Automatic Cataract Detection And Grading Using Deep Convolutional Neural Network

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Abstract*—Cataract is one of the most prevalent causes of blindness in the industrialized world, accounting for more than 50% of blindness. Early detection and treatment can reduce the suffering of cataract patients and prevent visual impairment from turning into blindness. But the expertise of trained eye specialists is necessary for clinical cataract detection and grading, which may cause difficulties to everybody's early intervention due to the underlying costs. Existing studies on automatic cataract detection and grading based on fundus images utilize a predefined set of image features that may provide an incomplete, redundant, or even noisy representation. This paper aims to investigate the performance and efficiency by using Depp Convolutional Neural Network (DCNN) to detect and grad cataract automatically, it also visualize some of the feature maps at pool5 layer with their high-order empirical semantic meaning, providing a explanation to the feature representation extracted by DCNN. The proposed DCNN classification system is cross validated on different number of population-based clinical retinal fundus images collected from hospital, up to 5620 images. There are two conclusions suggested in this paper: The first one is, the interference of local uneven illumination and the reflection of eyes were overcome by using the retinal fundus images after G-filter, which makes an significant contribution to DCNN classification. The second one is, with the increase of the amount of available samples, the DCNN classification accuracies are increasing, and the fluctuation range of accuracies are more stable. The best accuracy, our method achieved, is 93.52% and 86.69% in cataract detection and grading tasks separately. It is demonstrated in this paper that the DCNN classifier outperforms state-of-the-art in the performance. Further more, The proposed method has the potential to be applied to other eye diseases in future.

Keywords—cataract detection and grading; Deep Convolutional Neural Networks; feature maps

I. INTRODUCTION

Cataract is one of the most prevalent causes of blindness in the industrialized world, accounting for more than 50% of blindness [1]. By 2020, the number of blind people is projected to reach 75 million [2-3]. Generally there are three main types into which cataracts are divided: Posterior subcapsular, Nuclear Cataract and Cortical Cataract. There are a number of factors can resulting in the degeneration of the lens protein. Owing to these factors, the lens metabolism was disordered, and then leading to cataract. With cataract, the light hindered by the Turbid lens can not be projected on the retina, resulting in blurred vision. Cataract appears more in people over 40 years old, and the incidence rate increased with age. With the gradual increased incidence of cataract, the harm is gradually increasing, the cataract treatment has become a concern. And it is advocated to be early detected, early treated.

Research on risk factors of cataract is ongoing[4-6]. Personal factors, for example, nuclear and cortical cataracts are frequently observed in old age [7]. Risk factors such as UV-B contact and smoking can be a reason but are improbable to create great alteration to visual function. For cataract, early treatment, and prevention have been detected early, certain measures can be taken to slow their progression, such as by wearing antiglare sunglasses [8]. For severe cataracts that affect the patient's daily activities, surgical treatment is often effective. For cataract detection and grading, there are four main kinds of checking methods at present. The first one is light-focus method; The second one is iris image projection; The third one is slit lamp examination; The last one is ophthalmoscopic transillumination. However, manual assessment can be subjective, time-consuming and costly [9]. Therefore, from the social and economic points of view, it is very consistent to achieve automatic cataract detection using artificial intelligence. It was clear to us that we should focus on eye care because it is an area where we can make a real difference to people's lives across the world.

Usually cataract is graded to four classes: Non-cataractous, Mild, Moderate and Severe, as is defined in [10]. Fig. 1 shows samples from different degree of cataract patients. (a) is an image with no cataract, where the optic disc and large and small blood vessels can be seen very clearly. There are fewer blood-vessel details in the Mild cataract image in (b), while only the large blood vessels and optic disc are visible in the moderate cataract image in (c). Furthermore, almost nothing can be seen in (d), the severe cataract image. It can be summed up that, Based on retinal fundus images, blood vessels and optic disc are the main references for the cataract detection and grading.

The rest of the paper is organized as follows. Section II discusses the related work. Section III introduces the details of proposed classifier using Depp Convolutional Neural Network. Section IV presents experiments. Finally, Section V concludes the paper.

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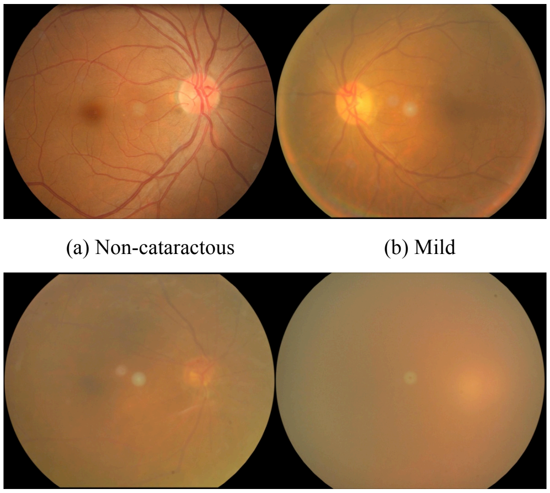

(a) Non-cataractous (b) Mild

(c) Moderate (d) Severe

Fig. 1.Standard retinal fundus images for different levels of Cataract Disease.

II. RELATED WORK

Studies on fundus image analysis have been conducted for years. Methods for cataract classification mainly comprise of four parts: preprocessing, feature extraction, feature selection and classifier. Noise can be consistently brought into images amid attainment and transference [11]. Therefore, in the method of preprocessing, it likewise requires few approaches to enhance the condition of images, for instance, image improvement and noise removal. Segmentation and location of retinal structures, such as retinal lesions, vessels, optic discs, and aneurysms have been widely studied. To prevent the complication of dimension mishap, feature extraction and selection is essential. Various of features of retinal fundus images have been extracted, such as color, texture, wavelet, sketch, acoustical and spectral parameters, and so on. The middle three parts, which are summarized as feature representation. Good feature representation played a very critical role for the accuracy of the final algorithm, and the main calculation and testing work of the system are consumed in this part. The last part, which is the part of machine learning, most work is done in this area. Classifiers based on different algorithms have been adopt to cataract detection and grading.

Existing automatic methods for cataract grading, such as [10], [17-19] and [24-25], usually utilize a predefined set of image features that may provide an incomplete, redundant, or even noisy representation. Moreover, all the predefined features were extracted artificially, which is a very laborious, heuristic (need professional knowledge) method, much depends on experience and luck, and its regulation takes a lot of time. In [12], the authors proposed a system to automatically learn features, with these features, support vector regression is applied to determine the cataract grade. [12] Achiving a 70.7% exact integral agreement ratio as the accuracy of cataract grading. But in [12], the feature extraction and classifier still were divided.

Our research is motivated by the efforts of understanding the representations learned by DCNN, and enable us to observe learned features' invariances at different levels and trace back high activations at the last fully connected layers back to image patches. These strategies provide some insight into factors which affect the classification performance most. In Zeiler et al [13] showed that feature maps following the later convolutional layers encode both spatial and semantic information of the dominant attributes and semantic concepts.

This paper focuses on understanding the representations learned by DCNN. The presented method uses the features maps from pool5 layer of the DCNN architecture, which has been shown to preserve coarse spatial information and is semantically meaningful [14]. In this paper, we examine the effect of the G-filter and the scalability of database on the DCNN classification accuracy as well as demonstrate superior performance on the cataract detection and grading task. The main differences of this paper compared with previous studies are as follows.

- The ever largest database was used in this study, which composed of 5620 standard retinal fundus images from Beijing Tongren Eye Center of Beijing Tongren Hospital.
- In this paper, the feature extraction and classification are combined into one step, reducing the work steps, which makes cataract grading more efficient.
- Our research provides the understanding of the feature representations learned by DCNN and provides a more detailed explanation for automatic detection.

III. METHODOLOGY

Our method for cataract consists of two components: preprocessing and DCNN classifier. In this section, we introduce the two parts in detail.

A. Preprocessing

1) Unify fundus images and Erase the patients' personal information

Because our experimental fundus images from different fundus cameras, resulting in different image sizes. the preprocessing step first sizes the fundus images uniformly as the size of 3048*2432 pixels making it convenient for a series of processing following.

The federal Privacy Rule, implemented in the United States in 2003, as part of the Health Insurance Portability and Accountability Act of 1996 (HIPAA), created new restrictions on the release of medical information for research, with hopes that it would allay growing concerns about the way personal medical information was being used for non-patient care purposes[15].we erase the patients' personal medical information to protect the patients' privacy, the Ellipse interception and Rectangle cutting function of MATLAB are adopted, while remaining more original information than the method applied in [10].

2) Eliminating uneven illumination

Owing to the local uneven illumination and the reflection of eyes, which makes it difficult to detect and grade cataract precisely. Considering the restriction, a method (Before the DCNN classification) is raised in this paper to eliminate the uneven illumination, assisting for cataract detection and classification as well as trimming the amount of data down.

The original fundus images are converted from RGB color space to the green channel. The RGB color model is composed of red, green and blue. In general, each pixel of the RGB image is represented by 24-bit data, the three primary colors each accounts for 8-bit, every primary colors can show 256 different concentrations of hue. Thus it can reduce the amount of data by 2/3 by extracting the single channel of the image, as well as achieving the effective compression of the data and greatly reducing the processing time of data.As is depicted in Fig. 2, the green component image is the most clear one. The green component image not only holds the most basic feature of the original color image with its data compressed down to 1/3, but also is convenient to acquire[16].

B. Deep Convolutional Neural Network

Deep Convolutional Neural Network is a kind of artificial neural network, which has become a hot research area in the field of image recognition. It's weight sharing network structure makes it more similar to the biological neural network, which reduces the complexity of the network model, and reduces the number of weights. This advantage is more obvious when the input of the network is multidimensional image, the image can be directly used as the input of the network, which avoids the complex feature extraction and data reconstruction process of the traditional recognition algorithm. Convolutional network is specially designed as a multi-layer perceptron for recognizing 2D shape. This kind of network structure has a high degree of invariance to translation, scaling, tilting or other forms of deformation.

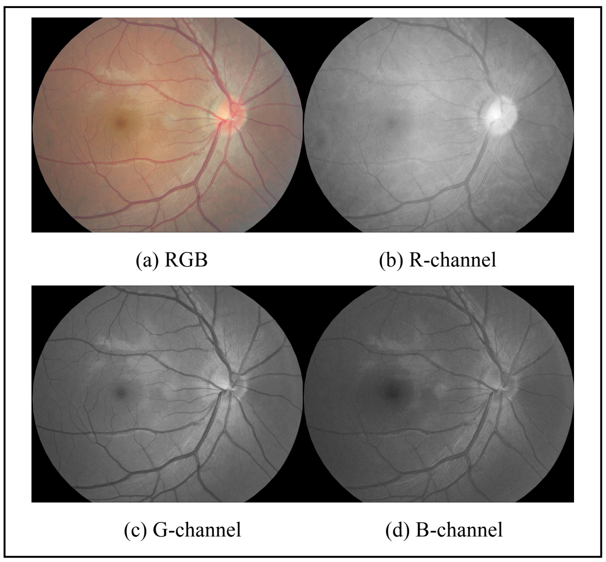

Fig. 2. Retinal fundus images and R/G/B channel images

For our problem, we employed DCNN with eight layers, the first five are convolutional layers and the remaining three are fully-connected layers. The output of the last fully-connected layer is fed to a four-way softmax which produces a distribution over the four class labels. The overview of Deep Convolutional Neural Networks (DCNN) based classifier for cataract detection and grading is exhibited in Fig.3. Each layer consists of several 2D feature maps where each feature map often capturing specific aspect of the image such as the color, object category, or attributes, while preserving the spatial information at coarse resolution. For instance, pool5 layer consists of 256 feature maps where the resolution of each is 6×6. Therefore, the feature maps at this layer preserves spatial information at the resolution of 6×6. While earlier layers captures rudimentary concepts such as lines, circles, and stripes, the feature maps in deeper layers can identify more high-order concepts. It has been demonstrated that it is possible to identify the meaning of each feature map in a stimuli-based data driven fashion [13].

Figure 4 visualizes some of the feature maps at pool5 layer with their high-order empirical semantic meaning. As it is shown, feature maps have high responses at the vicinity of the location of that concept.According to the knowledge of the ophthalmic doctor, with greater severity of the cataracts, the blood vessels that could be seen clearly are less, the contrast between the blood vessels and the background will be less obvious.

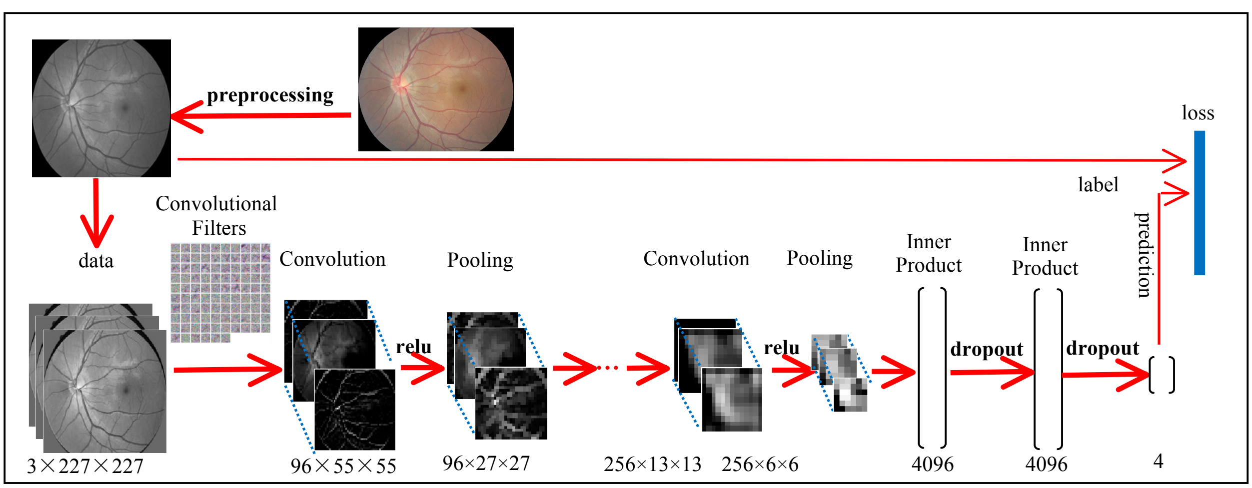

Fig. 3. Overview of Deep Convolutional Neural Networks (DCNN) based classifier for cataract detection and grading.

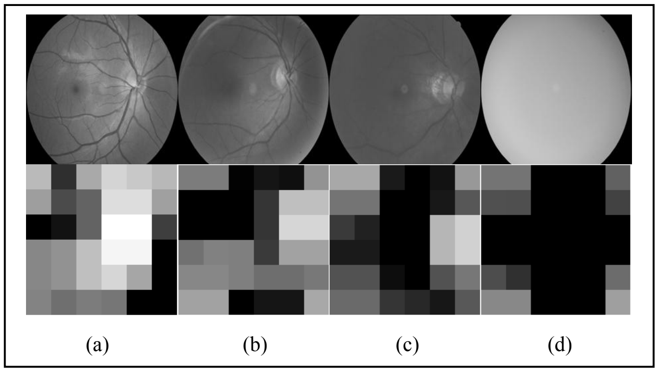

Fig. 4. Illustration of semantic information captured by each feature map of pool5 layer using DCNN trained on our database. The first row shows the G-channel retinal fundus images that are non-cataractous, mild, moderate and severe.The second row shows a selected feature map of the pool5 layer extracted from the picture above it separately.All feature maps are normalized separately and have the same scale. Note that not only each feature map localizes the concepts, but the magnitude of response is correlated to the number of blood vessels and the contrast between the blood vessels and the background.

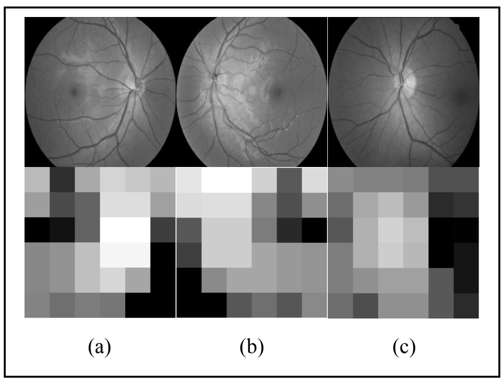

Fig. 5. Examples of the response at pool5 extracted from the retinal fundus images from different fundus camera and different angles.

As is illustrated in Fig. 4, not only the high activation cells localize the blood vessels. But the number of blood vessels and the contrast between the blood vessels and the background are expressed by the high activation cells. For example, the less blood vessels, the less high activation cells. And the stronger contrast between the blood vessels and the background is, the higher the pixel value of the high activation cells.

In the pooling layer, each feature map is subsampled by max pooling, which not only further reduce the feature map and increase the visual field of neurons, but also results in features that are invariant to translation and small deformations. The rationale behind max pooling is to gain invariance to translation over the region where pooling is performed. Max pooling is more invariant to the position and rotation changes, since the maximum response of a feature map does not change abruptly with the position and rotation changes. This position and rotation invariance are very good for the classification of fundus image. Fig. 5 shows the response of most active feature maps at pool5 layer for the fundus images from different fundus camera and angles.In Fig. 7, the First row shows three Non-cataractous retinal fundus images from different fundus camera and angles. The second row shows a selected most active feature map of the pool5 layer extracted from the picture above it separately. The number of blood vessels and the contrast between the blood vessels and the background do not change with the diversity of the blood vessel position and the the angle of fundus examination, which implies that the feature representation derived from DCNN can be used for cataract detection and grading.

IV. EXPERIMENTS

In this section, we first describe the setup of experiments, consisting of database, evaluation Criteria and implementation. And then exhibit and analyze the experimental results.

A. *Setup of experiments*

1) *Database*

All the experiments are performed on our database collected from Beijing Tongren Eye Center of Beijing Tongren Hospital, comprised of 5620 images, there are 3269 (1598, 472 and 281) non-cataractous (mild, moderate and serve) images. All the images are graded into 4 classes ranging from 0 to 3. The scores are determined by professional graders according to clinical grading protocol. This database is a subset of a population-based eye study database, and the age of the subjects is range from 10 to 90.

2) *Evaluation Criteria*

For the cataract detection and grading task, we use the usually used evaluation criteria, as in [10][17-19] , to measure Cataract detection and grading performance, namely Accuracy, Sensitivity(another name is Recall) and Specificity. Accuracy represents the judgment ability to the whole set of samples that the positive judgment is positive as well as the negative judgment is negative; Sensitivity represents the ability of predicting positive samples as positive samples; And Specificity represents the ability of predicting negative samples as negative samples. Statistical definitions are as follows.

$$\begin{aligned} Accuracy &= (TP+TN)/(TP+TN+FP+FN) \\ Sensitive &= TP/(TP+FN) \\ Specificity &= TN/(FP+TN) \end{aligned} \tag{1}$$

where TP, FN, FP and TN are explained in table I. In the table, we specified that cataract are positive samples and Non_cataractous are negative samples. For a standard classification problem of four classification, the Accuracy, Sensitivity and Specificity of each class can be calculated [20].

3) *Implementation*

The PC hardware environment used for our proposed retina fundus images classification with Deep Convolutional Neural Networks are:E5-2609 CPU , 8GB RAM, Qudro K620 GPU and Ubuntu 16 as the operational system. The fundus image preprocessing is implemented with the image processing toolbox in Matlab. Caffe [21] (Convolutional Architecture for Fast Feature Embedding) was employed to construct the automatic classifier with DCNN.

B. *Experimental results and analysis*

Two experiments were mainly carried out in this paper, the effect of G-filter on eliminating uneven illumination of fundus images and the The effect of data quantity on the classification accuracy of DCNN were verified separately.

1) G-filter effects on eliminating uneven illumination of fundus images.

First, we compared the performance of different image sets that are original RGB images and the database after G-channel in the tasks of automatic cataract detection and grading. But the two different image sets are from the same database. Among them, original RGB images are widely used in the image classification with Deep Convolutional Neural Networks, such as [12], and [22-23]. G-channel images are extensively used to feature extraction, such as [10] and [24-25].

As mentioned previously, the combination of se, sp and accr metrics measure performance at a finer scale and thus offer a better indication of a method's utility in disease progression monitoring. The results are listed in table II and table III. From the results, the database after G channel is shown to surpass the other in the three evaluation criteria. In the cataract detection task, the database after G channel achieves an improvement of 3.6% and 1.75% in accuracy over the database_2_RGB and database_4_RGB separately. More than that, the values of se and sp are also significantly higher than the previous methods.

The mathematical statistics show that the images after G-filter outperforms the RBG images and G-filter does help overcome the interference of local uneven illumination and the reflection of eyes.

2) Scalability of database effects on accuracy in DCNN classification

In this section, we focus on the effect of data scalability on DCNN classification accuracy. All the experimental results were generated using independent and randomly selected samples, while with the same proportion of each classe. The mathematical Mean and Variance were adopt to evaluate the performance of DCNN, that are commonly used to describe the characteristics of random variables. Mean reflects the average value of random variables, while Variance is a measure of the dispersion degree of the random variables or a set of data. The training results after cross validation are shown in Table IV and Table V. E(X) and D(X) stand for the mathematical Mean and Variance of accuracy over the 10 rounds separately. Fig. 6 and Fig. 7 demonstrate the distribution of the training results.

The experimental results in this chapter suggested that validating using at least 1606 samples gave generally referable results but not most reliable, while using fewer samples (such as 80, 401 or 803) was unreliable.This suggests the following conclusions:

- With the increase of the amount of data, the classification accuracy of DCNN is increasing. If no more than 1606 samples are available, the classification accuracies are significantly lower than the normal level, and with fast growth rate.When the available data is greater than 1606, the mean classification accuracy puts up slight gradual increase.
- If more samples are available, the classification accuracies are more stable. If no more than 1606 samples are available, the fluctuation range of accuracies is frequent with great high range, realize that it is impossible to fit or validate incontrovertibly models.

TABLE I. THE EXPLANATION OF TP, FN, FP AND TN

Confusion Matrix		Predicted	
		cataract	*Non_cataractous*
Actual	*cataract*	TP	FN
	Non_cataractous	FP	TN

TABLE II. THE CLASSIFICATION RESULTS FROM DIFFERENT IMAGESETS IN THE CATARACT DETECTION TASK.

database Name	Cataract(%) se	Non-cataractous(%) sp	accr(%)
database_2_RGB	87.82	91.06	89.92
database_2_G	92.53	94.84	93.52

TABLE III. THE CLASSIFICATION RESULTS FROM DIFFERENT IMAGESETS IN THE CATARACT GRADING TASK.

database Name	Non-cataractous (%)		Mild (%)		Moderate (%)		Severe (%)		accr (%)
	se	*sp*	*se*	*sp*	*se*	*sp*	*se*	*sp*	
database_4_RGB	94.84	70.45	78.74	86.96	41.58	88.58	71.90	85.30	84.94
database_4_G	95.63	77.99	83.28	90.22	57.92	91.04	81.67	88.60	86.69

TABLE IV. THE MEAN AND VARIANCE OF ACCURACIES FROM DIFFERENT DATA QUANTITY IN CATARACT DETECTION TASK

No. Of images	**80**	**401**	**802**	**1606**	**2409**	**3212**	**4015**	**4818**	**5620**
E(X)(%)	85.36	89.45	91.94	92.89	92.97	92.97	93.22	93.63	93.52
D(X) (10^{-5})	663.82	95.13	43.35	20.57	10.90	10.02	6.48	3.62	1.32

TABLE V. THE MEAN AND VARIANCE OF ACCURACIES FROM DIFFERENT DATA QUANTITY IN CATARACT GRADING TASK

No. Of images	**80**	**401**	**802**	**1606**	**2409**	**3212**	**4015**	**4818**	**5620**
E(X)(%)	70.48	82.51	84.64	86.26	86.38	86.79	86.32	87.10	86.69
D(X) (10^{-5})	608.42	57.08	61.26	35.20	17.69	9.76	10.46	7.37	3.60

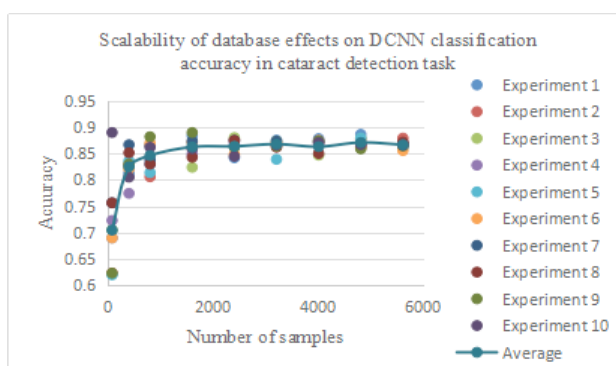

Fig. 6. Scalability of database effects on DCNN classification accuracy in cataract detection task

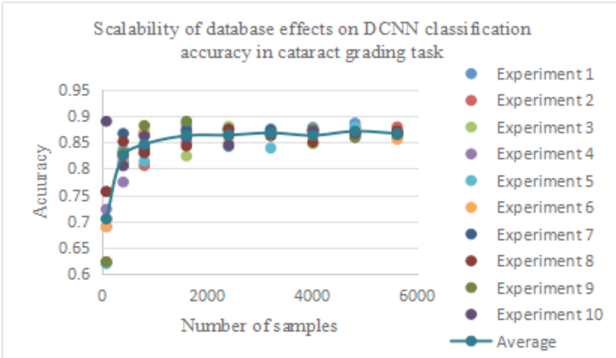

Fig. 7. Scalability of database effects on DCNN classification accuracy in cataract grading task

V. CONCLUSION

The proposed method in this paper with Deep Convolutional Neural Network(DCNN) is capable of achieving record breaking results in the challenging cataract detection and grading tasks using purely supervised learning. Our method surpass state-of-the-art in both accuracy and time efficiency. The interference of local uneven illumination and the reflection of eyes were overcome by using the retinal fundus images after G-filter, which makes an significant contribution to DCNN classification. Through DCNN, discriminative features that characterize highlevel information are extracted effectively and automatically, rather than artificially. Further more, the feature extraction and classifier were combined together, which demonstrates a higher level of intelligence. This approach has been confirmed to has great practical significance in early cataract screening and diagnosis, and has great potential to be applied in other eye diseases.

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