins by applying an alternating optimization to determine the reflectance and illumination components and correct each component using min-max approaches. When the iterative processes end, the illumination part is adjusted using a simple sigmoid function, followed by adaptive histogram equalization for the final adjustment of the illumination component. The information is then converted to the RGB domain, and the output is generated. The results of this method can be seen in Figure 2.

Figure 2. Sample results of the IR method

C. Probabilistic Method (PM)

Fu et al. (2015) [33] introduced a new probabilistic method with the core idea of utilizing linear regions for better enhancement. First, the probabilistic model uses a maximum posteriori (MAP) approach to estimate reflection and illumination in the linear domain. Then, logarithmic transformations are utilized for better reflectance and illumination estimation. Lastly, the MAP approach is employed for improved decomposition and then transformed to the alternating direction of the multipliers process for better estimation to produce the output. The results of this method can be seen in Figure 3.

Figure 3. Sample results of the PM method

D. Weighted Variational Model (WVM)

Fu et al. (2016) [34] introduced a WVM algorithm that converts the image to the HSV domain and only processes the V channel. Then, the V channel is decomposed into illumination and reflectance components using a customized variational model. Next, an optimization procedure is applied to minimize the energy and find the optimal illumination and reflectance that best fits the V channel. Next, weighting factors are incorporated into the variational model to balance the processing influence of different channel regions. Lastly, the information is converted to the RGB domain, and the output is generated. The results of this method can be seen in Figure 4.

Figure 4. Sample results of the WVM method

E. Physical Lighting Model (PLM)

Yu et al. (2017) [35] proposed a physical lighting model (PLM) based algorithm that involves four distinct phases. The first is applying an environmental light (EL) model to determine the ambient light. The second is determining information loss locally according to EL and light diffusion (LS) specifications. The third is a fine-tuning step that utilizes EL and LS information. Finally, different weighted bootstrap filters are applied to generate the output image. The results of this method can be seen in Figure 5.

Figure 5. Sample results of the PLM method

F. Camera Response (CR)

Ren et al. (2018) [36] proposed a camera response (CR) based algorithm wherein the CR model is selected, and its parameters are identified as a first step. Next, the illumination map is determined by calculating the input's exposer ratio. The final image is generated using the information mentioned earlier using a specialized function. The results of this method can be seen in Figure 6.

Figure 6. Sample results of the CR method

G. LightenNet (LNET)

Li et al. (2018) [37] developed an LNET algorithm that begins by inputting the low-light image into the trained LNET CNN. Next, the input is forward propagated to the network, and the successive layers are extracted from the input image. After that, the image is enhanced using the final network layer using a regression-based approach. The output is obtained from the network's production. The results of this method can be seen in Figure 7.

Figure 7. Sample results of the LNET method

H. Adaptive Image Enhancement (AIE)

Wang et al. (2019) [38] suggested an adaptable low-lighting picture expansion method based on an existing Multiscale merge. Although saving this detail from this picture, this suggestion method Balances this color more than this picture and discovers details that used to be Before the invisible dark area, immensely improving this picture's quality. First, convert the original RGB color image to HSV color spatial. The V component is used to extract lighting components via multiscale Gaussian functions. Then, a correction function based on the Weber- Fechner law is created, and two images are obtained using the adaptive method. Adjust the parameters of the image enhancement function Distribution profile based on lighting components. Finally, an image fusion strategy is used to extract the details of two images. The proposed algorithm balances the colors of the entire image. The results of this method can be seen in Figure 8.

Figure 8. Sample results of the AIE method

I. Gradient-Based Enhancement (GBE)

Tanaka et al. (2019) [39] proposed a gradient-based model (GBM), which first changes the input to the luma-chroma color domain. Then, the gradient of the brightness part is extracted through special processing to improve the visibility of details in the dark part of the image. Next, filter the gradient to enhance detail. A final integration operation considering a finite area is then performed to create the output image. The results of this method can be seen in Figure 9.

Figure 9. Sample results of the GBE method

1J. Variational bright channel prior (VBCP)

In 2019 [40], Fu et al. proposed a VBCP algorithm that stars by converting the received image from the RGB to the HSV domain. Wherein only the V channel is processed by the Retinex theory. The reflectance and illumination of the V channel are computed in that the reflectance is determined using the L2 norm process while the illumination is determined using the Lp. Once these components are determined, they are sent to an energy minimization function for refinement. These processes are repeated a number of times, and the output image is generated once done. The results of this method can be seen in Figure 10.

Figure 10. Sample results of the VBCP method

K. Retinex-Based Multiphase (RBMP)

In 2020 [41], Al-Hashim et al. developed an RBMP algorithm that receives the image in the RGB domain with a tuning parameter. Next, a Gaussian function is computed with the log of the illumination and the input images. After that, a modified subtraction process is applied to determine the reflectance image. The final image is created using two post-processing approaches: gamma correction and range expansion. The results of this method can be seen in Figure 11.

Figure 11. Sample results of the RBMP method

L. Global Local Adaptive Gamma Correction (GLAGC)

Yu et al. (2021) [42] introduced a GLAGC algorithm in which the DWT separates the input image into four sub-bands. Then, the quality of the low-low band is improved via adaptive gamma correction that considers the image's statistical and spatial properties. Adaptive punishment adjustment is used for the high-frequency sub-band to preserve naturalness. Ultimately, a stability factor is created for color restoration to use noise suppression to account for the extra low illumination and generate the output image. The results of this method can be seen in Figure 12.

Figure 12. Sample results of the GLAGC method

M. Triangle Similarity Criterion (TSC)

Hassan et al. (2022) [43] developed a hue-preserving uniform illumination triangle similarity-based algorithm. The two primary processes comprising the suggested technique are the intensity and saturation increases. While the saturation improvement uses a scaling operation to improve the saturation component, the intensity enhancement uses a linear translation operation to enhance the intensity component. The hue component is preserved, and the output image is generated by converting from the HSI to the RGB domain. The results of this method can be seen in Figure 13.

Figure 13. Sample results of the TSC method

Table 1. Synopsis of the studied low-light enhancement methods

No.	Researcher / Year	Concept	Complexity (RT)	Advantages	Disadvantages
1.	Fu et al. 2013	Bright Channel Prior	Average	Illumination increase	Improper colours with brightness amplification
2.	Fu et al. 2014	Improved Retinex	low	Adequate illumination equalization	Poor contrast
3.	Fu et al. 2015	Probabilistic Method	Lowest	Fast processing with decent illumination	Insufficient contrast
4.	Fu et al. 2016	Weighted Variational Model	Highest	Adequate sharpness and colour quality	Poor contrast
5.	Yu et al. 2017	Physical Lighting Model	High	Ability to improve the illumination	Colour distortions and noticeable halos
6.	Ren, Y. et al. 2018	Camera Response	Above low	Can choose a response model	Dark appearance with washed-out colours
7.	Li et al. 2018	LightenNet	Above high	Adequate contrast	Further illumination is needed
8.	Wang et al. 2019	Adaptive Enhancement	below average	Produces the best illumination quality	Apparent artifacts around the edges
9.	Tanaka et al. 2019	Gradient	Below high	New processing concept	Creates halo and saturation artifacts with improper colours
10.	Fu et al. 2019	Variational Bright Channel Prior	Very high	Supports acceptable sharpness	It needs further illumination and contrast adjustment
11.	Al-Hashim et al. 2020	Adapted Retinex	Below low	Low complexity and produced adequate illumination	It needs further colour adjustment
12.	Yu et al. 2021	Global Local Adaptive Gamma Correction	Very low	Can equalize the illumination	Inadequate contrast
13.	Hassan et al. 2022	Triangle Similarity Criterion	Above average	Sufficient illumination	Artifacts generation

III. RESULTS AND DISCUSSION

This part of the study demonstrates several aspects, including the dataset, the quality evaluation metrics, the attained results, and the related analysis. The dataset of this study is collected from four different sources. The first source is a collection of digitized standard images collected from various appropriate databases. The first dataset is taken from https://data.csail.mit.edu/graphics/fivek/. The MIT-Adobe FiveK Dataset is an online repository that contains 5,000 photos taken by different photographers using DSLR cameras. All these images are in RAW format, meaning all information recorded by the camera sensor is retained. The second dataset type is a self-collected dataset from different mobile devices such as iPhone 7, iPhone 13 ProMax, Samsung A36, and Galaxy Ultra 20. The images for all types are colored photos with different sizes, for example, a minimum of 2000*2000 pixels.

Images collected from MIT-Adobe FiveK Dataset a DNG format is the abbreviation of Digital Negative Format and is a universal RAW image format developed by Adobe. RAW files, also known as digital negatives, are a lossless format that captures uncompressed data from a camera. The evaluation metrics utilized in this study are three: lightness order error (LOE) [44], natural scene statistics (NSS) [45], and blind tone-mapped quality index (BTMQI) [46] are three sophisticated metrics used to assess the results of the reviewed methods. First, the illumination naturalness is assessed using the reduced-reference (RR) method called LOE. Second, contrast naturality is measured using the no-reference (NR) NSS method. The NR technique that evaluates structural naturalness is the third, called BTMQI. All the evaluation techniques employed produced a numerical result, whereas for LOE and BTMQI, a lower value was better. For NSS, a higher value is better. In addition, the runtimes are considered as a complexity indicator.

The reviewed methods are classified into 13 ranks: worst, very low, below low, low, above low, below average, average, above average, below high, high, above high, very high, and best. The used computer has specs. The MATLAB R2018a environment on a computer has been utilized for all experiments concerning hardware specifications and programming environment. The review results are demonstrated above in Figure 1 to Figure 13. Moreover, the numerical results of the utilized metrics and their average readings are given in Table 2 to Table 5. The average readings represented by charts are shown in Figure 14 to Figure 17.

According to the results, the BCP method produced deficient illumination, improper contrast, and abnormal colours, yet delivered acceptable sharpness. Therefore, it scored the worst readings according to LOE and NSS with above-average BTQMI and average runtime, ranking 8th among the competitors. The IR method delivers results with normal illumination, low contrast, amplified noise, and inaccurate colors. Therefore, it scored below average according to LOE, low according to NSS and BTQMI, with average runtime, ranking 7th among the competitors. The IR method has processed the illumination properly but has improper contrast, but it produces acceptable colours and sharpness. The PM method introduced respectable illumination, acceptable contrast, natural colours, and sharpness. That's why it is recorded below low for LOE and BTQMI above high for NSS. For processing time, it ranked the best among all other reviewed methods.

Table 2. The RT↓ scores

No	Methods	A36	iPhone7	iPhone13	MIT	Average
1	BCP	35.6935	33.2952	36.2832	27.8498	33.28043
2	IR	5.23499	5.4131	5.4015	4.5563	5.151473
3	PM	0.00027	0.00013	0.00012	0.00013	0.000163
4	WVM	535.1041	426.0413	750.5990	999.5426	677.8218
5	PLM	151.8835	163.3991	185.0226	136.2425	159.1369
6	CR	9.235091	7.961031	9.4079	6.9925	8.399131
7	LNET	190.2477	183.1182	195.1725	153.8157	180.5885
8	AIE	16.28327	19.3065	15.5360	12.9293	16.01377
9	GBE	136.2964	76.1545	91.3762	29.1815	83.25215
10	VBCP	371.1784	139.4534	412.8944	125.8787	262.3512
11	RBMP	3.915894	3.8195	3.8658	3.1975	3.699674
12	GLAGC	3.756283	3.6489	3.6654	3.1614	3.557996
13	TSC	37.19157	38.2953	39.0750	27.7790	35.58522

Table 3. The LoE↓ scores

No	Methods	A36	iPhone7	iPhone13	MIT	Average
1	BCP	1968.8	2150.3	1632.5	1,808.6	1890.05
2	IR	770.4018	45.3003	319.1367	339.8255	368.6661
3	PM	134.8700	75.3890	121.3854	157.4842	122.2822
4	WVM	160.4182	66.7254	181.2042	96.0171	126.0912
5	PLM	1135.9	1,069.8	1098.6	1037.5	1085.45
6	CR	1,076	552.1158	668.9063	499.1126	699.0337
7	LNET	588.4697	919.5994	470.3209	1,073.2	762.8975
8	AIE	120.6533	45.3003	111.0501	63.0005	85.00105
9	GBE	1033	270.7713	1,376.5	104.2945	696.14145
10	VBCP	495.7218	285.0928	358.5185	264.2463	350.89485
11	RBMP	122.5424	49.2666	128.8558	56.1603	89.206275
12	GLAGC	346.3739	205.4281	181.2919	266.6103	249.92605
13	TSC	292.7224	259.5922	224.5287	92.2624	217.276425

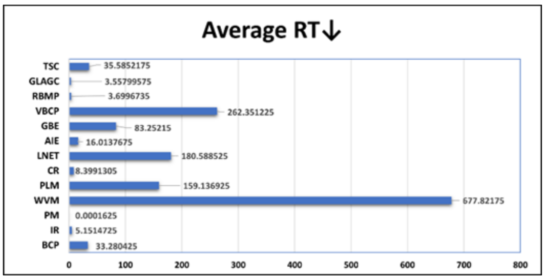

Figure 14. Average RT readings

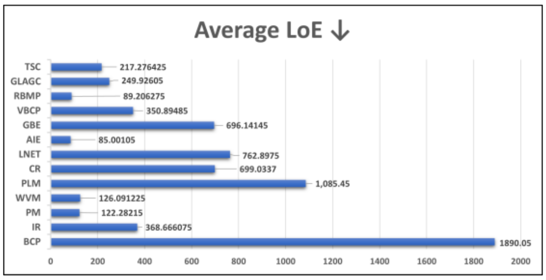

Figure 15. Average LoE readings

The WVM method provided acceptable results for illumination but improper contrast with sufficient naturalness. For this reason, it scored low in the LOE metric, above low in NSS, and very low in BTQMI. On the other hand, the PLM algorithm has insufficient results in general. It introduced different illumination errors, insufficient contrast, incorrect colours, and sharpness, and noticed haoles around some images. Therefore, its LOE NSS is unsatisfactory (high and very low). For BTMQI, it is ranked the least. The processing time is high.

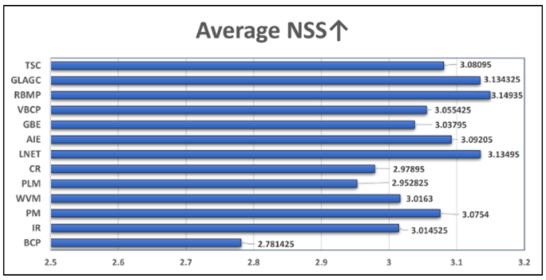

Figure 16. Average NSS readings

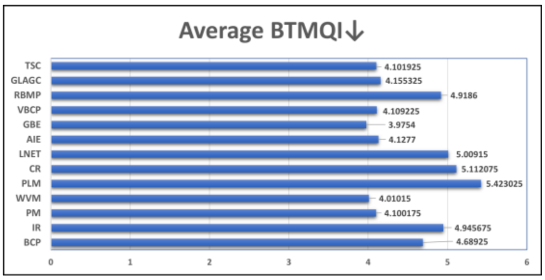

Figure 17. Average BTMQI readings

The CR method yielded results with acceptable illumination, improper contrast, washed-out colours, and sharpness that needed to be more accurate with general artifacts like noise. The process time is considered above low. Thus, it is scored below high, with LoE below low for NSS and very high for BTMQ. The LNET algorithm improved images with unsatisfactory results for illumination and naturalness like halos around edges and presenting incorrect colour appearance. However, the contrast attribute of this method is sufficient. Therefore, it is scored above high for LoE, very high for NSS, and above high for BTMQI. In addition, it scored above high for processing time.

Table 4. The NSS↑ scores

No	Methods	A36	iPhone7	iPhone13	MIT	Average
1	BCP	3.0880	2.1199	3.3965	2.5213	2.781425
2	IR	3.3659	2.3729	2.8828	3.4365	3.014525
3	PM	3.4400	3.2319	2.7313	2.8984	3.0754
4	WVM	3.4216	3.2195	2.8180	2.6061	3.0163
5	PLM	3.4381	2.3163	2.7116	3.3453	2.952825
6	CR	3.4703	2.6688	3.1824	2.5943	2.97895
7	LNET	3.4482	2.7965	2.9202	3.3749	3.13495
8	AIE	3.4630	3.3751	3.2525	2.2776	3.09205
9	GBE	3.5339	3.0800	2.6146	2.9233	3.03795
10	VBCP	3.4401	3.2436	2.8015	2.7365	3.055425
11	RBMP	3.4504	3.3476	3.2251	2.5743	3.14935
12	GLAGC	3.4554	3.3538	3.4055	2.3226	3.134325
13	TSC	3.4294	3.1481	2.7676	2.9787	3.08095

Table 5. The BTMQI↓ scores

No	Methods	A36	iPhone7	iPhone13	MIT	Average
1	BCP	2.8909	5.8645	5.3807	4.6209	4.68925
2	IR	5.3861	5.3861	5.2183	3.7922	4.945675
3	PM	2.9902	5.1983	4.7595	3.4527	4.100175
4	WVM	2.7335	4.1792	4.8545	4.2734	4.01015
5	PLM	4.9213	5.4717	5.8155	5.4836	5.423025
6	CR	4.2009	5.1498	5.9253	5.1723	5.112075
7	LNET	3.9850	5.3967	5.3764	5.2785	5.00915
8	AIE	2.9352	4.2046	5.2763	4.0947	4.1277
9	GBE	2.8210	3.6652	5.2809	4.1345	3.9754
10	VBCP	3.3334	3.7262	5.4616	3.9157	4.109225
11	RBMP	3.9152	4.9348	5.0771	5.7473	4.9186
12	GLAGC	1.7734	4.6906	4.4881	5.6692	4.155325
13	TSC	2.7775	5.8007	4.5179	3.3116	4.101925

The AIE method candied the best for providing sufficient illumination. The result showed an insufficient contrast with dimmed colour and some artifacts like noise and sharpness that could have presented better, in addition to no apparent smooth edges. For this reason, it scored best for LoE, high for NSS, and below average for BTMQI. The processing time is scored as below average. The GBE algorithm introduces the best naturalness and visual details. On the contrary, it provides error illumination and insufficient contrast. Thus, it scored high in LoE, below average for NSS, and best for BTMQI. This method scored below high for runtime.

The VBCP method introduced reasonable results for illumination and contrast, but it also had some artifacts like noise and faded colours. Therefore, it scored average in LoE, average in NSS, and above low for BTNQI. In terms of processing time, it scored very low. The RBMP method provides sufficient results for both illumination and contrast. On the other hand, there are drawbacks, such as washed-out colours. It could have delivered more adequate sharpness. So, it scored very low in LoE, was best in NSS, and was below high in BTMQI. According to the processing time, it has fast performance and a higher score. The GLAGC method produces acceptable brightness (illumination) and proper contrast, but some artifacts, like dimmed colour and improper sharpness, are unacceptable.

Thus, this method scored below average in LoE, above high in NSS, and above average in BTQMI. This method scored very high for processing time, which is considered second best among all the reviewed methods. The last reviewed method was the TSC, and its result showed that it has proper illumination quality and contrast, and some artifacts were noticed through some images, such as halos and noise. Therefore, it is scored above low in LoE, below high in NSS, and low in BTMQI. It scored above average processing time, which is reasonable.

IV. CONCLUSION

To conclude, thirteen state of art algorithms for low-light images have been reviewed in this paper. Each method was addressed and explained with its mechanism. Different data images were tested using each method, and the results were given accordingly.

A synopsis table of these low-light enhancement methods has been written and contains each method's method, year, author name, concept, and pros and cons. The data was taken from different sources. The first one is a website that specializes in natural images. The second source is different mobile devices such as the iPhone 7, iPhone 13, Galaxy A36, and Galaxy Ultra 20. The implementation time of each method and each tested image was recorded and reviewed in a table with the rate of the implementation time. Then, three advanced methods were used to measure the accuracy of the images used for each method, and all results were listed in a table and charts with the determined readings. Finally, all these results were analyzed according to the performance of each method in terms of implementation time and accuracy of the method in terms of illumination, contrast, and naturalness.

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