DIAGNOSIS OF DIABETIC RETINOPATHY IN ETHIOPIA: BEFORE THE DEEP LEARNING BASED AUTOMATION

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ABSTRACT

Introducing automated Diabetic Retinopathy (DR) diagnosis into Ethiopia is still a challenging task, despite recent reports that present trained Deep Learning (DL) based DR classifiers surpassing manual graders. This is mainly because of the expensive cost of conventional retinal imaging devices used in DL based classifiers. Current approaches that provide mobile based binary classification of DR, and the way towards a cheaper and offline multi-class classification of DR will be discussed in this paper.

1 INTRODUCTION

DR is a complication caused when diabetes damages blood vessels in the retina. It is one of the leading causes of vision loss in adults aged between 20 and 65 years. Globally, in 2010, 0.8 million out of 34 million blind people, and 3.7 million out of 191 million visually impaired people were caused by DR [Leasher et al., 2016]. According to a 2015 report by IDF, there were more than 2.5 million cases of diabetes in Ethiopia [IDF, 2017].

1.1 PREVALENCE OF DIABETIC RETINOPATHY IN DIABETIC PATIENTS

To the best of the authors knowledge, prevalence of DR in Ethiopia have not been studied before 2016. That started improving after the World Diabetes Foundation (WDF) in partnership with the Ethiopian Diabetes Association (EDA) underwent two projects on improving DR diagnosis process in Ethiopia, one of which equipped 12 hospitals, in different regions of the country, with resources for DR diagnosis [WDF, 2012]. Various studies that targeted Ethiopian hospitals have shown high incidence of DR among diabetic people. By surveying studies performed in Oromia, Addis Ababa, SNNPR and Amhara regions, Fite et al. [2019] showed that overall prevalence of DR among diabetes patients in Ethiopia was at 19.48%.

2 CURRENT APPROACHES

2.1 DEEP LEARNING BASED CLASSIFICATION

If DR is not treated at early stages, it can lead to permanent vision loss or impairment. In order to proceed with medical treatment, ophthalmologists employ different retinal imaging techniques such as fundus photography. DL have been employed for automated diagnosis of DR from retinal images, and it has proven successful [Gulshan et al., 2016;Abramoff et al., 2018; Gulshan et al., 2019]. But these techniques have been seen to be expensive for diagnosis centers with limited budget. Shortage of trained ophthalmologists, and equipped healthcare centers are added challenges that affect availability of DR diagnosis in Ethiopia, especially the rural and remote areas.

1A leading diabetes and DR diagnosis center in Ethiopia, Diabetes Center at the Black Lion Hospital, isnt currently providing DR diagnosis service because their fundus camera failed, and they couldnt afford to replace or fix it.
2.2 Mobile based Diagnosis

A viable option to overcome the challenge with DL based diagnosis would be to incorporate a portable and cheaper retinal imaging device. A portable imaging device would make it easy to provide a point-of-care diagnosis. And, to circumnavigate shortage of professionals and diagnosis centers, DL algorithms could be used for automatic identification and classification of the disease. Portable fundus cameras in combination with smartphones have been proposed and used for internet based (Rajalakshmi et al., 2018) and offline (Sosale et al., 2020) DR detection. While internet based diagnosis systems communicate with a central server to classify fundus images, offline diagnosis provides an instant service that is carried out on a smartphone, starting from image capturing until displaying diagnosis results. Offline methods are preferred to internet based DR diagnosis systems for areas with limited or no availability of internet connection. Standalone smartphone based offline DR diagnosis methods that provide binary classification have been developed in Hagos et al. (2019) and Sosale et al. (2020). Smartphone based DR diagnosis systems require a handheld retinal image capturing device to be installed on a host phone’s camera. The Remidio Fundus on Phone (FOP) Non-mydriatic device, which was used for experimentation in Sosale et al. (2020), and oDocs nun (oDocs Eye Care, 2018) are some of the smartphone based fundus cameras on market.

Even though portable fundus cameras can be cheaper than conventional fundus cameras, one downside they have is the reduced quality of retinal images they capture (Gosheva et al., 2017). With a reduced image quality, let alone employing DL for identification, the chances of an ophthalmologist manually diagnosing for DR could get lowered (Yao et al., 2016). If image quality of portable fundus cameras could reach that of conventional cameras, it could lead the way towards providing a cheaper automated DR diagnosis for diabetic people residing in (rural) Ethiopia.

2.3 Performance of Deep Learning based Classifiers on Portable Fundus Cameras

Rogers et al. (2019) evaluated performance of a publicly available DL based DR classifier system, Pegasus (Visulytix, 2018), in identifying referable and proliferative DR, by performing binary classification on retinal images captured using a handheld fundus camera from 6404 patients. Although binary, Rogers et al. (2019) also goes on to report that performance of the DL classifier on portable fundus cameras was comparable with its classification performance on images collected using conventional fundus cameras.

Although not publicly available, retinal images have been collected using portable fundus cameras for automated classifiers’ performance evaluation (Rogers et al., 2019) and retinal images quality assessment purposes (Wang et al., 2015). To this date, and to the best of the author’s knowledge, the CHASE_DB1 (Kingston, 2011) is the only publicly available retinal pictures dataset, which have used handheld fundus cameras for data collection. The CHASE_DB1 dataset contains only 28 retinal images, which is insufficient if DL algorithms are to be used for DR identification (Lim et al., 2019).

2.4 The Curse of Binary Classification

In a study performed by Warwick et al. (2017), it has been seen that it can take more than 20 years until DR becomes sight threatening and requires medical treatment. Full DR diagnosis result that includes stage of the disease is necessary, in order for ophthalmologists to proceed with correct retinal treatment. Although the above offline mobile based DR diagnosis works can be seen as a good start, they don’t provide severity scales (which can be one of normal, mild, moderate, severe, and proliferative according to Wilkinson et al. (2003)) of DR as diagnosis result, and they can’t be used for early detection and treatment of the disease before vision loss or impairment is imminent.

3 Challenge Towards A Fully Offline Diabetic Retinopathy Diagnosis

Quality of retinal pictures collected by fundus cameras’ have been seen to be affected by Field of Views (FOV) and lens’ diameter (DeHoog & Schwiegerling, 2009). Higher FOV and smaller diameter are preferred camera properties. Even though conventional fundus cameras that are currently on the market seem to achieve these specifications, which helps in classifying DR into different
stages, portable fundus cameras output images of low quality; hence their use in binary classification only (Rogers et al., 2019; Sosale et al., 2020). Since identification of DR severity scale provides practitioners with the necessary information for treatment, automated fundus images classification systems should provide degree of DR by performing multi-class classification.

In the production of an offline, smartphone based, multi-class identifying DR diagnosis system for Ethiopia, the author recommends the development of a high quality portable fundus camera as the first priority over DL based fundus images classification. This is mainly because fundus images with reduced quality were found to be unsuitable for automated and manual diagnosis of DR (Yao et al., 2016; Lin et al., 2019). Producing high quality cameras would lead the way towards solving challenges associated with absence of medical equipments for diagnosing the disease (Foster & Resnikoff, 2005). It can be used as a mobile diagnostic equipment for manual DR grading. This can also help in collecting, and publicly providing dataset of fundus images, captured using handheld cameras, for the wider DL applications research community.

4 CONCLUSION

The challenge associated with providing DR diagnosis in Ethiopia could be solved by combining high quality portable fundus cameras and mobile application development. Classification performance of automated DR diagnosis (into one of the five stages) has been seen to surpass manual grading (Gulshan et al., 2019). After installing portable high quality fundus cameras to a smartphone, trained DR classifier models could be incorporated into a mobile application to provide instant diagnosis result. This approach could also be adapted to other underdeveloped countries with similar challenges.

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