Convolution neural network model for fundus photograph quality assessment

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ABSTRACT

The excellent quality of color fundus photograph is crucial for the ophthalmologist to process the correct diagnosis and for convolutional neural network (CNN) models to optimize output classification. As a result of main causes as acquire devises efficiency and experience of a physician most fundus photographs can have uneven illuminance, blur, and bad contrast, in addition to micro-features of retinal diseases, which need to force their contrast. Fundus photograph quality assessment method is proposed to find out the perfect enhanced color fundus Technique in fundoscopy photographs-based CNN model. Five photograph quality measurements, in addition to five CNN metrics, were used as standard in this study. In this research innovative approach combining photograph quality measurement and CNN metrics analysis is proposed to find out the best enhance method that is set for the multiclass CNN model. The contrast enhancement techniques are evaluated using 267 color fundus photographs divided into three retina diseases cases were downloaded from the open-source database "FIGSHARE". The study outcome showed that the presented system (single-CNN) can determine well the contrast enhancement method, as well as the low-quality fundus photograph then it can boost CNN metrics to achieve superior.

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1. INTRODUCTION

Fundus photographs are one of the most shared eye ailments photographs that are used for diagnosis, identification, and classification of retina illness conditions [1]. Retinal tomography is extensively used in the medical judgment of visual illnesses, for instance, diabetic retinopathy, cataract, age-related degeneration, and glaucoma. Especially the fundus photographs of diabetic retinopathy are used for identifying the onset symptoms of illness conditions such as (hard-exudates, red-lesions, and cotton-wool spots) that may lead to blindness [2]. In 2015, 0.4 million patients are partially blind while 2.6 million patients suffered from critical vision weakness because of diabetic retinopathy [3]. Furthermore, diabetic retinopathy is the main reason for vision loss among patients whose age range is 20–74 years [4] in third world countries such as Malaysia, Indonesia, and Iraq. It has gained the interest of researchers to develop different artificial intelligence (AI) models to identify the retinopathy symptoms and classify them accurately [5]-[12]. Both ophthalmologists and the AI model require good quality fundus photographs to produce accurate diagnosis results. However, several factors could affect the fundus photograph's quality during the acquiring process, such as reflection, diffusion, and refraction of light in eye lenses, artifacts of camera noise that is caused by the unstable power supply, and movement of the camera [13]. Therefore, it is required to preprocess those fundus photographs which include contrast-enhancing to solve the aforementioned problems before conducting further analysis. Various contrast enhancement techniques for medical photographs have been presented depending on the domain requirement such as median filter, sharpening, and filters-based histogram equalization [14]-[19]. Diabetic retinopathy could damage the fine retina vessels, cause bleeding, form blood spots on the retina with a variety of sizes along the illness period and eventually cause blurring vision. It is crucial to develop a very impressive method to enhance contrast visuality on those fine details to help the ophthalmologist or the AI for accurate diagnosis [20], [21]. In this study, many contrast enhancement methods have been compared. Their performance in improving the classification accuracy by the convolutional neural networks (CNN) was studied. The procedure started with pre-selections of the best contrast enhancement methods in the image quality assessments. The enhancement techniques with decent performance would be applied to understand their contributions in improving the classification by the CNN model. Generally, this study is designed to study the relevance of various contrast enhancements in boosting the CNN in classifying the diseased photographs into their respective cluster.

Levels and low levels. Moreover, pre-processing the contrast between the vessels and the background of the retina can boost the segmentation of the vessels in the following stage [22]. Image enhancement is a stage to map the distribution of the pixels to a new level to achieve the desired contrast level. Nonetheless, not all the enhancement techniques deliver pleasant enhancement. As the accuracy of CNN classification of the fundus image strongly depends on the quality of the resulting image, the choice of enhancement technique is crucial.

Histogram equalization is a simple and easy method but tends to over-enhance the image [23]. Pizer *et al.* [24] uses histogram equalization and data augmentation in a CNN-based emotion recognition system and achieve an accuracy of 78.52%. An improvement of histogram equalization, namely adaptive histogram equalization (AHE), was introduced by Wang *et al.* [25]. AHE divides the image into specified tiles and computes them respectively so that the lightness value of the image can be redistributed evenly at its respective tiles. AHE-based hybrid CNN model is widely utilized in digital dental X-ray position classification [26]. However, AHE is susceptible to noise amplification, typically in relatively homogeneous regions in an image. Pizer later improved the AHE by limiting the amplification, hence it was called contrast-limited adaptive histogram equalization (CLAHE) [27]. The implementations of CLAHE in CNN models include the classification of mammograms [28], improved facial expression [29], and early detection of skin cancer [30]. A novel CLHAE called upgraded CLAHE that is adaptive clip limit-CLAHE (ACL_CLAHE), through solving the drawbacks of (CLAHE) which is belong to predefined clip limit value that either cause intensive enhancement leads to adding more artifacts or weak enhancement, the author proposed to replace the predefine climb limit value with global thresholding dividing by 80 constant [21]. These according to the writer shows a big improvement in fine details of fundus photographs and boost the CNN performance better than the conventional (CLAHE).

In 1997, Kim [30] introduced the preservation of the mean brightness of the phtotgraph method, bi-histogram equalization (BBHE) that provides a natural look of the image. In 1999, Wang *et al*. [31]. proposed an extension of BBHE, equal area dualistic sub-image histogram equalization (DSIHE), which partitions the histogram based on the median threshold value. The minimum mean brightness error Bi-histogram equalization (MMBEBHE) attempted to output the enhanced image which gave the lowest absolute mean brightness error [32]. However, its application in processing medical photographs remained unknown. Turgay proposed to consider the contextual information in transformation curve generation [33]. Therefore, a 2-dimensional histogram, which consisted of the original mapping curve and its mutual relationship between the targeted pixel and the surrounding pixels, was generated instead of single distribution as applied in the other state- of-arts methods. The amount of contextual information relied on the window size where more information would be referred to when the bigger window was applied.

According to Yin *et al*. [33] introduced Bi-histogram bezier curve contrast enhancement (BBCCE) in magnetic resonance imaging (MRI) knee photographs that aims to improve the contrast between the knee cartilage and tissue background. Later, Teh *et al*. [34] introduced an extension of BBCCE, namely prominent region of interest contrast enhancement (PROICE), which is an explicitly designed technique to process the knee MRI. Therefore, PROICE attempted to improve the distinctiveness of the cartilages instead of the whole image. Despite BBCCE and PROICE, several techniques are being introduced to enhance medical photographs while retaining the important details in the photographs, such as gamma correction adaptive extreme-level eliminating with weighting distribution (GCAELEWD) [35], tuned single-scale retinex (TSSR) [36], and tuned brightness controlled single-scale retinex (TBCSSR) [37]. GCAELEWD was created to improve brain CT images by removing the extreme intensity levels, and the degree of augmentation was determined by the weight of the intensities. The local HE method was prone to cause blocking effect thus required additional interpolation to eliminate the effect between the sub-tile. Meanwhile, TSSR and TBCSSR were kernel-based methods that could improve the photographs promptly. The kernels were designed experimentally and statistically. These techniques altered the image brightness with a controllable parameter, lambda. Generally, a higher lambda value tends to adjust the image to a higher degree, and vice versa. However, the author claimed that TBCSSR offered greater flexibility in improving photographs at a higher degree of enhancement without causing saturation effect, which could be expected in TSSR.

According to the results of both the traditional image quality assessment (IQA) and the eye vision evaluation, the previous studies showed evidence on enhancing image contrast while also showing weakness. However, just because you get a strong quality score with traditional IQA doesn't indicate you'll get better computer vision. As a result, unveiling a new picture quality evaluation approach that can suggest the best image quality and improve CNN output prediction is critical, as is establishing the best enhancement method for the CNN model. To address the flaws in previous research, In comparison to standard IQA, this study shows how to employ deep learning to build single-CNN as an image quality evaluation. In addition, test the proposed CNN-IQA on a multiclass fundus detection system by identifying which images with poor quality should be enhanced and comparing them to traditional full enhancement techniques to show that it can boost CNN performance.

2. METHOD

The present study proposed a single-CNN model for comparing various contrast enhancement methods and the techniques with good achievements in assessments will be applied to improve the fundus photographs of three diabetic retinopathy diseases. The enhanced photographs were input into a trained CNN model to evaluate their performance and their contributions in classification improvement were identified. The main dataset used in this study was collected from the FIGSHARE database that provides photographs for the valuation and comparison [36]. A total of 267 samples for three classes (hard-exudates, red-lesions, and cotton-wool spots) were collected and then grouped into the respective cluster according to the annotation conducted by experienced specialists. Figure 1 shows the overall framework of the proposed study.

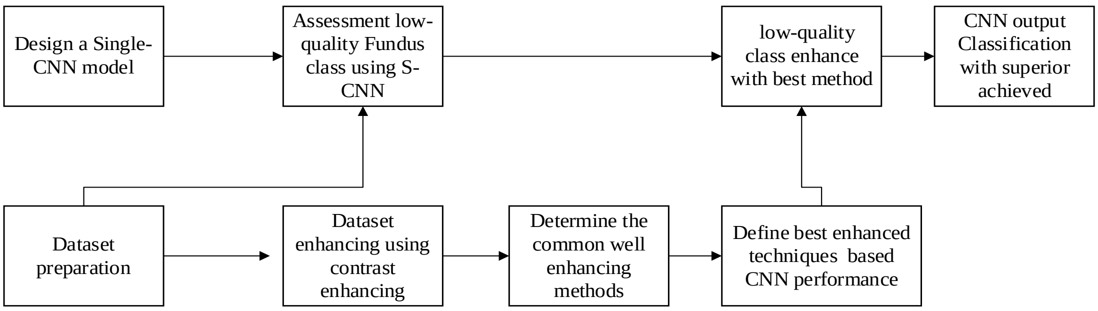

Figure 1. The workflow of the proposed system is identifying the best contrast enhancement techniques to assist the CNN model

2.1. Pre-processing contrast enhancement methods

A color retinal fundus photographs are commonly influenced by various factors, for instance, the blurring effect initiated by the cataract [36], [37], noises caused by electrical switching from neighborhood equipment [3]. The selected fundus photographs were enhanced with contrast enhancement techniques [38], such as TBCSSR, TSSR, MMBEBHE, CLAHE, BBHE, DSIHE, and 2DHE. The performance of the techniques was evaluated with image quality assessments (IQA), such as enhancement measure (EME), peak signal-to-noise ratio (PSNR), root mean square error (RMSE), image quality indicator (IQI), and minimum absolute error (MAE). The enhancement methods are comprised of TBCSSR, TSSR, BBHE, DSIHE, BBCCE, 2DHE, MMBEBHE, CLAHE, and ACL-CLAHE. The result of the compared contrast enhancement methods was summarized in Tables 1-5.

Table 1. Different contrast enhancement approaches yielded EME values

Photographs	Contrast enhancement techniques						
	TBCSSR	TSSR	MMBEBHE	CLAHE	BBHE	DSIHE	2DHE
Normal	4.29	3.15	19.758	17.73	23.27	20.42	28.27
Cotton-wool spot	3.58	2.13	17.676	15.69	18.14	18.82	27.39
Hard exudate	3.92	2.46	12.385	16.62	17.16	13.07	25.43

Table 2. PSNR (dB) values for various contrast enhancement methods as a result

Samples	Contrast enhancement techniques							
	TBCSSR	TSSR	MMBEBHE	CLAHE	BBHE	DSIHE	2DHE	BBCCE
Normal	20.19	22.48	14.82	24.25	12.76	17.43	13.43	17.84
Cotton-wool spot	16.331	23.86	15.12	26.58	13.02	16.89	13.27	18.26
Hard exudate	15.070	27.58	16.25	26.36	13.57	17.26	13.84	18.07

Table 3. RMSE values are achieved by different contrast enhancement techniques

Samples	Contrast enhancement techniques							
	TBCSSR	TSSR	MMBEBHE	CLAHE	BBHE	DSIHE	2DHE	BBCCE
Normal	127	2.61	42.13	12.77	21.59	66.62	2.89	0.06
Cotton-wool spot	127	2.47	46.45	12.47	22.29	67.70	3.86	0.03
Hard exudate	128	4.24	50.68	22.48	22.38	64.82	3.60	0.03

Table 4. IQI measurements were obtained using various contrast enhancement techniques

Samples	Contrast enhancement techniques							
	TBCSSR	TSSR	MMBEBHE	CLAHE	BBHE	DSIHE	2DHE	BBCCE
Normal	0.44	0.49	0.71	0.61	0.44	0.61	0.44	0.76
Cotton-wool spot	0.34	0.50	0.70	0.62	0.44	0.69	0.45	0.78
Hard exudate	0.30	0.51	0.70	0.62	0.46	0.60	0.46	0.78

Table 5. MAE values as a result of various contrast enhancement techniques

Samples	Contrast enhancement techniques							
	TBCSSR	TSSR	MMBEBHE	CLAHE	BBHE	DSIHE	2DHE	BBCCE
Normal	18.269	1.058	8.505	1.222	2.061	14.07	0.34	0.012
Cotton-wool spot	28.099	1.022	9.812	1.253	2.433	15.30	0.42	0.005
Hard exudate	32.362	1.262	10.511	2.239	2.238	14.25	0.42	0.007

The MATLAB program was used to calculate the data in Tables 1-5. The superior contrast enhancement approaches can be identified with their achievements in different assessments, based on the value of these methods that have good scores the enhancement approach has been selected. The chosen techniques, namely TBCSSR, MMBEBHE, BBCCE, DSIHE, and 2DHE, according to their performance derived from Tables 1-5. The ACL-CLAHE, which is a novel filter, is an improved algorithm from the conventional CLAHE by replacing the fixed clip limit with an adaptive clipping mechanism that utilizes a global threshold method.

2.2. Enhancement based on single CNN

In this section, a CNN model was established to classify the diseased fundus photographs, including raw photographs and enhanced photographs [39]. The CNN model applied in this study comprised of convolution layers with a depth of 4, the kernel filter's size (3*3), the max-pooling layer with a scope of 2*2. The last layer was a fully connected dense layer, which attempted to convert the soft-max activation into 1×6 vectors in the base model and was finally suited to 1×2 vectors. CNN performance can be evaluated with the three metrics, which are output classification accuracy (ACC), precision, sensitivity (Sen), specificity (Spe), and F-Score. According to (1)-(5) calculate these CNN metrics [4]:

$$ACC = \frac{(T_N+T_P)}{(T_N+F_P+T_P+F_N)} \quad (1)$$

$$Prec = \frac{T_p}{(T_p+F_P)} \quad (2)$$

$$Sen = \frac{T_P}{(T_P + T_N)} \tag{3}$$

$$Spe = \frac{T_N}{(T_N + F_P)} \tag{4}$$

$$F - Score = \frac{T_P}{T_P + \frac{1}{2}(F_P + F_N)} \tag{5}$$

Table 6 presented the comparison of single CNN performance values based on using or not the enhancement method. besides, it can be seen that using an elective enhancement approach could boost the CNN performance. The output value 93% has been chosen as a median value among the values (89, 92, 93, 95, 89), so the enhancement process will apply to the two classes only (cotton-wool spots, and hard-exudates). Finally, the choice to apply enhancements corresponding to weaker classes resulted in a profit for them.

Table 6. Single CNN classification accuracy comparison table

Dataset class	Note:1 for enhanced,0 for raw							
Cotton-wool spots	0	1	0	1	0	1	0	1
Hard-exudates	0	0	1	1	0	0	1	1
Red-lesions	0	0	0	0	1	1	1	1
Average of output classification %	65	98	94	93 1st chosen value	95	89	92	72

2.3. Transfer learning

When huge data samples (i.e., photographs) are involved, there will be some parameters in CNN layers to be considered [40], [41]. However, small datasets will cause overfitting [40]. To overcome both the overfitting problem and fine-tune the pre-trained CNN models, the deep transfer learning concept was used. Transfer method can be mathematically expressed as A field and D field, which entails the feature zone, X, and peripheral probability, P(X), where X is a sample data point. Thus, the domain can be expressed mathematically as D=(X, P(X)). Hence, transfer learning is defined as shown in:

$$T = \{\gamma, p(Y|X)\} = \{\gamma, \eta\} \tag{6}$$

$$Y = \{y_{1,..,}y_n\}, y_i \epsilon\, \gamma \tag{7}$$

where γ is a label space, η is the predictive label learned from feature weights vector (x_i, y_i).

Undeniably, training a network from scratch was beneficial in terms of their ability to distinguish multiclass fundus photographs [42], [43]. Nonetheless, a transfer learning approach has been applied to determine the fitting number of classification layers that greatly shorten the training time and allow the CNN to attain a strong performance of fundus classification [42], [44], [45]. The deep fully connected layer was modified from 1000 classes to classify the photographs into three classes (with diabetic retinopathy symptoms) as mentioned above. In this study, For the suggested multiclass retinal diagnostic model, the VGG19 network was used. The choice was made due to the previous studies that reported that the VGG19 net could optimize the classification and detection of diseases from the medical photographs and ECG waveform [18], [46], [47].

3. RESULTS AND DISCUSSION

Photograph enhancement is crucial to highlight fine details, eliminate noise and elevate overall brightness. These contributions potentially boost CNN performance. The constructed system was thoroughly evaluated employing a variety of statistical assessment measures, including output classification accuracy (ACC), precision (pre), sensitivity (Sen), and specificity (Spe), as well as the F-factor. The full method is employing the contrast models on the fundus of the three classes while the selecting enhancement method is on the determined fundus classes.

Table 7 presented the experimental results obtained by the proposed multiclass model using the pre-trained VGG19 net that was fed with the pre-processed dataset, which shows that the classification finding in terms of accuracy, sensitivity, specificity, precision, and F-score, despite all classes had been enhanced with the best-chosen contrast-enhancing techniques according to results of quality test algorithms but still in range of 60%. Finally, using ACL-CLAHE shows the highest CNN metrics overall.

Based on the outcomes presented in Table 8, we have also determined the accuracy, sensitivity, specificity, precision, and F-score values for the presence of diabetic retinopathy (cotton-wool spots, red-lesions, and hard-exudates), and they are found to be 80% for TBCSSR and 90.3% for both DSIHE and BBCCE, respectively. Furthermore, 93.1% for 2DHE, and 100% for both MMBEBHE and ACL-CLAHE. It is expected that the presented scheme would produce the best results if it tested using photographs enhanced according to the comparison enhance Table 6, in another word the contrast enhancement procedure will apply only for the dataset that proves their needing for enhancement based on single CNN performance. To evaluate the performance of the produced system and allow the user to engage with its features, a simulation was conducted.

Table 7. CNN metrics with applying enhancing process on the three classes (full enhance)

Enhancement model	ACC	Pre	Sen	Spe	F-score
TBCSSR	33.33%	51.11%	25.83%	67.66%	28.72%
DSIHE	45.83%	53.70%	45.08%	73.11%	45.44%
BBCCE	51.39%	51.85%	51.38%	75.78%	50.59%
MMBEBHE	54.55%	59.09%	54.13%	77.36%	54.17%
2DHE	45.83%	52.78%	46.66%	72.72%	46.21%
CLAHE	57.58%	60.10%	56.85%	79.02%	56.77%
ACL_CLAHE	60.61%	65.66%	60.56%	80.33%	60.52%

Table 8. CNN metrics using dataset enhanced based on selecting method (only the class with fair quality had been enhanced)

Enhancement model	ACC.	Pre.	Sen.	Spe.	F-score.
TBCSSR	80.00%	80.00%	80.56%	90.24%	79.80%
DSIHE	90.28%	90.28%	90.65%	95.25%	90.24%
BBCCE	90.28%	90.28%	92.47%	95.76%	90.07%
MMBEBHE	100%	100%	100%	100%	100%
2DHE	93.06%	93.06%	93.10%	96.54%	93.05%
CLAHE	100%	100%	100%	100%	100%
ACL-CLAHE	100%	100%	100%	100%	100%

Furthermore, as shown in Table 8, the superior results were for MMBEBHE, CLAHE, ACL-CLAHE, and 2DHE, demonstrating that contrast enhancement algorithms based on histogram equalization performed better than the other contrast enhancement approaches. In addition, Table 8 shows that MMBEBHE, CLAHE, and ACL-CLAHE achieved the highest performance values equal to 100%. Finally, Table 7 reveals that for the ACL-CLAHE CNN measure, TBCSSR performance is the best using the full enhance method (the entire dataset has been improved), however, Table 8 shows that the TBCSSR enhancing strategy failed to improve CNN performance when using the select enhance method (only the selected classes had been enhanced).

4. CONCLUSION

Algorithms using the convolution neural network model for fundus photograph quality detection and contrast enhancement of diabetic retinopathy for the three cases (hard-exudates, red-lesions, and cotton-wool spots) from color fundus photographs have been proposed. A decision-support model for choosing the best contrast-enhancing technique with determining who is the disease class to enhance has been designed based on the quality of output photograph and single CNN performance. Finally, a contrast enhancement method derived from histogram equalization proved their excellent ability to boost the CNN performance compared with other methods. Moreover, the improved CLAHE filter achieved superior results in improving the performance multiclass CNN system, compared with previous procedures of contrast-enhancing color fundus photographs. The presented system can further be employed to additional medical photographs with different acquired methods.

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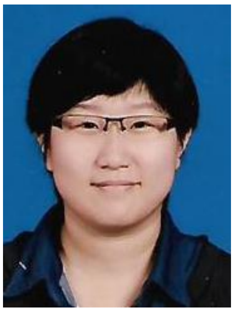

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