A Deep Learning Method for Microaneurysm Detection in Fundus Images

Thao Truong, Mentored by Lin Li, PhD
Department of Computer Science, Seattle University

SEATTLE U
COLLEGE OF SCIENCE AND ENGINEERING

Abstract

Diabetic retinopathy (DR) is an eye disease caused by long-term diabetes. Microaneurysms (MAs) is an indicator of DR when high blood sugar levels damage blood vessels in the retina and lead to vision loss or even blindness. In this work we propose a a deep learning method for MA detection in Fundus Images.

Introduction

DR is the leading cause of blindness if not detected and treated in time and is a serious complication of diabetes. Since DR is a progressive eye disease, the early detection and diagnosis of DR is important to prevent patients from blindness.

Existing studies have trained thousand of images to detect DR using different models such as CNN models AlexNet and GoogLeNet. These models have achieved high performance at detecting DR at its severe stage, but they have not performed well with DR's mild and moderate stages such as MA - the early sign of DR [1]. In this study we focus on the automated detection of MAs, using a deep learning technique.

Data and Methods

DR images were acquired from a public dataset - DIARETDB dataset of 89 mages, and from another public dataset - ROC datasets of 49 images. Both datasets consists of fundus images and sets of XML files that contains ground truth of radius and central points of MAs.

1. **Image Preprocessing**

Image preprocessing has involved several steps: Blood vessels are extracted into separate images using DenseBlock-Unet architecture for Biomedical Image Segmentation . Blood vessels are then removed from the extracted-green channel of the

Data and Methods (Cont.)

original RGB images to reduce the interference with the detection of MAs. We extract The green channel because it has the highest contrast compared to other color planes.

Figure1: Left: original color image; Middle: blood vessel of the original image; Right: green channel of the image with blood vessel removed.

2. **Data Augmentation**

Because of the limited dataset, we performed data augmentation to increase the number of pictures by rotating images in different angles.

3. **Training and Testing Model**

YOLOv3 model (You Only Look Once version 3) with prebuilt convolutional neural networks for object detection is used to train data[2]. It not only classifies the image into a category, but it can also detect multiple objects within an image. Before training, dataset is split into training set (248 images) and testing set (28 images). The model resized the image size into 832 x 832 pixels and divided into 64 batches to speed the training process. The model contains of 53 convolutional layers, each followed by batch normalization layer and Leaky ReLU activation. We performed training on GPU of Google Colab.

	Type	Filters	Size	Output
	Convolutional	32	3 × 3	256 × 256
	Convolutional	64	3 × 3 / 2	128 × 128
1×	Convolutional	32	1 × 1	
	Convolutional	64	3 × 3	
	Residual			128 × 128
	Convolutional	128	3 × 3 / 2	64 × 64
2×	Convolutional	64	1 × 1	
	Convolutional	128	3 × 3	
	Residual			64 × 64
	Convolutional	256	3 × 3 / 2	32 × 32
8×	Convolutional	128	1 × 1	
	Convolutional	256	3 × 3	
	Residual			32 × 32
	Convolutional	512	3 × 3 / 2	16 × 16
8×	Convolutional	256	1 × 1	
	Convolutional	512	3 × 3	
	Residual			16 × 16
	Convolutional	1024	3 × 3 / 2	8 × 8
4×	Convolutional	512	1 × 1	
	Convolutional	1024	3 × 3	
	Residual			8 × 8
	Avgpool		Global	
	Connected		1000	
	Softmax			

Figure2: YoloV3 Model

4. **Transfer Learning**

Transfer learning was conducted with the pretrained Darknet.conv.53 architectures from ImageNet. The transfer learning retains initial pretrained model weights and extracts image features via a final network layer.

Results

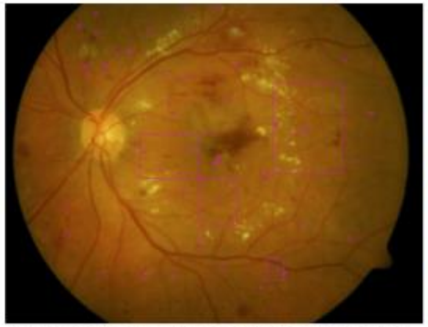

Figure3: A sample image to show the MA detection results using our approach - MAs marked by purple bounding boxes

Threshold	Precision	Recall	Average IOU	F1-score
15	52	28	30.01	37
25	51	28	29.89	36
50	36	20	24.55	26
75	8	4	6.48	6

Our approach achieved 26% accuracy. The lower threshold the higher accuracy score we could get. Since YOLOv3 needs at least 2000 images to train per each classification for real-time detection, our result arrived at low performance. We would like to have access to a larger dataset, to see how much we can improve accuracy with this model.

Conclusion and Future Work

In this work, we propose a deep learning approach for automated detection of MAs in fundus images. A possible reason for the low performance is the limited dataset. One of the future work will be collecting a large enough dataset to retrain the model.

References

[1] Lam C, Yi D, Guo M, Lindsey T. Automated Detection of Diabetic Retinopathy using Deep Learning. AMIA Joint Summits on Translational Science proceedings. AMIA Joint Summits on Translational Science. 2018 ;2017:147-155.

[2] AlexeyAB. (n.d.). AlexeyAB/darknet. Retrieved September 29, 2020, from https://github.com/AlexeyAB/darknet