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A Deep Learning Method for Microaneurysm Detection in Fundus Images

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***Abstract*—Diabetic Retinopathy (DR) is the leading cause of blindness in the working-age population. Microaneurysms (MAs), due to leakage from retina blood vessels, are the early signs of DR. However, automated MA detection is complicated because of the small size of MA lesions and the low contrast between the lesion and its retinal background. Recently deep learning (DL) strategies have been used for automatic feature extraction and classification problems, especially for image analysis. In this paper, a Stacked Sparse Autoencoder (SSAE), an instance of a DL strategy, is presented for MA detection in fundus images. Small image patches are generated from the original fundus images. The SSAE learns high-level features from pixel intensities alone in order to identify distinguishing features of MA. The high-level features learned by SSAE are fed into a classifier to categorize each image patch as MA or non-MA. The public benchmark DIARETDB is utilized to provide the training/testing data and ground truth. Among the 89 images, totally 2182 image patches with MA lesions, serve as positive data, and another 6230 image patches without MA lesions are generated by a randomly sliding window operation, to serve as negative data. Without any blood vessel removal or complicated preprocessing operations, SSAE learned directly from the raw image patches, and automatically extracted the distinguishing features to classify the patches using Softmax Classifier. By employing the fine-tuning operation, an improved F-measure 91.3% and an average area under the ROC curve (AUC) 96.2% were achieved using 10-fold cross-validation.**

Keywords— deep learning; stacked sparse autoencoder; feature representation; automated microaneurysm detection; diabetic retinopathy.

I. INTRODUCTION

Diabetic retinopathy (DR) is an eye abnormality caused by long term diabetes and it is the most common cause of blindness before the age of 50 [1]. Microaneurysms (MAs) are the first sign of DR to be visible to an ophthalmologist, therefore the detection of MAs is critical to diagnose DR in its early stage. A number of methods have been proposed for the automated detection of MAs. Quellec et al. [2] described a supervised MA detection method based on template matching in wavelet-subbands. To advance the detection accuracy of MAs, the University of Iowa introduced the Retinopathy Online Challenge database and held international competition on MA detection [3]. The performance of five methods from the participating groups were reported after the first international competition. Reference [4] presented a method based on successive clutter rejection. In a recent work, a comprehensive grading system for DR was proposed [5]. The system can detect different signs of DR (including MAs) and classify the level of disease using a hybrid classifier.

Feature representation is a common and critical step for MA detection methods. Most of the existing MA detection methods reply on hand-crafted features. Deep learning (DL) approaches, famous for the strong learning ability to automatically extract high-level features, have been applied to medical image processing in recent years. Xu et al. [6] utilized a Stacked Sparse Autoencoder (SSAE), to extract features for nuclei detection. Our work is inspired by [6] since MA detection shares many similarities with nuclei detection. In this work, we employed SSAE as the automatic feature extractor to learn from the image patches with and without MAs. The learned features are fed into a Softmax Classifier (SMC) to categorize a patch into lesion-present or non-lesion-present classes.

II. STACKED SPARSE AUTOENCODER (SSAE)

A Stacked Sparse Autoencoder (SSAE) is an instance of a DL strategy, which can be constructed by incorporating multiple layers of Sparse Autoencoder. As shown in Fig. 1, a two-layered SSAE is formed and the Softmax Classifier (SMC) is connected to the second layer of SSAE to generate the final classification result. The first hidden layer extracts features from the raw image pixels while the second hidden layer continues extracting higher level features based on the output of the first layer. Please refer to [6] for details about SSAE and SMC.

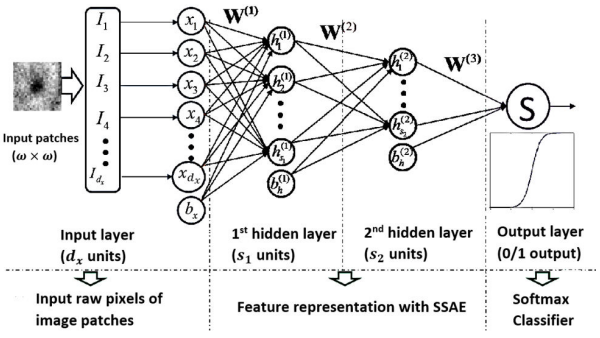

Fig. 1. Architecture of a Stacked Sparse Autoencoder (SSAE) with two hidden layers plus a Softmax Classifier (SMC)[1] [6].

1. Fig. 1 is adapted from paper [6]. Since we utilized the similar structure of SSAE and SMC as in [6], only slight changes are made to this figure.

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III. Experimental Setup and Results

A. Dataset

The public benchmark database DIARETDB is used to evaluate the proposed MA detection method. In this work, every marked MA lesion by any expert is considered as a positive sample. For each MA lesion, an image patch is generated by a 25×25 square window, with the annotated coordinates as the center. Among the 89 images in the database, totally 2182 MA lesions are annotated. The non-MA patches are randomly generated by identifying 25×25 square image windows whose centers were far away (greater than 25 pixels) from the annotated MA centers. The sample rate is 70 patches per image, therefore 6230 image patches are generated as negative data. On each round of the 10-fold cross-validation, SSAE and SMC models are trained using the image patches from 80 images and tested using image patches from the other 9 images.

B. Parameter setting

We use the green channel images. Before feeding the image patch into the network, a simple image adjust operation is done on each patch to scale the intensities into the whole range [0, 1]. Using all pixels of each image patch as input, there are 625 input units in the input layer. The numbers of neurons in the first and second hidden layers are $s_1 = 225$ and $s_2 = 100$, respectively. The training of the two SSAE layers are carried out one by one, and the training iterations for both layers are set as 100. The training iteration of the SMC is set as 50. The training iteration of the fine-tuning, is set as 5, to avoid over-fitting problem.

Our implementation of the SSAE and SMC is based on the online tutorial authorized by Dr. Andrew Ng and his group [7]. The default parameters are adapted directly.

C. Results

The average performance of 10-fold cross-validation is summarized in Table I. Six commonly used evaluation metrics are employed. They are precision, recall (sensitivity), F-measure, specificity, overall accuracy, and an average area under the ROC curve (AUC). The results of all metrics are improved after the fine-tuning operations. The ROC curves of the SSAE + SMC model before and after the fine-tunings are plotted in Fig. 2. Fine-tuning is shown as a powerful tool to improve the classification performance of SSAE+SMC model on the diabetic retinopathy database.

D. Patch-size tuning

Fig. 3 plots the F-measure of SSAE+SMC model with variable window size. It is shown patch size affects the performance dramatically without fine-tuning while fine-tuning can bring the performance to a steady and higher range.

TABLE I. Performance of the Proposed Method Before and After Fine-Tuning

Proposed Method	Lesion-level Evaluation					
	Precision (%)	Recall (%)	Specificity (%)	F-measure (%)	Accuracy (%)	AUC (%)
Before fine-tuning	88.50	86.52	88.73	87.42	87.62	93.41
After fine-tuning	91.57	91.16	91.60	91.34	91.38	96.20

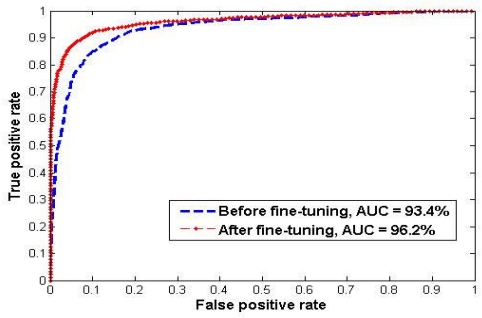

Fig. 2. ROC curves of the proposed method before and after the fine-tuning.

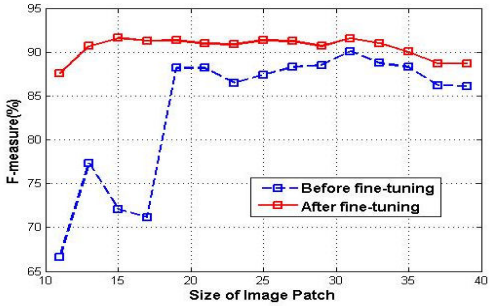

Fig. 3. F-measure of SSAE+SMC model with various patch sizes

IV. Conclusion

In this paper, a two-layered Stacked Sparse Autoencoder framework is presented for automated MA detection on fundus images. The SSAE model can capture high-level features from pixel-level input in an unsupervised learning manner. These high-level features enable the SMC classifier to detect MA lesions from fundus image with complicated background. The performance before and after fine-tuning are compared and it is shown that fine-tuning is helpful to boost the performance of patch classification. In future work, we will extend the experiment on more databases and vary the structures of SSAE for better characterization of MA lesions.

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