

Cotton-wool spots, red-lesions and hard-exudates distinction using CNN enhancement and transfer learning

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ABSTRACT

The automatic retinal disease diagnosis by artificial intelligent is an interesting and challenging topic in the medical field. It requires an appropriate image enhancement technique and a sufficient training dataset for the specific retina conditions. The aim of this study was to design an automatic diagnosis convolutional neural network (CNN) model which does not require a large training dataset to specifically identify diabetic retinopathy symptoms, which are cotton wool, exudates spots, and red lesion in colour fundus pictures. A novel framework comprised image enhancement method by using upgraded contrast limited adaptive histogram equalization (CLAHE) filter and transferred pre-trained networks was developed to classify the retinal diseases regarding to the symptoms. The performance of the proposed framework was evaluated based on accuracy, sensitivity, and specificity metrics. The collected results have proven the robustness of the proposed framework in offering good accuracy in retina diseases diagnosis.

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1. INTRODUCTION

Diabetic retinopathy is one of the main reasons that lead to vision loss for diabetic patients. Automatic retinal disease diagnosis is in demand to detect its symptoms in the early stage to prevent blindness [1], [2]. According to [3], there were 0.4 million and 2.6 million patients who were partially blind and had critical vision weakness respectively due to diabetic retinopathy in 2015. At the beginning of the retina ailment, retina abnormality, for instance, observable retina in the fundus pictures, signifying the deviations in the eye vision. The automatic detection of retina abnormalities offers an active method to gain a prompt judgement of diabetic retinopathy [4].

Diabetic retinopathy can be categorized into several stages: mild, moderate, and severe [5]. The diseases are classified based on the types of retina disorder, including hard exudates, cotton wool spots and red lesion. These are the common symptoms that indicate retinopathy in the eye. To obtain an accurate diagnosis, a detection model is required to identify and also differentiate these symptoms from each other [3] since the result may lead to different diagnostic status and implications [6]. Another novel enhancement

approach to boost the edge detection performance an eight-directional filters were used for normalizing intensity and maximize the edge magnitude for Mini Kirsch diagnosis [7].

Moving from human inspection to machine inspection will impose a new approach in the medical field to analyze the multilane classification and the disease conditions [8]. The strategy of implementing deep learning (DL) approach for the disease recognition and image distinction requires a primary training set which is annotated with those lesion symptoms. The most common technique used in the eye imaging field is the fundusoscopic method due to its simplicity to be handled, widely reachable, and suitability for documentation [9]-[11]. It is possible to further process those fundus pictures based on the desirable features through adjustment in spatial domain.

Orlando *et al.* had presented a remarkable indication on selecting the suitable image pre-handling method before they fed the dataset to convolutional neural network (CNN) [12]. The contrast limited adaptive histogram equalization (CLAHE) filter shows a great performance to enhance and remove the noise in eye retina images [13]-[15]. However, it has a drawback on its predefined clip limit that causes some irregular illuminance and excessive artifacts in the images [16]. On the other hand, deep transfer learning (DTL) approach, which uses pre-trained CNN dataset, appears to be a great solution to overcome the dataset shortage problem. In the pre-trained model, the universal pictures from “Image-Net” can be used as a primary weightage values in the DTL approach [17].

Several studies had presented several methods to detect the diabetic retinopathy of different conditions, either utilizing an extractor to obtain the diseases features and fed it to support vector machine (SVM) classifier, or applying a combined pre-trained model to optimize the output classification [18]-[20]. Most of these studies implemented multiple segmentation techniques to determine the region of interest (ROI), and then input the segmented dataset to pre-trained models. However, the output results prone to experience disease information lost, such as disease symptoms. In addition, the studies that used the unrefined fundus pictures resulted in a low accuracy classification output. Therefore, a pre-processing stage is required to improve the image appearance, and eventually reducing the risk of information loss to secure a better disease recognition [21], [22]. The purpose of this study was to propose a DL model with great performance and a good accuracy to distinguish the exudates, cotton-wool spots and red lesion in fundus picture.

The study utilized the sample pictures of diabetic patients which are obtained from “Fishare” website that covers 169 and 98 fundus pictures that are bright and red lesion abnormalities respectively. The bright lesion is caused by the exudates and cotton wool spots. The assessment and verification of the proposed method are also carried and the framework performance is compared with the previous studies.

2. RESEARCH METHOD

Overall, the pre-trained dataset from deep CNN transfer learning was used for the detections of exudates, cotton-wool spots, and red lesion in fundus pictures. The DTL method is preferred as it does not require big quantities of image samples [23]. Figure 1 illustrates the process of the proposed method.

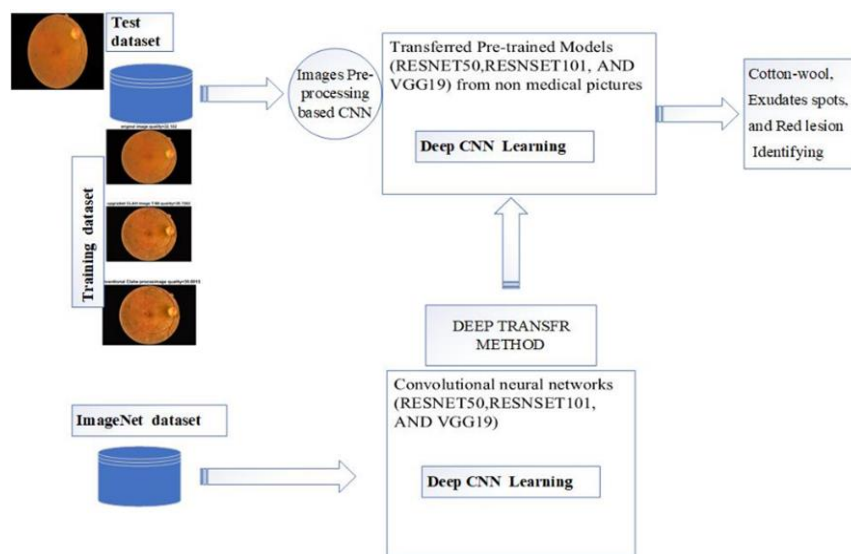


Figure 1. Workflow of exudates, cotton-wool, and red lesion classification using deep CNN enhancement and transfer learning

Several image processing approaches were conducted on the fundus picture before feeding it into the pre-trained network [24]. The CNN was trained intently to extract the important image features for enhancement. The whole fundus image was fed into the pre-train model without segmentation to obtain the calculation of the whole features where using segmentation method to detect the retina abnormalities may leading to losing important information, as an example, the following study used segmentation to focus on a specific region and ignored the rest area of the retina which may have very useful syndromes [22], [25].

2.1. Image dataset

Initially, there are a total of 617 fundus pictures, downloaded from the Fishare website, that are provided by the ophthalmologists for clinical analysis. After examining all those pictures, there are 90, 79 and 98 pictures that contain the cotton wool, exudates spots and red lesion selected respectively [26]. Meanwhile, 70% of the images for each category are used for CNN training purpose while the rest of the images are used for Test purpose.

2.2. Image pre-processing

Fundus pictures may have some defects owing to the retinal leaning, inaccurate and blurred spot due to limitation of acquiring devices, and certain unexpected circumstances that lead to miscellaneous poor-quality pictures. It is significant to improve the picture quality to improve the performance and accuracy of CNN classification model.

2.2.1. Upgraded CLAHE

The upgraded CLAHE filter, also known as the enhanced version of conventional CLAHE was picked according to its ability to produce the best enhancement output among the existing enhancement methods. The fixed clip limit was replaced with a global threshold that is adaptive to the gray level of the pictures. The conventional and upgraded CLAHE equations are denoted as in (1) and (2) [16]:

$$\text{CLIP LIMIT} = \left\lfloor \frac{\varphi}{L} \right\rfloor + \left\lfloor \beta \cdot \left(\varphi - \left\lfloor \frac{\varphi}{L} \right\rfloor \right) \right\rfloor \quad (1)$$

$$\text{CLIP LIMIT} = \frac{T}{80} \quad (2)$$

Where T is the global threshold, φ is the pixels population in each block, β is the clip factor, and L is the grayscale of the image. Figure 2(a)-(c) shows an example of the original fundus images and the output images that have been processed with conventional and upgraded CLAHE filters.

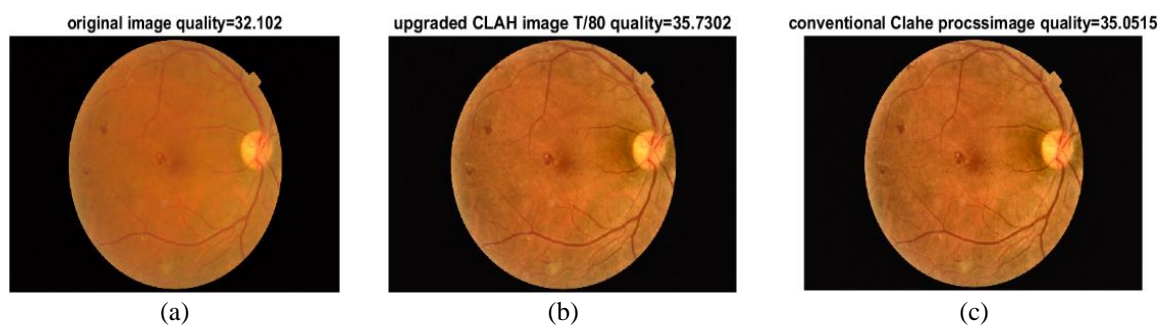


Figure 2. Example of; (a) original fundus image; (b) output image from upgraded CLAHE filter; (c) the output image from conventional CLAHE filter

2.2.2. CNN Enhancement step

In this section the single CNN has been developed for using it as test device for give the last decision for enhancement the fundus images or not. Tables 1-3 show the test result, Tables present four phases, phase 1 for no enhancement, phase 2 for limit enhancement on single disease case, in a Table can be seen that “0” for non-enhancement, while “1” for applying the enhancement. Based on the supreme results of these Tables the enhancement topology has been chosen.

Table 1. CNN enhancement decision truth Table for cotton-wool spots

Preparing method	(Class labels) Cotton-wool Spots					
	Sigle CNN1			Sigle CNN2		
No enhancement=0	Cotton-wool Spots	Red Lesions	Result	Cotton-wool Spots	Hard Exudates	Result
Using MCLAHE=1						
Phase 1	0	0	80.4	0	0	84.3
Phase2	0	1	94.6	0	1	90.2
Phase3	1	0	100	1	0	95.7
Phase4	1	1	100	1	1	93.5

Table 2. CNN enhancement decision truth Table for red lesions

Preparing method	(Class labels) Red Lesions					
	Sigle CNN1			Sigle CNN2		
No enhancement=0	Red Lesions	Cotton-wool Spots	Result	Red Lesions	Hard Exudates	Result
Using MCLAHE=1						
Phase 1	0	0	80.4	0	0	20.8
Phase2	0	1	100	0	1	86.6
Phase3	1	0	94.6	1	0	96.2
Phase4	1	1	100	1	1	24.5

Table 3. CNN enhancement decision truth Table for hard exudates

Preparing method	(Class labels) Hard Exudates					
	Sigle CNN1			Sigle CNN2		
No enhancement=0	Hard Exudates	Cotton-wool Spots	Result	Hard Exudates	Red Lesions	Result
Using MCLAHE=1						
Phase 1	0	0	84.3	0	0	20.8
Phase2	0	1	95.7	0	1	96.2
Phase3	1	0	90.2	1	0	86.6
Phase4	1	1	93.5	1	1	24.5

Finally, from Tables 1-3, the best performance can be obtained when the cotton-wool spots images are processed with optimized CLAHE filter, while the red lesions can be processed with either upgraded filter processing or without can be obtained higher performance. Lastly, the hard exudates can be input into classification model without needing for enhancement process to get the best performance.

2.3. Augmentation

In order to overcome the problem of dataset shortage for each category, the augmentation method is applied. The pictures are rotated with a step size of 30 degrees ranging from 0° to 330°. This allows the introduction of more pictures feature to improve the model generalization and reduce the tendency of over-fitting. The augmentations of dataset are shown in Figure 3(a)-(d).

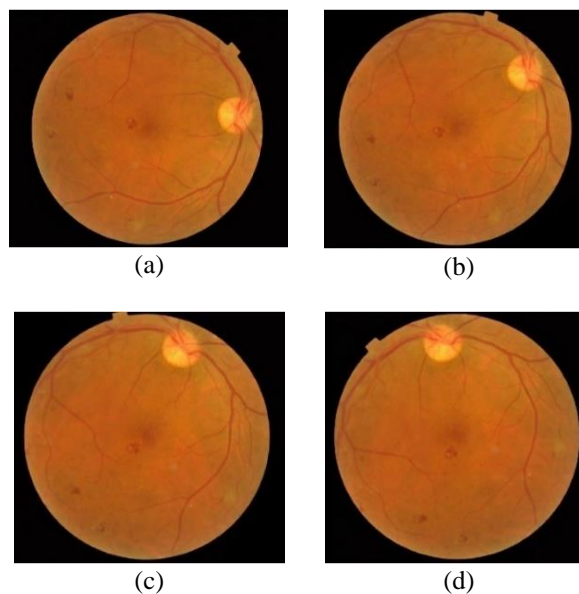


Figure 3. Result of augmentation method for rotation of; (a) 0°; (b) 30°; (c) 60°; and (d) 90°

2.4. Deep transfer learning

A pre-trained network was chosen based on its ability to distinguish multiclass of fundus pictures samples [27]. However, the final network layer, which is able to classify the three types of aforementioned diabetic retinopathy symptoms, is added to the pre-trained network. This approach could shorten the training time instead of training the new network from scratch. The selected pre-trained models include RESNET50, RESNET101, and VGG19, which have been used in the previous studies for the analysis, recognition and classification of medical images and signals [28]. Figure 4 shows one of the results from VGG19 model where there is exudate detected as labelled in the Figure.

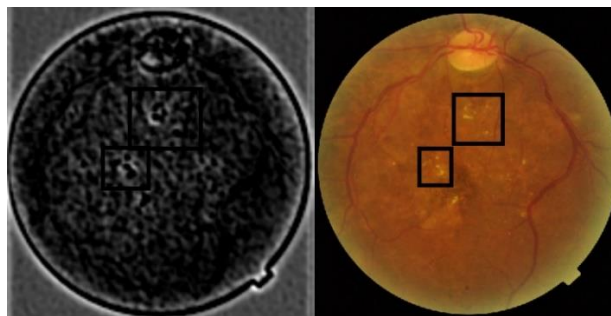


Figure 4. Detected exudate in fundus picture in VGG19 model

3. RESULTS AND DISCUSSION

Image enhancement is important to highlight the desired feature to improve the classification performance [10], [21], [29], [30]. In this study, a revised version of CLAHE filter was applied to improve the picture quality and to emphasize the fine vessels in the retinal pictures. Moreover, a novel step was introduced where a single CNN model is employed to measure the quality of the enhancement dataset based on optimistic output CNN classification accuracy.

At the end of the image pre-processing stage, the dataset was fed to a few deep transfer pre-trained networks which were RESNET50, RESNET101, and VGG19 model. Table 4 shows the results obtained using the conventional and upgraded CLAHE filters for image enhancement for the three CNN models. CNN models which use the input enhanced image from upgraded CLAHE filter show a better classification accuracy than those of conventional CLAHE filter. It is consistent with the result of primary single CNN enhancement but not with the elective mode method.

Table 4. Comparison of image classification accuracy among different CNN models for input images enhanced by conventional and upgraded CLAHE filter

Pretrained CNN model	Conventional CLAHE	Upgraded CLAHE
RESNET50	56%	56%
RESNET101	57.57%	59.1%
VGG19	57.57%	60%

The upgraded CLAHE filter, which is modelled by the primary single CNN model, exhibited noTable improvement based on the elective enhancement approach (decision truth Table) that can be seen in Table 5. The elective enhancement procedure has improved the output classification for all three pre-trained models. The classification accuracy for RESNET50 model shows consistent performance for different input datasets, and has the lowest accuracy 97%, among the CNN models as shown in Figure 5. Next, to elevate the performance of RESNET50 model, an augmentation approach was used to increase the variation of the training data set. Figure 6 shows the better classification result accuracy after the implementation of the augmentation method, typically in hard exudates detection.

Table 5. Performance metric Table for each CNN models

Pretrained model	Accuracy (%)	Sensitivity (%)	Specificity (%)
RESNET50	100	100	100
RESNET101	100	100	100
VGG19	100	100	100

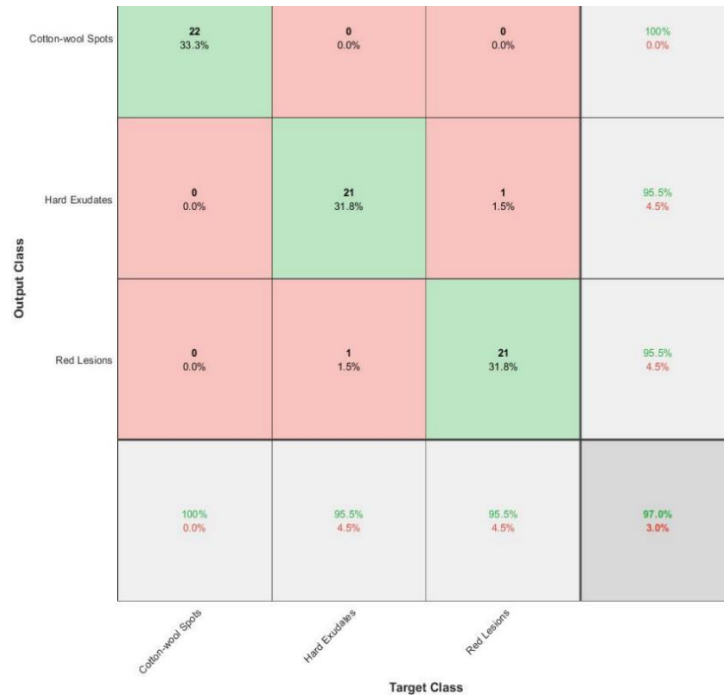


Figure 5. Confusion matrix of RESNET50 model



Figure 6. Confusion matrix of RESNET50 after the implementation of augmentation preprocessing

Performance analysis to determine the modelling uncertainties was carried out, based on the classification accuracy (ACC), sensitivity (Sen), and specificity (Spe). The equations for these three parameters are expressed as follows [4]:

$$ACC = \frac{(T_N+T_P)}{(T_N+FP+TP+FN)} \quad (3)$$

$$Sen = \frac{TP}{(TP+TN)} \quad (4)$$

$$Spe = \frac{TN}{(TN+FP)} \quad (5)$$

Where TP is the rate of true classified, TN is the rate of true negative classified, FP is the false sample classified, and FN is the false negative classified.

Table 5 presents the calculated performance metrics for each pre-trained CNN model. Nevertheless, these results suggest that data obtained using elective enhancement and deep learning transfer approach has optimized the accuracy of diabetic retinopathy symptoms detection by highlighting the important features in the image. Comparing the result with a previous study [31] that used automated machine learning, the proposed method in this study shows consistent and higher performance metrics as shown in Table 6.

Table 6. Comparison Table with the previous study

Retinopathy condition	Proposed method (sensitivity/specificity)	Previous study [31] (sensitivity/specificity)
Exudates	100/100	0.95/0.86
Cotton-wool spots	100/100	0.70/0.93
All bright lesions	100/100	0.95/0.88

4. CONCLUSION

CNN enhanced and transfer learning method was proposed for detecting diabetic retinopathy symptoms such as hard exudates, cotton wool spots and red lesion. This approach potentially assists the retinal specialists to analyze and automatically classify the fundus picture of diabetic patients regarding the symptoms. Results show that the proposed method has a better classification accuracy compared to the previous study. Furthermore, the use of a deep transfer learning approach could reduce the dataset needed to train the network. For future development, more fundus pictures with other retinal diseases would be input to the network for wider applications. Provide a statement that what is expected, as stated in the "Introduction" chapter can ultimately result in the "Results and Discussion" chapter, so there is compatibility. Moreover, it can also be added the prospect of the development of research results and application prospects of further studies into the next (based on result and discussion).

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