Retina Disease Classification Based on Colour Fundus Images using Convolutional Neural Networks

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***Abstract*—This paper explores Convolutional Neural Networks (CNN) as a classifier to recognize retinal images. The dataset used in this research is public STARE color image dataset comprises of $61 \times 70, 46 \times 53$, and 31×35 pixels. The dataset is categorized into 15 classes. The experimentation shows that the CNN model can achieve 80.93 percent.**

***Keywords*—classification; retina disease; deep learning;CNN**

I. Introduction

Retinal eye image classification is an interesting computer vision problem with wide applications in medical field. Understanding of retinal image, for example, is very important for ophthalmologists to assess eye diseases such as glaucoma and hypertension; if left untreated, these diseases can caused visual impairment and blindness. Many previous studies conclude that understanding vascular abnormalities from retinal image helps medical doctors in providing early diagnosis and treatment to stroke [1-2], cerebral damage [3], carotid atherosclerosis [4], artery disease [5], cerebral amyloid angiopathy [6]. Some evidences from these studies have shown that periodic examination of retinal eye by specialists improve patients' quality of life.

Human retinal eye is a light-sensitive tissue which is essential and necessary for human vision. Anatomically, the retina of the eye has some similarities to the central nervous system. The fact that the retinal blood vessels are affected by the brain's microvascular condition [7] causes damage to the retinal eye to indicate systemic microvascular damage associated with several diseases such as hypertension or diabetes [8].

In the past decade, retinal image classification has gained wide research attention resulted in a vast number of reports in literature [9-12]. Although there have been many proposed methods, recognizing retinal eye images remain a challenging computation problem. The challenge, among others, is fundus variability of each patient

The objective of this research; therefore, is to build a robust retinal image classifier using retinal color images as input. The remaining of this paper is divided into four sections, after this introductory section will be described the related works section will discuss relevant previous research. Then, the third section discusses methods and outcomes as well as discussions, In the last section, we conclude the result of this study and our future work.

II. Related Works

In the past two decades, a vast number of studies in retinal image analysis have been proposed resulted in a plethora of methods thanks to the advent technology in digital imaging and analysis [13-18]. Many researchers have developed an automatic detection system of retinal disease and diabetic retinopathy disease using the Support vector machine (SVM) method [19]. Classification of the exudate region using the C-means fuzzy grouping method has been proposed by [20].

The study by [21] presents automatic segmentation of retinal colored blood vessels. The diabetic retinopathy classification method using the visual-forward neural visual neutral spectral component has been proposed by [22]. Further study by [ ] also proposes artificial neural networks to perform the detection of diabetic retinopathy. The detection of retinal eye bleeding which is a symptom of diabetic retinopathy has been proposed by [23] using a support vector machine (SVM).

The development of an automatic detection system of diabetic retinopathy in digital retinal images as well as evaluation of its potential in screening of diabetic retinopathy has been proposed by [24]. An intelligent automatic detection system of diabetic retinopathy for diagnostic purposes has been performed by [25] using feed-forward neural networks.

III. Research Method

A. Research Framework

The framework of this research in general can be summarized in Fig. 1. As can be seen from Fig 1, the main processes are: image preprocessing, classifier training, and classifier testing.

B. Dataset

The dataset for this research is the public STARE dataset which contains 400 of 605×700 pixels of retinal color images in 24 bit RGB format [26]. This dataset can be downloaded from the site http://cecas.clemson.edu/~ahoover/stare/.

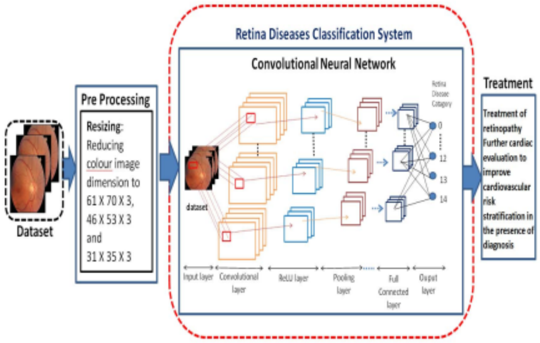

Fig. 1. Retina disease classification model

In this study, the image dataset is resized into three image sizes: 61×70, 46×53 and 31×35 pixels respectively. The dataset is categorized by experts into 15 categories (classes) of retinal diseases. Category distribution of the dataset is summarized into Table 1.

TABLE I. IMAGE LABELING

Label	Classification	
	Diagnosis	*Number of image*
0	Normal	39
1	Hollenhorst Emboli	13
2	Branch Retinal Artery Occlusion	7
3	Cilio-Retinal Artery Occlusion	9
4	Branch Retinal Vein Occlusion	11
5	Central Retinal Vein Occlusion	25
6	Hemi-Central Retinal Vein Occlusion	12
7	Background Diabetic Retinopathy	70
8	Proliferative Diabetic Retinopathy	23
9	Arteriosclerotic Retinopathy	34
10	Hypertensive Retinopathy	35
11	Coat's	14
12	Macroaneurism	8
13	Choroidal Neovascularization	60
14	Macular Degeneration	156

As can be seen from Table I, data distribution for each category is imbalance. We use random oversampling mechanisms to increase the number of samples from a randomly selected minority class by replicating the selected samples to a certain amount for the balance of the dataset [29]. The oversampling method is chosen because it is simple to understand and visualize. In our research, the dataset is up-samples so that the number of retinal images for each class label becomes 200 images. So, the total image becomes 3,000 retinal images.

C. Preprocessing

In this research, the retinal image dataset is resized by factors: 10%, 7.5% and 5% resulted in three resolution datasets namely: 61×70, 46×53, and 31×35 pixels respectively. Fig. 2 shows, the size comparison between the original image with image resizing results.

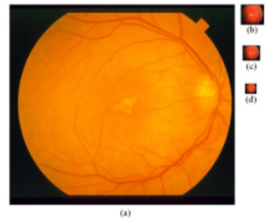

Fig. 2. Retina image from STARE dataset. (a) original image, (b-d) Resizing image to 61x70, 46x53 and 31x35 pixels

D. Classifier Configuration

Following LeCun [27], in this research, we used Convolutional Neural network (CNN) as classifier for retinal image classification. As stated by Karpathy *et al.* [28], architecture of CNN model enables researchers to build neural networks with many parameters to learn from a given input dataset to solve many classification problems.

Table II shows the proposed CNN architectural configuration.

TABLE II. CNN CONFIGURATION

Layer	*Layer Type*	*Number of Map and neuron*	*Kernel*
1	Input	1 map for each size of 61x70x3, 46x53x3 and 31x35 neurons	
2	Convolutional	20 maps for for each size of 61x70x3, 46x53x3 and 31x35 neurons	5 x 5
3	ReLU	20 maps for for each size of 61x70x3, 46x53x3 and 31x35x3 neurons	
4	Max Pooling	Stride=1	2 x 2
5	Fully Connected	For each size of image 3255, 2106 and 864 neurons	1 x 1
6	SoftMax	15 neurons	

E. Model Training and Cross-validation

The CNN model is then supervisedly trained using stochastic gradient rise with momentum as optimizer to minimize the lost as formulated in equation (1).

$$Loss = \frac{1}{N}\sum_{i=1}^{b}\sum_{j=1}^{b_i}\left(t_{ij} - o_{ij}\right)^2 \quad (1)$$

Where: t_{ij} be actual class of j^{th} sample of i^{th} training batch; t_{ij} be predicted class of j^{th} sample of i^{th} training batch; and N is the total training or testing samples.

In this research, cross-validation uses leave-one out technique. We use this method because based on experiments by [30] show that the leave-one-out cross-validation achieves training time seven times faster and have error rate considerably less than these of k-fold cross-validation. Using this technique, we divide the dataset into two parts randomly to become training dataset and testing dataset. Each category consisted of 200 images taken 75% or 150 images for training data and 25% or 50 images used for test data.

Finally, performance of the model is measured using accuracy metric which is computed using the following formula:

$$Accuracy = \frac{TF+TN}{N} \quad (2)$$

Where: TF is true positive; TN is true negative; and N is the total training or testing samples.

IV. Result and Discussion

Training process up to 100 epochs or 1700 iterations of the three types of input image resolutions of $61 \times 70, 46 \times 53$, and 31×35 pixels respectively are shown in Fig 3.

As can be seen from Fig 3, due to its input size, the longest training time is achieved with input size 61x70 pixels; whilst, the fastest training time is achieved with input size 31x35 pixels. As we expected, the greater input image resolution, the longer computational time will be.

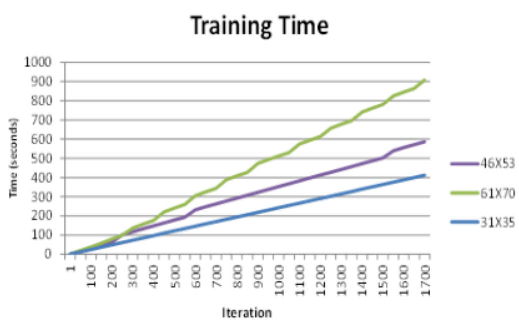

Fig. 3. The CNN training time

Training loss and accuracy rates of the CNN for all three types of image resolution are represented in Fig 4. As can be seen from Fig. 4, surprisingly, the highest training accuracy is achieved by the input image size 61×70 *and* 31×35 with an accuracy of 82.03%; whilst, training accuracy of the input image 46×53 pixel is 78.91%.

For training losses from 1700 iteration, the highest loss (37.75 %) is achieved from the smallest input image 31×35. Whilst, the loss from input images 46×53 is 42.80% and from input images 61×70 is 47.05%. Surprisingly, in this research, the higher input resolution, the higher accuracy and the lower losses are achieved.

Fig. 5 shows a comparison graph of training accuracy and test accuracy of each network model for input image sizes of $61 \times 70, 46 \times 53$ and 31×35 pixels. From Fig. 5 shows that the highest training accuracy is obtained from image input resolution 61×70 and 46×53 that is 82.03%, while the highest test accuracy is obtained from 31×35 input image resolution of 80.93%.

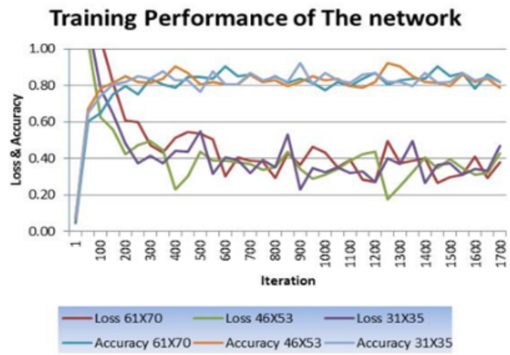

Fig. 4. Training performance of the three types of image input resolution

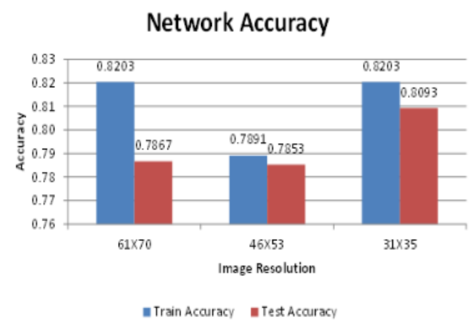

Fig. 5. The CNN training and testing accuracy

Table III shows the comparison of methods and results of previous researchers, it appears that although our method of accuracy is relatively lower but our contribution is our method of exploring deep-learning methods for the detection of fifteen retinal diseases based on the public STARE database, Other researchers to develop methods using the same dataset as ground truth.

TABLE III. Comparison with others method

Authors	*Classification Method*	*Number of diseases detected*	*Dataset*	*Accuracy*
Marin. et al [12]	A Neural network	1	STARE DRIVE	95.2% 94.5%
You. et al [19]	Support Vector Machines	1	STARE DRIVE	93.5% 94.3%
Kande. Et al [20]	Fuzzy C-Means clustering	1	STARE DRIVE	89.7% 89.1%
Palomera-Pérez,et al [21]	Multi-scale differential	1	STARE DRIVE	92.4% 92.2%
Ricci. et al [23]	Support Vector Machines	1	STARE DRIVE	96.4% 95.9%
Our method	Deep Learning	15	STARE	80,93%

V. CONCLUSION

Classification of retinal image will get benefit from robust classifier. Our experiments show that the highest training accuracy is obtained from input images measuring 61×70 and 31×35 pixels. Whilst, the highest test accuracy obtained from the network configuration used is the size of the input image with the smallest resolution of 31×35 pixels with an accuracy of 80.93%. Our next research plan will be to explore further on the various CNN configuration to obtain higher accuracy, such as selecting training algorithms for fully connected layers and the use of ensemble learning machines.

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