A Novel Hybrid Machine Learning Model for Auto-Classification of Retinal Diseases

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Abstract

Automatic clinical diagnosis of retinal diseases has emerged as a promising approach to facilitate discovery in areas with limited access to specialists. We propose a novel visual-assisted diagnosis hybrid model based on the support vector machine (SVM) and deep neural networks (DNNs). The model incorporates complementary strengths of DNNs and SVM. Furthermore, we present a new clinical retina label collection for ophthalmology incorporating 32 retina diseases classes. Using EyeNet, our model achieves 89.73% diagnosis accuracy and the model performance is comparable to the professional ophthalmologists.

1. Introduction

Computational Retinal disease methods (Tan et al., 2009; Lalezary et al., 2006) has been investigated extensively through different signal processing techniques. Retinal diseases is accessible to machine driven techniques due to their visual nature in contrast other common human diseases requiring invasive techniques for diagnosis or treatments. Typically, the diagnosis accuracy of retinal diseases based on the clinical retinal images is highly dependent on the practical experience of physician or ophthalmologist. However, not every doctor has sufficient practical experience. Therefore, developing an automatic retinal diseases detection system is important and it will broadly facilitate diagnostic accuracy of retinal diseases. For the remote rural area, where there are no ophthalmologists locally to screen retinal disease, the automatic retinal diseases detection system also can help non-ophthalmologists to find the patient of the retinal disease, and further, refer them to the medical center for further treatment.

The developing of automatic diseases detection (ADD) (Sharifi et al., 2002) alleviate enormous pressure from social healthcare systems. Retinal symptom analysis (Abramoff et al., 2010) is one of the important ADD applications. Moreover, the increasing number of cases of diabetic retinopathy globally requires extending efforts in developing visual tools to assist in the analytic of the series of retinal disease. These decision support systems for retinal ADD, as (Bhattacharya, 2014) for non-proliferative diabetic retinopathy have been improved from recent machine learning success on the high dimensional images processing by featuring details on the blood vessel. (Lin et al., 2000) demonstrated an automated technique for the segmentation of the blood vessels by tracking the center of the vessels on Kalman Filter. However, these pattern recognition based classification still rely on hand-crafted features

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Figure 2. The figure shows the result of U-Net tested on (a), an unseen eyeball clinical image. (b) is the ground truth and (c) is the generated result of U-Net. Based on (b) and (c), we discover that the generated result is highly similar to the ground truth.

and only specify for evaluating single retinal symptom. Despite extensive efforts using wavelet signal processing, retinal ADD remains a viable target for improved machine learning techniques applicable for point-of-care (POC) medical diagnosis and treatment in the aging society (Cochocki & Unbehauen, 1993).

To the best of our knowledge, the amount of clinical retinal images are less compared to other cell imaging data, such as blood cell and a cancer cell. Yet, a vanilla deep learning based diseases diagnosis system requires large amounts of data. Here we, therefore, propose a novel visual-assisted diagnosis algorithm which is based on an integration of support vector machine and deep neural networks. The primary goal of this work is to automatically classify 32 specific retinal diseases for human beings with the reliable clinical-assisted ability on the intelligent medicine approaches. To foster the long-term visual analytics research, we also present a visual clinical label collection, EyeNet, including several crucial symptoms as AMN Macular Neuroretinopathy, and Bull’s Eye Maculopathy Chloroquine.

Contributions.

- We design a novel visual-assisted diagnosis algorithm based on the support vector machine and deep neural networks to facilitate medical diagnosis of retinal diseases.
- We present a new clinical label collection, EyeNet, for Ophthalmology with 32 retina diseases classes.
- Finally, we train a model based on the proposed EyeNet. The consistent diagnostic accuracy of our model would be a crucial aid to the ophthalmologist, and effectively in a point-of-care scenario.

2. Methodology

In this section, we present the workflow of our proposed model, referring to Figure 1.

2.1. U-Net

DNNs has greatly boosted the performance of image classification due to its power of image feature learning (Simonyan & Zisserman, 2014). Active retinal disease is characterized by exudates around retinal vessels resulting in cuffing of the affected vessels (Khurana, 2007). However, ophthalmology images from clinical microscopy are often overlayed with white sheathing and minor features. Segmentation of retinal images has been investigated as a critical (Rezaee et al., 2017) visual-aid technique for ophthalmologists. U-Net (Ronneberger et al., 2015) is a functional DNNs especially for segmentation. Here, we proposed a modified version of U-Net by reducing the copy and crop processes with a factor of two. The adjustment could speed up the training process and have been verified as an adequate semantic effect on small size images. We use cross-entropy for evaluating the training processes as:

$$E = \sum_{x \in \Omega} w(x) \log(p_l(x))$$

(1)

where $p_l$ is the approximated maximum function, and the weight map is then computed as:

$$w(x) = w_c(x) + w_0 \cdot \exp\left(-\frac{(d_{x1} + d_{x2})^2}{2\sigma^2}\right)$$

(2)

d_{x1} designates the distance to the border of the nearest edges and $d_{x2}$ designates the distance to the border of the second nearest edges. LB score is shown as (Cochocki & Unbehauen, 1993). We use the deep convolutional neural network (CNNs) of two $3 \times 3$ convolutions. Each step followed by a rectified linear unit (ReLU) and a $2 \times 2$ max pooling operation with stride 2 for downsampling; a layer with an even x- and y-size is selected for each operation. Our proposed model converges at the 44th epoch when the error rate of the
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Retina Image Bank (RIB) is an international clinical

Principal component analysis (PCA) is a statistically
matrix-based method by orthogonal transformations.
We use PCA combined with SVM classifier to lower
the computing complexity and avoid the result of over-
fitting on the decision boundary. We optimize SVM
classifier with PCA at the 62nd principle component.

Support Vector Machine
Support Vector Machine is a machine learning tech-
nique for classification, regression, and other learning
tasks. Support vector classification (SVC) in SVM,
map data from an input space to a high-dimensional
feature space, in which an optimal separating hyper-
plane that maximizes the boundary margin between
the two classes is established. The hinge loss function
is shown as:

\[ \frac{1}{n} \sum_{i=1}^{n} \max(0, 1 - y_i(\vec{w} \cdot \vec{x}_i)) + \lambda \|\vec{w}\|^2 \]  \hspace{1cm} (3)

Where the parameter \( \lambda \) determines the trade off be-
tween increasing the margin-size and ensuring that the
\( \vec{x}_i \) lie on the right side of the margin. Parameters are
critical for the training time and performance on ma-
chine learning algorithms. We pick up cost function
parameter c as 128 and gamma as 0.0078. The SVM
has comparably high performance when the cost coeffi-
cient higher than 132. We use radial basis function
(RBF) and polynomial kernel for SVC.

3. Efforts on Retinal Label Collection
Retina Image Bank (RIB) is an international clinical
project launched by American Society of Retina Spe-
cialists in 2012, which allows ophthalmologists around
the world to share the existing clinical cases online
for medicine-educational proposes. Here we present
EyeNet which is mainly based on the RIB. To this
end, we manually collected the 32 symptoms from
RIB, especially on the retina-related diseases. Differ-
ent from the traditional retina dataset (Staal et al.,
2004) focused on the morphology analysis, our given
open source dataset labeled from the RIB project is
concentrated on the difference between disease for fea-
sible aid-diagnosis and medical applications. With
the recent success on collecting high-quality datasets,
such as ImageNet (Krizhevsky et al., 2012), we believe
that collecting and mining RIB for a more developer-
friendly data pipeline is valuable for both Ophthalmol-
ogy and Computer Vision community enabling develop-
ment of advanced analytical techniques.

4. Experiments
In this section, we describe the implementation de-
tails and experiments we conducted to validate our
proposed method.

4.1. Dataset
For experiments, the original EyeNet is randomly di-
vided into three parts: 70% for training, 10% for val-
ification and 20% for testing. All the training data
have to go through the PCA before SVM. All class-
sification experiments are trained and tested on the
same dataset.

4.2. Setup
The EyeNet has been processed to U-Net to gener-
ate a subset with the semantic feature of a blood
vessel. For the DNNs and Transfer Learning mod-
els, we directly use the RGB images from reti-
nal label collection. EyeNet is published online:
github.com/huckiyang/EyeNet

4.3. Deep Convolutional Neural Networks
CNNs have demonstrated extraordinary performance
in visual recognition tasks (Krizhevsky et al., 2012),
and the state of the art is in a great many vision-
related benchmarks and challenges (Xie et al., 2017).
With little or no prior knowledge and human effort
in feature design, it yet provides a general and effec-
tive method solving variant vision tasks in variant do-
 mains. This new development in computer vision has
also shown great potential helping/replacing human
judgment in vision problems like medical imaging (Es-
teva et al., 2017), which is the topic we try to address in this paper. In this section, we introduce several baselines in multi-class image recognition and compare their results on the EyeNet.

### 4.3.1. Baseline1-AlexNet

AlexNet (Krizhevsky et al., 2012) verified the feasibility of applying deep neural networks on large scale image recognition problems, with the help of GPU. It brought up a succinct network architecture, with 5 convolutional layers and 3 fully-connected layers, adopting ReLU (Nair & Hinton, 2010) as the activation function.

### 4.3.2. Baseline2-VGG11

VGG(Simonyan & Zisserman, 2014) uses very small filters (3x3) repeatedly to replace the large filters (5x5, 7x7) in traditional architectures. By pushing depths of the network, it achieved state-of-the-art results on ImageNet with fewer parameters.

### 4.3.3. Baseline3-SqueezeNet

Real world medical imaging tasks may require a small yet effective model to adapt to limited resources of hardware. As some very deep neural networks can cost several hundred megabytes to store, SqueezeNet (Iandola et al., 2016) adopting model compression techniques has achieved AlexNet level accuracy with ~500x smaller models.

### 4.4. Transfer Learning

We exploit a transfer learning framework from normalized ImageNet (Krizhevsky et al., 2012) to the EyeNet for solving the small samples issue on the computational retinal visual analytics. With sufficient and utilizable training classified model, Transfer Learning can resolve the challenge of Machine Learning in the limit of a minimal amount of training labels by means of Transfer Learning, which drastically reduce the data requirements. The first few layers of DNNs learn features similar to Gabor filters and color blobs and these features appear not to be specific to any particular task or dataset and thus applicable to other datasets and tasks (Yosinski et al., 2014). Experiments have shown significant improvement after applying pretrained parameters on our deep learning models, referring to Table 1 and Table 2.

### 4.5. Hybrid-SVMs Results

All SVM are implemented in Matlab with libsvm (Chang & Lin, 2011) module. We separate both the original retinal dataset and the subset to three parts included 70% training set, 20% test set, and 10% validation set. By training two multiple-classes SVM models on both original EyeNet and the subset, we implement a weighted voting method to identify the candidate of retina symptom. We have testified different weight ratio as Hybrid − Ratio, SVM model with {RGB Images: SVM model with U-Net subset}, between EyeNet and the subset with Vessel features to make a higher accuracy at Table 1. We have verified the model without over-fitting by the validation set via normalization on the accuracy with 2.31% difference.

### 4.6. Deep Neural Networks Results

All DNNs are implemented in PyTorch. We use identical hyperparameters for all models. The training lasts 400 epochs. The first 200 epochs take a learning rate of 1e-4 and the second 200 take 1e-5. Besides, we apply random data augmentation during training. In every epoch, there is 70% probability for a training sample to be affinely transformed by one of the operations in {flip, rotate, transpose} × {random crop}. Though ImageNet and our Retinal label collection are much different, using weights pretrained on ImageNet rather than random ones has boosted test accuracy of any models with 5 to 15 percentages, referring to Table 2. Besides, pretrained models tend to converge much faster than random initialized ones as suggested in Figure 4. The performance of DNNs on our retinal dataset can greatly benefit from a knowledge of other domains.

### 5. Conclusion and Future Work

In this work, we have designed a novel hybrid model for visual-assisted diagnosis based on the SVM and U-Net. The performance of this model shows the higher accuracy, 89.73%, over the other pre-trained DNNs models as an aid for ophthalmologists. Also, we propose the EyeNet to benefit the medical informatics research community. Finally, since our label collection
not only contains images but also text information of the images, Visual Question Answering (Huang et al., 2017b; c; a) based on the retinal images is one of the interesting future directions. Our work may also help the remote rural area, where there are no ophthalmologists locally, to screen retinal disease without the help of ophthalmologists in the future.

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